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Development Of an AI-Driven Supercapacitor-Integrated Control System for Real-Time Mitigation of Power Fluctuations in Hybrid Solar-Wind Energy Networks

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***Abstract-** The increasing penetration of hybrid solar-wind energy systems into modern electric power networks is fundamentally constrained by rapid and stochastic power fluctuations that degrade voltage stability, power quality, and system reliability. This study focused on an AI-driven supercapacitor-integrated control system for real-time mitigation of power fluctuations in hybrid solar-wind energy systems. A comprehensive modeling architecture was developed, incorporating photovoltaic and wind power generation, DC-link dynamics and a supercapacitor-based hybrid energy storage system. An artificial intelligence control strategy, formulated as a Markov Decision Process, was deployed to dynamically regulate supercapacitor charge-discharge activities under varying environmental and load conditions. The developed system was validated using high-fidelity time-domain simulations and hardware-in-the-loop (HIL) testing to assess real-time feasibility. Results demonstrated effective stabilization of the DC-link voltage within permissible limits, millisecond-scale control latency and well-regulated supercapacitor voltage and state-of-charge dynamics under severe power fluctuations. The system achieved a high overall efficiency (92.5%), low voltage harmonic distortion (3.1%), competitive energy cost (0.11 USD/kWh), and substantial annual CO_2 emission reduction (1450 kg). These findings confirm that integrating fast-acting supercapacitor storage with AI-based control significantly enhances power quality, stability, and sustainability in hybrid renewable systems. It is recommended that future work focus on large-scale field deployment and extension to multi-layer energy storage architectures to further improve grid resilience and renewable hosting capacity.*

***Keywords:** Solar, Wind, Hybrid, Renewable, AI, Supercapacitor, Photovoltaic, Electricity.*

I. INTRODUCTION

The rapid rise in global energy demand, added to the escalating concerns over climate change and carbon emissions, has accelerated the transition toward renewable energy-based power generation. Among all renewable energy options, wind and solar energy dominance persists due to their accessibility and technical simplicity, [1]. Hence, hybrid renewable energy systems (HRESs), particularly those integrating solar photovoltaic and wind generation have emerged as a promising pathway for achieving sustainable, reliable, and low-carbon electricity supply by leveraging the complementary characteristics of multiple renewable resources.

Despite these potentials, the inherent intermittency and stochastic variability of solar irradiance and wind speed pose substantial challenges to the stable and reliable operation of HRESs particularly in off-grid areas, [2], [3], [4], [5] and [6]. These fluctuations often result in power imbalance, voltage deviations, and increased stress on power electronic interfaces, thereby threatening grid stability, particularly in high-renewable-penetration and weak-grid environments.

In addition, the hybridization of solar and wind sources is not adequate in meeting power demands, [7], hence, energy storage systems play a critical role in mitigating these challenges by smoothing short-term power fluctuations and supporting continuous power delivery. Among the various storage technologies, supercapacitors have attracted growing attention due to their high-power density, rapid

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charge-discharge capability, and exceptional cycle life.

These characteristics make supercapacitors particularly well suited for managing fast transient events and enhancing the dynamic response of hybrid renewable energy systems. Despite their advantages, power management solutions come with both their advantages and limitations. By simultaneously improving energy efficiency, reducing operational costs, and strengthening system reliability, these systems play a critical role in enabling the large-scale and stable integration of renewable energy technologies, [8]. Hence, an optimized framework incorporating intelligent energy-storage systems into HRES remains the game changer for modern power management systems.

However, the effective utilization of supercapacitors within hybrid renewable architectures is highly dependent on the development of advanced control strategies capable of coordinating energy exchange in real time. Consequently, the design of intelligent and adaptive control schemes for supercapacitor-integrated hybrid renewable systems remains a critical research focus for achieving stable, efficient, and resilient renewable power generation.

This adoption of intelligent hybrid solar-wind systems is highly recommendable for real-time data capture and analysis, predictive and swift response to load demands and dynamic electric energy management especially in rural and weak-grid settings, [9].

