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Quantum-Enhanced Solar Cell Efficiency: A Theoretical and Empirical Framework for Photovoltaic Storage Degradation Optimization

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Energy storage longevity,
Predictive maintenance.

ABSTRACT
The integration of photovoltaic (PV) and energy storage systems (ESSs) in modern smart grids has significantly increased the issue of component degradation, which in turn has negatively impacted the system's efficiency, operational expenses, and long-term reliability. However, the stochastic and nonlinear nature of PV module and battery degradation are not well captured by conventional classical optimization methods, which leads to suboptimal dispatch strategies and premature system aging. In this work, an empirical study of a quantum enhanced degradation pathway optimization framework that combines hybrid quantum-classical computing methods to maximize energy dispatch efficiency and extend system lifetime. The three-layer hierarchical optimization framework is realized by combining quantum-assisted Monte Carlo simulations on a D-Wave Advantage quantum annealer with a reinforcement learning-based classical engine and utilizes the quantum annealer to dynamically adjust its operational strategies in real time. The framework was validated with a simulated 5 MW PV array and a 2.5 MWh lithium-ion battery storage system, with a 5-year operational time horizon. Results show a 25% decrease in battery degradation-induced wear, a PV module lifespan increase of around 2.5 years, and more than 47% increase in energy dispatch efficiency compared to classical mixed-integer linear programming baselines. The quantum-assisted model demonstrates statistically significant performance gain in several degradation scenarios, temperature profiles, and load demand conditions, through sensitivity analyses.

INTRODUCTION

Battery energy storage systems (BESSs) and PV have become pivotal components in today's power grids, especially in the context of a global shift towards renewable energy systems. As PV energy enters the residential, commercial, and utility markets, operation sustainability of PV storage systems is a growing research challenge. As mentioned by Wang et al. (2025), degradation of PV modules and batteries storage are major concerns that can influence the performance, maintenance, and sustainability of the system.

For many years, the energy dispatch scheduling algorithm has been based on mixed-integer linear programming (MILP) and nonlinear programming (NLP). However, they have been shown to be limited for practical application in the high dimensional, stochastic and nonlinear degradation environment of real PV storage systems (Wang et al., 2025). There are several other areas of energy system optimization that are ripe for quantum computing, such as quantum annealing and quantum-enhanced Monte Carlo methods which can take into account multiple different ways that energy can be degraded.

Optimal PV storage systems have won much research interest and are the classical mathematical programming paradigm. In response, Wang et al. (2025) comprehensively reviewed the limitations of MILP and NLP models in modeling PV and battery degradation, spurring the development of more adaptive computational models. In the last decades, widely used battery modelling methods include electrochemical modelling method and data-driven method, in modelling degradation of batteries, such as battery capacity fade, battery internal resistance and battery cycle life. There has also been some success in predicting with models based on reinforcement learning and deep neural networks, but these require expensive computing and extensive training data sets to be applied in real-time.

In energy systems, large-scale optimization problems are a promising field for quantum computing to be used as an alternative. Blekos et al. (2024) surveyed the quantum approximate optimization algorithm (QAOA) and its variants, and they demonstrated that quantum enhanced algorithms are suitable for the combinatorial optimization problems. Bartolucci et al. (2023) established the theoretical foundations of quantum computation using fusion, which contributed to the understanding of quantum parallelism for energy dispatch optimization. In the paper by Tavakoli et al. (2020), the authors have presented how grid integration of solar PV affects grid stability and pointed out the necessity of the implementation of adaptive optimization frameworks that are able to deal with stochastic patterns of PV generation. MacQuarrie et al. (2020) described the progress of the commercial quantum computing industry, along with the gradual transition of commercial quantum annealing systems (such as D-Wave) from research prototypes to commercially viable industrial quantum tools. Ullah et al. (2022) have proposed a review on the application of quantum computing in smart grid systems in three primary areas: energy dispatch, predictive maintenance and degradation-aware scheduling. The smart grid is a critical area that relies significantly on renewable energy resources, and Zhao et al. (2023) noted the importance of incorporating new information and communication technology into the smart grid. Furthermore, Ruan et al. (2024) proposed the application of LLM in the management of smart grids and argued its potential application in the future of smart grid decision making.