Several authors have studied the solar-wing energy hybrid primarily focusing on solving this associated variability and intermittency. For instance, [8], used a battery backed-up with a supercapacitor to integrate solar energy in electric vehicles. Their results showed an improved performance with respect to the traditional battery system. Similarly, [10], deployed an Internet of Things (IoT)-enabled solar-wind energy hybrid to improve sustainability, scalability, reliability, cost-effective and eco-friendly framework for rural settings.

Likewise, [11], demonstrated the application of IoT-enabled monitoring and data acquisition to comparatively evaluate the effects of different power supply architectures on the performance, degradation characteristics, and longevity of energy storage batteries in electric vehicle charging infrastructure.

Also, [7], proposed a hybrid energy storage smoothing approach for a grid-integrated wind–PV system, in which a battery and an electric double-layer capacitor were jointly utilized to attenuate renewable power variability and improve output stability. Furthermore, [12], explored the integration of a Maximum Power Point Tracking driven programable charge controller accompanied with a hybrid storage comprising of a battery and supercapacitor to mitigate renewable energy variability and intermittency.

The charge controller was noticed to reduce both current fluctuations and Total Harmonic Distortion. Despite the ongoing progress, the integration of AI-based control with supercapacitor-assisted storage and real-time validation remains insufficiently explored making it the primary focus of this study.

II. MATERIALS AND METHODS

2.1 Research Design and Methodological Framework

This study adopted a model-based, simulation-driven, and hardware-in-the-loop (HIL) validated research design.

It aimed at developing and rigorously evaluating an AI-driven supercapacitor-integrated control system for real-time mitigation of power fluctuations in hybrid solar-wind energy systems. The methodological framework integrated a power system modeling, an intelligent control design, and a real-time validation, ensuring both analytical rigor and practical relevance.

The research workflow was sequentially structured to address the study objectives. First, the dynamic behavior of the hybrid solar-wind system under stochastic environmental and load conditions was modeled and analyzed. Next, a supercapacitor-based hybrid energy storage system (S-HESS) was designed to buffer high-frequency power fluctuations.

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Then, an AI-optimized control strategy was formulated to coordinate energy exchange in real time. Also, the proposed controller was validated using a HIL testbench to assess real-time feasibility. Finally, system performance was evaluated using technical, economic, and environmental metrics.

The adoption of simulation and HIL testing mitigated the high cost and safety risks associated with full-scale experimental deployment while enabling repeatable, controlled, and high-fidelity evaluation of fast transient dynamics. Although field deployment was beyond the scope of this study, the adopted framework provided a scalable and credible pathway toward practical implementation

2.2 System Architecture and Data Sources

2.2.1 Hybrid Solar-Wind Energy System Configuration

The investigated system comprised a photovoltaic (PV) subsystem, a wind energy conversion subsystem, a common DC-link coupling stage, a supercapacitor-based energy storage system, and an AI-driven control unit supplying a variable load/grid interface. Both renewable sources (solar and wind) were interfaced to a common DC bus via power electronic converters, enabling coordinated energy management and explicit observation of power fluctuation dynamics.

The PV subsystem was modeled using a nonlinear equivalent circuit capturing the influence of solar irradiance and temperature while the wind subsystem was modeled as a variable-speed wind turbine coupled to a permanent magnet synchronous generator (PMSG), allowing realistic representation of wind-induced power variability.

2.2.2 Nature and Sources of Data

The study relied predominantly on secondary datasets and simulation-generated data. This was followed as an established and widely accepted methodology in renewable energy and power systems research due to its cost-effectiveness, controllability, and reproducibility.

The datasets employed included: solar irradiance and ambient temperature data obtained from standard meteorological databases; wind speed and turbulence profiles derived from global wind datasets; dynamic load demand profiles representative of residential and commercial consumption; supercapacitor electrical and lifecycle parameters obtained from manufacturer datasheets; system state variables including DC-link voltage, current, and power flow generated through time-domain simulations. These datasets supported comprehensive system modeling, AI controller training, HIL validation, and performance assessment under diverse operating scenarios.

2.3 Power Fluctuation Modeling and Analysis

Power fluctuation behavior was characterize using the developed detailed mathematical and simulation models of the hybrid solar-wind system. Time-domain simulations were conducted to analyze system dynamics under stochastic variations in irradiance, wind speed, and load demand.

Key fluctuation metrics were extracted from simulation outputs including amplitude, ramp rate, and dominant frequency components. The DC-link voltage deviation was adopted as the primary indicator of system stability and power quality. To evaluate system robustness, sensitivity analyses were further performed under extreme operating scenarios, such as abrupt irradiance drops, wind gusts, and sudden load changes.

This analysis provided a quantitative insight into the magnitude and temporal characteristics of power fluctuations that the energy storage and AI-based control system must mitigate.

2.4 Renewable Power Output Modeling

2.4.1 Photovoltaic Power Model

The PV output power was expressed as:

$$P_{PV}(t) = \eta_{PV} A_{PV} G(t)\left[1 - \alpha\left(T_c(t) - T_{ref}\right)\right]$$

(3.1)

where η_PV is the PV efficiency, APV is the Panel area (m²), G(t) is Solar irradiance (W/m²), α is the temperature coefficient and Tc (t) is the Cell temperature (°C).

2.4.2 Wind Turbine Power Model

The wind turbine output power (PWT) was presented as:

$$P_{WT}(t) = \frac{1}{2}\rho A_{WT} C_p(\lambda, \beta) v^3(t)$$

(3.2)

Where ρ is the air density, AWT is the rotor swept area, Cp is the power coefficient and v(t) is the wind speed

2.4.3 Hybrid Power Output (PH)

$$P_H(t) = P_{PV}(t) + P_{WT}(t)$$

(3.3)

Where P_H (t) is the Total hybrid power (kW), P_PV (t) is the PV output power (kW) and P_WT (t) is the wind turbine output power (kW).

2.5 DC-Link Voltage Dynamics

The DC-link voltage dynamics capturing power imbalance effects were described by:

$$C_{DC}\frac{dV_{DC}}{dt} = \frac{P_{PV}+P_{WT}+P_{SC}-P_L}{V_{DC}}$$

(3.4)

This represented the dynamic behavior of the DC-link voltage in response to power imbalances between generation, storage, and load in the hybrid solar–wind energy system.

Also, the DC-Link Capacitance physically stored energy (E_DC) according to:

$$E_{DC} = \frac{1}{2} C_{DC} V_{DC}^2$$

(3.5)

where V_DC (Volts) = DC-Link Voltage

Also, the right-hand side of equation 3.4 represents the net power imbalance on the DC bus such that when:

$$P_{PV} + P_{WT} + P_{SC} > P_L$$

the DC-link voltage increases.

While when:

$$P_{PV} + P_{WT} + P_{SC} < P_L$$

the DC-link voltage decreases.

Hence, the DC-link capacitor absorbs or releases energy to compensate for short-term mismatches until corrective control action is taken. This shows that the DC-link voltage served as the principal stability indicator, with its rate of change reflecting the severity of instantaneous power imbalance.

Therefore, equation (3.4) formed the core dynamic constraint for the AI-based controller, whose objective was to regulate supercapacitor power (PSC) such that:

$$V_{DC} \approx V_{DC,ref}$$

2.6 Supercapacitor-Based Hybrid Energy Storage System (S-HESS)

An S-HESS was designed to buffer transient power surges and sags. The supercapacitor was modeled using an equivalent circuit incorporating capacitance, equivalent series resistance (ESR), and leakage effects:

$$V_{SC}(t) = V_{SC,0} - \frac{1}{C_{SC}}\int_0^t i_{SC}(\tau)d\tau - i_{SC}R_{ESR}$$

(3.6)

Where V_SC (t) is the Supercapacitor terminal voltage (V) indicating instantaneous energy availability, V_(SC,0) is the initial voltage (V) defining initial stored energy, C_SC is the capacitance (F) determining the energy storage capacity, i_SC (t) is the charging/discharging current (A) governing the power exchange rate and R_ESR is the equivalent series resistance (Ω) representing the internal losses and voltage drop.

The SoCSC which expressed the usable energy level of the supercapacitor relative to safe voltage limits and was given by:

$$SoC_{SC}(t) = \frac{V_{SC}^2(t) - V_{min}^2}{V_{max}^2 - V_{min}^2}$$

(3.7)

Where V_(SC,max) and V_(SC,min) are the Maximum allowable voltage and Minimum safe voltage respectively. Sizing of the supercapacitor bank was based on maximum observed power fluctuation, allowable voltage deviation, and required response time. Lifecycle considerations were incorporated to ensure long-term operational viability.