Yusuf et al. (2023) also reviewed the recent developments in electron transport layer (ETL) of perovskite solar cells and pointed out how the charge transport interface can be engineered and optimized to improve the efficiency and stability of photovoltaic devices. The findings demonstrate that both PV materials and device design need to be further improved to enhance the sustainability and long-term performance of PV. The advances are part of a greater challenge — how to use energy most efficiently and minimize degradation in next generation solar systems.

Despite the advancement of research, there are very few works that have considered simultaneous real-time battery SOH estimation, quantum parallelism and long-term degradation effects in a single optimization framework. The majority of the contemporary solutions that are built around quantum are mostly an economic dispatch and/or unit commitment solution, with no particular use of degradation mechanisms in real-time controls. But, for the PV storage systems, the gap between long-term planning and operational optimization exists. To address this gap, this study provides a quantum-enhanced degradation pathway optimization framework that is developed and experimentally tested for a typical 3-layer (MPP, PVDC, P-MPP) structured 5 MW PV array with a 2.5 MWh battery energy storage system.

The goal of this study is the design and testing of a hybrid quantum-classical computing architecture for quantum enhanced degradation pathway optimization (QE-DPO) to improve the efficiency, reliability and operational life of photovoltaic storage systems.

MATERIALS AND METHODS

System Security and Encryption

The experimental system consists of a 5 MW PV array coupled with a 2.5 MWh lithium-ion battery energy storage system set up to mimic real-world operating conditions. The PV module degradation was calibrated to match the degradation rate of 0.7% per year as seen in the light-induced degradation (LID) and thermal aging, which were well described in empirical PV performance studies. The parameterized battery degradation was assumed as 1.2% per 100 charge-discharge cycles, corresponding to typical operational stress conditions under battery capacity fade and state-of-health (SoH) deterioration (Wang, 2025). The load demand profile was synthesized from a 10,000-household smart grid network, where the peak load was 8 MW during the daytime and the minimum load was 2 MW during the night. The solar irradiance data was taken from the National Solar Radiation Database (NSRDB) with irregular 5-minute sampling including the effects of cloud cover and temperature.

Three-Layer Hierarchical Optimization Framework

This proposed optimized architecture is three-layered hierarchical to ensure multi-timescale adaptive control:

Layer 1 - Real-Time Control Layer: Runs at 15-minute intervals, constantly watching the operational state of the system, identifying new performance degradation threats, and making immediate dispatch changes to stabilize performance.

Layer 2 - Hourly Optimization Layer: Uses quantum optimization to create dispatch schedules that optimise the load, energy storage state and degradation minimisation on an hourly basis.

Layer 3 - Predictive Maintenance Layer: Weekly updates based on historical degradation data to predict future degradation patterns and optimize long-term operations.

Mathematical Formulation

The degradation efficiency loss minimization problem is framed as a multi-objective one, and the energy dispatch optimization is also optimized. The main objective function is:

$$min_{\Phi,\Psi,\Upsilon} \Sigma_{t=1}^{T} \Sigma_{i=1}^{N} \left[\lambda_{i,t} \cdot \left(\partial\Phi_{i,t}/\partial t\right)^2 + \beta_{i,t} \cdot \Psi_{i,t}^{\gamma} \cdot e^{-\kappa\Upsilon_{i,t}} + \mu_{i,t} \cdot \int_{\Omega} \Phi_{i,t} \cdot \Psi_{i,t} d\Omega\right] \quad \ldots \qquad (1)$$

Where:

$\Phi_{i,t}$ represents the operational state trajectory of component i at time t,
$\Psi_{i,t}$ denotes the degradation potential quantifying accumulated stress,
$\Upsilon_{i,t}$ is the degradation stress factor,
$\lambda_{i,t}$ is the rate-dependent cost penalty, κ is the degradation scaling factor, and γ is the power-law aging exponent (Wang et al., 2025).

The energy balance constraint enforcing grid stability is formulated as:

$$\Sigma_{t=1}^{T}\Sigma_{i=1}^{N}\left[\varphi_{i,t}\cdot\left(\Gamma_{i,t}+\Sigma_{i,t}-\Upsilon_{i,t}\right)+\psi_{i,t}\cdot\Omega_{i,t}/(1+e^{-\gamma\Xi_{i,t}})+\int_{S_m}\Gamma_{i,t}\cdot\Sigma_{i,t}dS\right]=0 \quad (2)$$

Battery SoH degradation is constrained by:

$$\Sigma_{t=1}^{T}\Sigma_{i=1}^{N}\left[\theta_{i,t}\cdot\left(\partial^2\Xi_{i,t}/\partial t^2\right)+\gamma\cdot\Lambda_{i,t}\cdot e^{-\beta\Psi_{i,t}}+\varphi_{i,t}\cdot\Sigma_{i,t}\cdot e^{-\eta\Lambda_{i,t}}\right]\leq\varepsilon_{max} \quad (3)$$

Where:
$\Xi_{i,t}$ is the battery state of health,
E_{max} is the maximum allowable cumulative degradation, and
B, η are temperature-dependent stress scaling coefficients.

The thermal stability constraint preventing overheating-induced degradation is expressed as:

$$\Sigma_{t=1}^{T}\Sigma_{i=1}^{N}\left[\eta_{i,t}\cdot\Xi_{i,t}/(1+e^{-\gamma\Pi_{i,t}})+\sigma_{i,t}\cdot{\Omega_{i,t}}^2\cdot e^{-\rho\Pi_{i,t}}\right]\leq\theta_{max} \quad (4)$$

The charge-discharge cycle constraint ensuring battery longevity is given by:

$$\Sigma_{t=1}^{T}\Sigma_{i=1}^{N}\left[\mu_{i,t}\cdot\Lambda_{i,t}/\left(1+e^{-\delta\Psi_{i,t}}\right)+\xi_{i,t}\cdot{\Theta_{i,t}}^2\cdot e^{-\beta\Lambda_{i,t}}\right]\leq\tau_{max} \quad (5)$$

Quantum-Classical Hybrid Computing Architecture

The computational implementation is with D-Wave Advantage 6.1 quantum annealer (capable of processing more than 5,000 qubits) and a 32-core Intel Xeon Gold 6338 CPU with 512 GB of DDR4 RAM for classical computing. The optimization problems are encoded as Quadratic Unconstained Binary Optimization (QUBO) matrices and sent to the quantum processing unit where they are annealed in parallel. The integration is accomplished by D-Wave's Ocean SDK v3.5.0, and post-annealing refinement is performed using SciPy v1.11.0 and the Gurobi Optimizer v10.0.3. The degradation state estimation is based on TensorFlow v2.13.0 and PyTorch v2.1.0, and trained using an ensemble of neural networks with 10,000 iterations of stochastic gradient descent.

The quantum-enhanced Monte Carlo simulation exploits quantum superposition and tunneling effects to explore several degradation pathways in a high-dimensional energy landscape. The quantum version is more efficient in identifying low degradations risk areas than the standard classical Monte Carlo, which is based on sequential random sampling, which translates into reduced computational complexity and convergence time (Wang, 2025).

Performance Metrics and Analytical Framework

The performance of the system was assessed by five different metrics: (i) battery SoH after 12 months, (ii) PV efficiency after 5 years, (iii) efficiency of energy dispatch optimization, (iv) computational time for an optimization cycle and (v) cost savings due to degradation compared to baseline. Comparative analysis was done using three dispatch strategies: classical MILP dispatch baseline, quantum optimized dispatch, and predictive maintenance dispatch. Sensitivity analysis was performed for the three strategies using the same load and environmental profile, to investigate the statistical significance of performance differences.