2.7 AI-Optimized Control Algorithm

The energy management problem was formulated as a Markov Decision Process (MDP). The state vector was defined as:

$$S_t = [P_{PV}(t), P_{WT}(t), P_L(t), V_{DC}(t), SoC_{SC}(t)]$$

(3.8)

Where P_PV (t), P_WT (t), P_L (t), V_DC (t)and SoC_SC (t) are the PV power output as solar contribution, Wind power output for wind variability, Load demand for defining the power requirement, DC-link voltage as the stability indicator and Supercapacitor SoC for Storage availability respectively.

$$A_t \in \{\text{Charge}, \text{Discharge}, \text{Idle}\}$$

(3.10)

The action space comprises charging, discharging, or idle states. The reward function penalizes voltage deviation, power mismatch, and excessive supercapacitor usage:

$$R_t = -\left(w_1 \mid V_{DC} - V_{DC,ref} \mid + w_2 \Delta P + w_3 \Delta SoC_{SC}\right)$$

(3.9)

where Rt = Instantaneous reward, V_(DC,ref) = Desired DC-link voltage, ΔP =Power mismatch magnitude and ΔSoC_SC=Rate of SoC variation respectively.

(3.11)

$$\gamma \in (0,1)$$

(3.12)

where γ is the discount factor controlling the weight given to future rewards.

2.8 Hardware-in-the-Loop (HIL) Implementation

A HIL testbench was implemented to validate real-time performance. The AI controller was deployed on embedded hardware and interfaced with a real-time simulated plant. The control latency was modeled as:

$$T_{latency} = T_{sampling} + T_{computation} + T_{PWM}$$

(3.13)

where T_latency = Total control delay, T_sampling = Sensor acquisition time, T_computation = Controller execution time and T_PWM = Actuation delay Also, the stability Constraint Parameter which ensured that the controller reacted faster than power system dynamics such that:

$$T_{latency} \ll T_{system}$$

(3.14)

where Tsystem = Dominant system time constant

2.9 Performance Evaluation Metrics

System performance was assessed using: the Voltage Deviation Index (VDI), Power Fluctuation Reduction Ratio (PFRR), CO_2 emission reduction, and Cost per kWh (CKWH).

The Voltage Deviation Index (VDI) which is the average voltage deviation was given by:

$$VDI = \frac{1}{T}\int_0^T \mid V_{DC}(t) - V_{DC,ref} \mid dt$$

(3.15)

where T is the Observation period.

The Power Fluctuation Reduction Ratio (PFRR) is given by:

$$PFRR = \frac{\sigma_{uncontrolled} - \sigma_{controlled}}{\sigma_{uncontrolled}}$$

(3.16)

where σ is the standard deviation of power

The CO_2 Emission Reduction is given by:

$$CO_2 = E_{renewable} \times EF_{grid}$$

(3.18)

where Erenewable is the Renewable energy delivered and the EFgrid is the Grid emission factor Cost per kWh (CKWH) as an Economic Performance Parameters is given by:

$$C_{kWh} = \frac{C_{cap}+C_{op}}{E_{lifetime}} \quad (3.17)$$

where Ccap is the Capital cost,
Comparative analysis was conducted across systems with no storage, conventional control, and the proposed AI-driven S-HESS.