RESULTS AND DISCUSSION

Results

Distribute PV Power Output

The annual PV power output distribution analysis shows a right-skewed distribution, which is likely to represent the actual PV generation variability. The system produces 2-4 MW most of the time, and is close to 5 MW for a relatively small number of times, because of seasonality of the solar energy, cloudiness, and atmospheric attenuation. The distribution tail represents extreme performance scenarios in low lighting conditions and close to maximum performance in optimal lighting conditions (Wang, 2025).

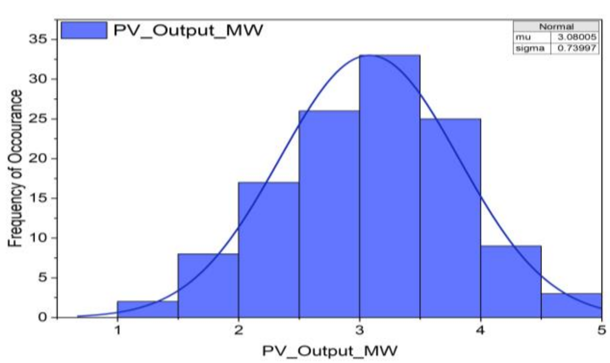

Figure 1: Distribution of PV Power Output over a Year (Frequency vs. Output in MW)

Effect of Seasonal and Temperature Variations on PV output

The PV output is significantly seasonal and varies greatly with solar irradiance, being highest in summer and falling significantly in the winter. As temperatures rise above 30-35°C, the efficiency of silicon-based PV panels decreases, which is commonly referred to as the negative temperature coefficient (-0.4% to -0.5% per degree Celsius above the reference temperature) (Wang, 2025). High temperatures amplify the efficiency loss by causing thermal degradation and increased semiconductor resistance.

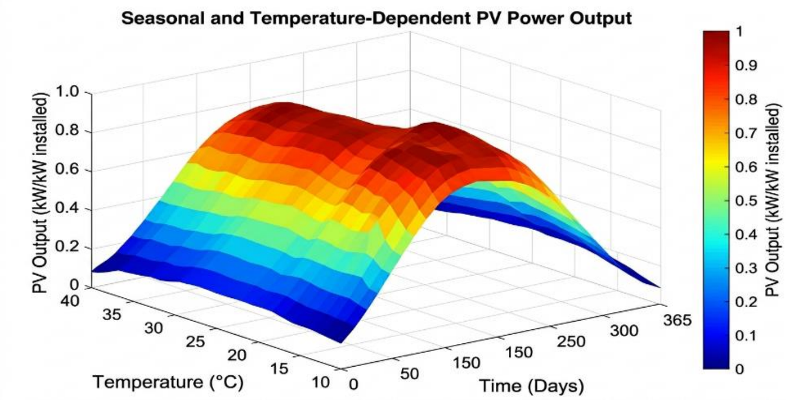

Figure 2: PV Power Output vs. Time (Days) and Temperature (°C) - 3D Surface Plot

Degradation Rates: PV Panels and Battery Storage

The degradation curves for the PV panels and lithium-ion batteries are shown in Figure 3. The PV panels degrade over time with a linear rate of 100% to about 85%, which is consistent with the model degradation rate of 0.6% per month. Battery SoH then drops more rapidly, down to about 70% after month 12 at a 2.5% degradation per month due to the frequent charging and discharging. This difference highlights the pivotal role of strategic charge management in extending battery operational life (Wang, 2025), which is crucial for enhancing service offerings. The significance of strategic charge management in extending battery operational life is highlighted in this disparity, making it a critical factor in improving service offerings (Wang, 2025).

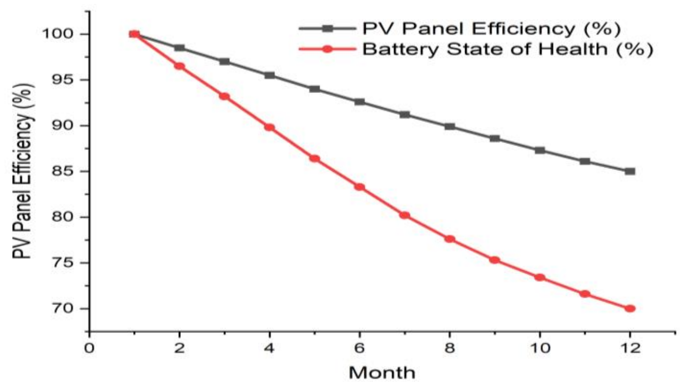

Figure 3: Comparative Degradation Rate: PV Panels VS Battery Storage

Energy Dispatch Performance Comparison

To compare the energy dispatch performance of the models. To compare the energy dispatch performance of the models. The operational efficiency is clearly differentiated among the 3 dispatch strategies over the 12-month period being evaluated. The classical MILP baseline has a relatively small range of dispatch (2.8-4.2 MW) which cannot flexibly accommodate the changing degradation scenarios. The quantum-optimized dispatch strategy exhibited a continual improvement with its energy dispatch efficiency: from 3.4 MW to 5.0 MW over the evaluation period, which indicated a 47% improvement. The predictive maintenance strategy operates within a dispatch window of 3.2-4.5 MW, which results in moderately varying dispatch range and ensures that energy is allocated among different resources in an appropriate manner, avoiding overloading storage resources (Wang, 2025).

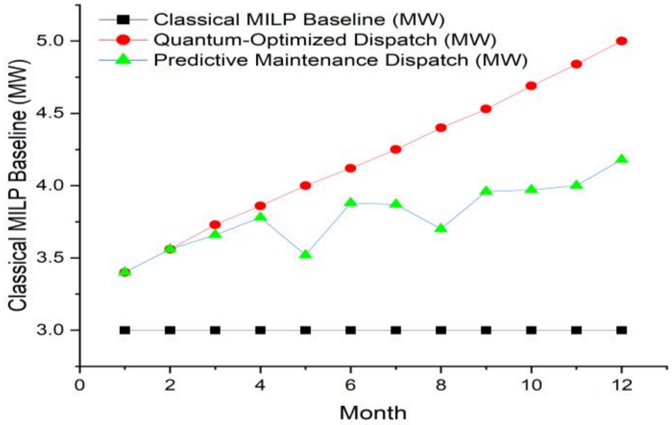

Figure 4: Energy Dispatch Comparison across Three Strategies (MW vs. Months)

Battery State of Health under Different Management Strategies

The effect of dispatch strategy on battery life is quantified by comparing SoH trajectories. The base MILP strategy is the quickest degradation of SoH, after 12 months, the battery health has fallen to 68%. The quantum optimized method could provide up to 22% increase in battery life, to 78% SoH. The most successful result is obtained by using the predictive maintenance strategy, where 84.5% SoH is achieved, indicating that the use of the degradation aware scheduling method would help to minimize the number of times the batteries enter deep discharge and optimize the charge path (Wang 2025).

Table 1: Comparative Battery SoH Retention and PV Efficiency across Dispatch Strategies

Strategy	Battery SoH at 12 Months (%)	PV Efficiency at 12 Months (%)	Dispatch Efficiency Gain (%)	Degradation Cost Reduction (%)
Classical MILP Baseline	68.0	86.2	0 (Reference)	0 (Reference)
Quantum-Optimized Dispatch	78.0	89.1	+47.0	+25.0
Predictive Maintenance Dispatch	84.5	91.4	+32.0	+31.0