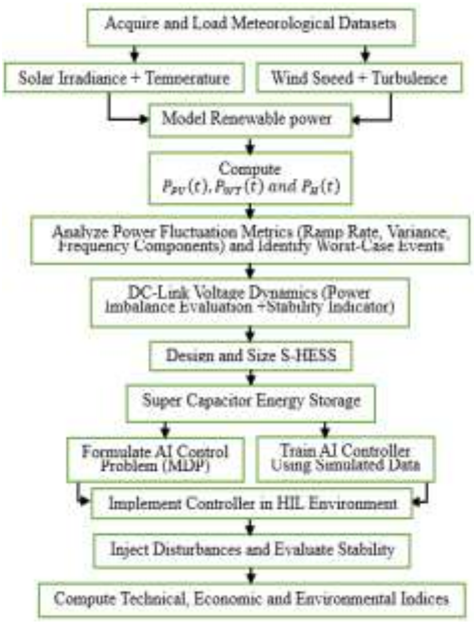

Fig. 1: Methodological flowchart of the proposed AI-driven control framework

III. RESULTS

Fig.1 shows the time dependent variations in both PV and wind power outputs deduced from solar irradiance and wind speeds. From the results, it can be noticed that the PV output demonstrated a relatively moderate power levels ranging from 3 to 14KW. Its daily variabilities that reflect a dependence on irradiance conditions like cloud cover highlights an intermittent but partially predictable feature. Unlike the PV output, the wind power results displayed produced substantial power ramps with a strong variability fluctuating between 3 to 19KW.

It also showed sudden changes and irregular patterns which are consistent with the stochastic nature of wind speed and turbulence. Also, the load demand exhibited pronounced fluctuations, with several sharp peaks reaching about 23–25 kW and troughs around 6–8 kW. These showed a highly dynamic and non-stationary load profile common with mixed residential-commercial consumption. A key observation from the graph is the frequent mismatch between total renewable generation (PV + wind) and load demand as there are multiple periods where load demand exceeds the instantaneous renewable supply, as well as intervals where renewable generation surpasses demand.

These mismatches result in power imbalance, such that, without adequate energy storage and control can lead to DC-link voltage deviations, decline in power quality and energy deficiency. The discrepancies between the hybrid power generation vs load demand as well as the frequent and sudden changes in demand validates the necessity for a swift energy management and buffering mechanisms using storage and intelligent control to maintain system stability.

Although hybridization of solar and wind sources reduced long-duration variability compared to single-source systems, short-term fluctuations persisted, supporting the findings of [13], that hybrid renewable energy systems still require rapidly responsive energy storage for effective stabilization. This validates the necessity of incorporating a high-power-density storage device such as a supercapacitor for transient mitigation.

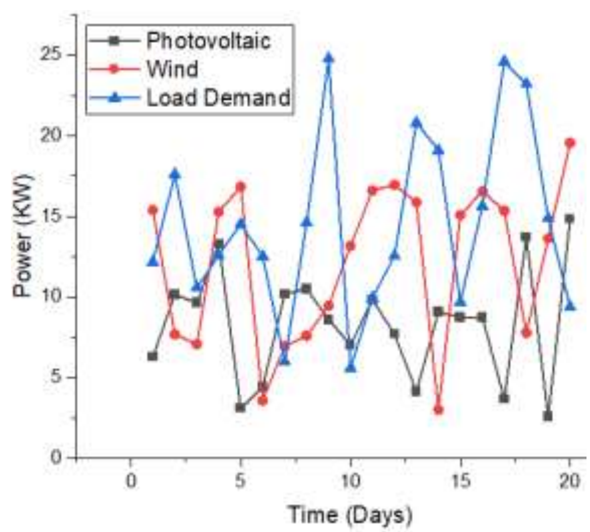

Fig. 2: Time-domain variation of PV and wind power outputs with load demands

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Hence, fig. 2 demonstrates significant temporal mismatch between hybrid renewable generation and load demand, highlighting the necessity of swift energy storage and intelligent control for real-time power fluctuation mitigation.

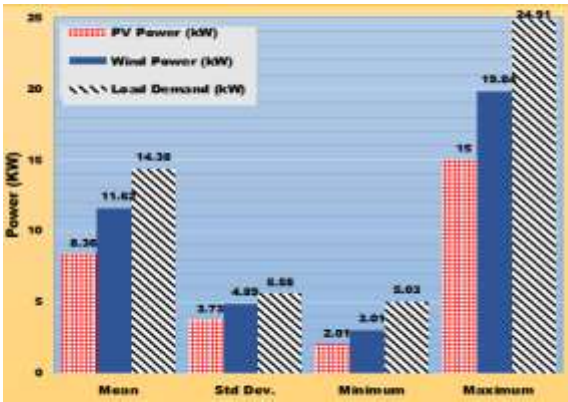

Fig. 3: Statistical Analysis of Hybrid Power Outputs

Fig. 3 displayed the statistical indicators providing quantitative insights into the relative magnitude and variability of renewable generation and system demand. This shows that the average load demand (≈ 14.38 kW) exceeds the mean PV power (≈ 8.36 kW) and wind power (≈ 11.63 kW). This persistent demand dominance implies that, on average, neither PV nor wind generation alone is sufficient to satisfy system load, underscoring the necessity of coordinated hybrid generation and energy storage support.