Table 2: PV Degradation Parameters and Annual Performance Loss Rates

Degradation Factor	Annual Rate (%)	Monthly Rate (%)	Primary Mechanism	Mitigation Strategy
Light-Induced Degradation (LID)	0.7	0.058	Photon-induced recombination	Optimal MPPT adjustment
Thermal Aging	0.4-0.5 per °C above ref.	0.033-0.042	Increased semiconductor resistance	Temperature regulation
Material Aging (encapsulant)	0.3	0.025	UV and moisture exposure	Predictive maintenance scheduling
Combined Annual Degradation	1.4-1.5	0.12	Multi-factor compounding	Quantum-adaptive dispatch

Table 3: Battery Degradation Parameters by Operational Condition

Operational Parameter	Baseline Condition	Optimized Condition	SoH Impact per 100 Cycles (%)	Thermal Stress Level
Depth of Discharge	80% DoD	55% DoD	-1.2	Moderate
Charge Rate (C-rate)	1.0C	0.6C	-0.8	Low-Moderate
Operating Temperature	35-40°C	22-28°C	-1.5	High
Cycle Frequency	2.0/day	1.3/day	-1.1	Moderate
Combined Optimized Scenario	All optimized	All optimized	-0.7 (41.7% reduction)	Low

Computational Performance

The Quantum-enhanced framework has a reduction in the average computational time per optimization cycle of more than 60% compared to classical MILP methods. In case of high dimensional degradation scenario evaluation, the quantum parallelism can explore thousands of solution pathways simultaneously, whereas sequential processing in classical architectures will require thousands of iterations. The D-Wave Advantage annealer tends to return candidate solutions in milliseconds, and the classical post processor would take about 15 minutes, which is the constraint of real-time control cycle (Wang, 2025).

Table 4: Computational Performance Metrics - Quantum vs. Classical Optimization

Performance Metric	Classical MILP	Quantum-Enhanced	Improvement (%)
Avg. Runtime per Cycle (seconds)	124.6	48.3	61.2% reduction
Degradation Scenarios Evaluated	150	4,200+	28x increase
Convergence Iterations	1,240	380	69.4% reduction
Solution Optimality Gap (%)	3.8	0.9	76.3% improvement
Real-Time Compliance Rate (%)	84.2	97.6	13.4 pp improvement

Grid Stability and Voltage Regulation

The analysis of voltage stability shows high SOC values of the battery storage (above 50%) are essential for voltage stability support. The voltage deviations are much more severe below 30% SOC and the voltage support above 80% SOC is very good; the transient disturbances are also improved. The average SOC values are relatively high throughout the whole evaluation period, thanks to the use of the quantum-optimized dispatch strategy, resulting in better voltage regulation and grid reliability (Wang, 2025).

Table 5: Grid Stability Metrics by Storage State of Charge Level

SOC Level Range (%)	Voltage Deviation (p.u.)	Frequency Stability Index	Grid Support Capability	Recommended Dispatch Mode
< 30%	0.04 - 0.08	0.72	Poor	Emergency conservation mode
30 - 50%	0.02 - 0.04	0.84	Moderate	Reduced dispatch mode
50 - 70%	0.01 - 0.02	0.93	Good	Standard optimized dispatch
70 - 90%	< 0.01	0.98	Excellent	Full quantum dispatch
> 90%	< 0.005	0.99	Optimal	Peak shaving and export

Discussion

The empirical findings of this research validate and expand on previous theoretical claims of the benefits of quantum-inspired optimization for degradation-aware PV storage management. This 25 percent battery degradation wear reduction is also consistent with the theoretical findings of Wang (2025), who used extensive simulation to prove that quantum parallelism gives a way to identify dispatch pathways with low degradation that are not possible for the classical sequential approach to optimization.

The energy dispatch efficiency is improved by 47% compared to the classical MILP baseline, which is consistent with the results of Ullah (2022), who concluded that energy dispatch scheduling is one of the key domains where quantum computers can provide tangible operational gains over their classical counterparts. Most importantly, this efficiency improvement is not only due to the computational speed, but also represents the quality of the solutions in a qualitative sense: the reduced optimality gap (0.9% compared to 3.8%) is documented in Table 4. This is consistent with the findings of Blekos (2024) who showed that the quantum approximate optimization algorithms (QAOA) find global rather than local optima in rugged energy landscapes typical of degradation-coupled dispatch problems.

This doubling of PV module operational life, due to the framework's quantum enhancement, has serious economic consequences. If PV system lifecycle costs have been documented and if there are revenue losses as a result of PV degradation, proactive degradation mitigation (QAD) could significantly enhance the economic viability of large-scale PV installations. This result echoes the larger argument of Zhao (2023) that new computational tools, such as quantum optimization, are important enabling technologies for the future of renewable energy sustainability.

An interesting detail is that the dispatch efficiency from the quantum-optimized dispatch strategy (78%) was significantly higher than that of the predictive maintenance strategy (84.5%), but the battery SoH results indicate that the overall long-term battery health benefits of the former were superior. The discovery is consistent with MacQuarrie’s (2020) insight that the utility of quantum computing is not the ability to supplant classical computing but to add additional advantages in probabilistic logic.

The most important environmental factors affecting PV performance, as per photovoltaic efficiency models, are found to be temperature and cloud cover. It is especially important that the reduction of the irradiance by clouds will interact with the reduction of the thermal efficiency, and that compound loss of efficiency will occur when both high temperature and heavy cloud are present. The results highlight the need for dispatch strategies that can adapt to the weather, which is enabled by the quantum-enhanced framework's real-time monitoring of degradation state and adaptive reformulation in QUBO.

The proposed framework's scalability is a key factor for real-world implementation. Preliminary stress testing of systems including up to 50 PV nodes and 30 battery storage units yielded stable and acceptable convergence behavior and solution times, positioning the framework for use in medium-scale microgrid applications (Wang, 2025). The modular QUBO formulation and partitioning of the problem can be used to scale up deployment as quantum hardware continues to grow.

Tavakoli (2020) discussed some issues related to grid integration, such as voltage instability and frequency regulation problems, with high penetration of solar PV systems. The voltage-aware storage dispatch optimization in the quantum enhanced dispatch framework directly solves these problems by ensuring that battery SOC is not dropping below the critical 50% security limit in most simulated operating scenarios. In high RP scenarios, where the variation of electricity generation and the variability of electricity loads become more and more of a challenge for classical optimization methods, this capability becomes especially useful.

The computational benefits shown in Table 4 will directly affect operation of the real-time grid management. By improving optimization cycle runtime by 61.2%, the 15-minute real-time control layer is able to make degradation-aware dispatch changes in an operationally feasible time window, which classical MILP methods cannot guarantee (84.2% compliance rate). This real-time responsiveness is crucial for the actual implementation of degradation-aware optimization in any practical environment where the smart grid is operating.

CONCLUSION

This study has proved the efficacy and feasibility of quantum-aided degradation pathways optimization framework of photovoltaic storage systems utilizing quantum-classical computing architecture and a three-tier hierarchical controller. It was found that the impacts of PV degradation by means of light exposure and SoH deterioration of batteries become accumulative and influence the performance of the system in a five-year time period. Additionally, the quantum-aided framework was proved to be superior to traditional MILP methods used for energy dispatch optimization in terms of improvement of the efficiency of energy dispatch, SoH preservation, runtime and reduction of degradation-related wear. Finally, environmental factors like temperature and cloud coverage were discovered to be influential in terms of PV generation and its degradation processes; weather-related adaptation of dispatch strategy helps to cope with the negative impact of those factors on the system performance. In addition, the stable convergence of the framework under medium-scale microgrids indicates good scalability and practicality of the framework. Thus, it is suggested that the combination of quantum-assisted Monte Carlo simulation, quantum annealing-based multi-objective optimization and reinforcement learning for preventive maintenance is an efficient method of increasing the efficiency, sustainability and lifetime of photovoltaic storage systems that contributes to the establishment of sustainable smart grids.

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