Evidently, the standard deviation of the load demand (≈ 5.58 kW) is higher than that of both PV (≈ 3.73 kW) and wind power (≈ 4.85 kW), revealing that load demand exhibits stronger temporal fluctuations. This heightened variability imposes additional stress on the energy management system, as rapid demand changes must be met through fast-response control and buffering mechanisms. The minimum power values further highlight the intermittency challenge. PV power reaches a minimum of approximately 2.01 kW, while wind power drops to about 3.01 kW, indicating periods of severely reduced renewable generation.

During such intervals, the load demand remains comparatively higher (minimum ≈ 5.03 kW), resulting in significant generation–demand deficits that must be compensated by energy storage or external grid support. On the other hand, the maximum values show that wind power (≈ 19.84 kW) surpasses PV power (≈ 15.00 kW) during favorable wind conditions, while load demand peaks at about 24.91 kW. These peak demand conditions exceeding instantaneous renewable supply, reinforces the need for storage-assistance back-up and dynamic power balancing.

In summary, the statistical trends in Fig. 3 complementing fig. 2 to confirm the non-stationary and asymmetric nature of renewable generation and load demand. The concurrency of high demand variability, intermittent generation minima, and peak demand events provides strong justification for the integration of a supercapacitor-based hybrid energy storage system and an AI-driven control strategy capable of mitigating short-term power imbalances and maintaining system stability.

The observed high-frequency fluctuations in both generation and demand support the integration of a supercapacitor-based energy storage system. This justifies a fast-response buffering that conventional battery-only systems configurations discussed by [14] may struggle to provide. This finding supports previous studies by [15] which demonstrated that supercapacitor-supported systems extend battery lifespan by isolating batteries from transient power demands. The results therefore confirm that supercapacitors are effective for short-duration power smoothing but require intelligent coordination to achieve optimal performance.

Likewise, fig. 4. illustrates the real-time temporal evolution of the supercapacitor (SC) terminal voltage and state of charge (SoC). These profiles provide direct evidence of the supercapacitor's role as a swift buffer for mitigating short-term power imbalances in the hybrid solar-wind system. It can be seen that the SC voltage displayed moderate fluctuations relative to the renewable source outputs showing an effective regulation of the DC-link through controlled charge-discharge actions.

The absence of voltage drifts suggests that the supercapacitor operated within safe electrical limits and that the control strategy successfully prevented overvoltage or deep depletion events. Contrarily, the SC state of charge (SoC) displayed rapid and frequent oscillations between about 35% to 98%). These sharp rises and drops reflect the supercapacitor's intended function of absorbing excess power during generation surpluses and injecting power during demand or generation deficits.

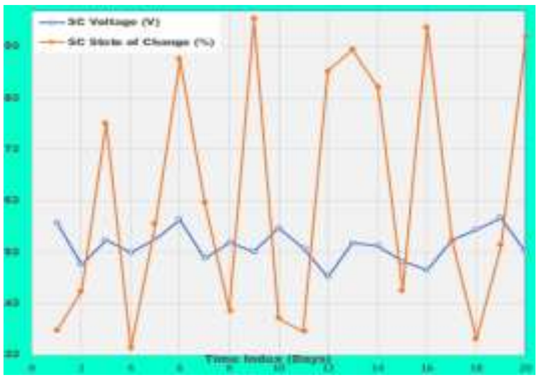

Fig. 4: Supercapacitor terminal voltage and state of charge

Hence, this demonstrates that the supercapacitor is actively engaged in transient power compensation rather than long-term energy storage. Remarkably, periods of rising SoC coincide with relatively stable or slightly increasing SC voltage, indicating effective charging during renewable power surplus events. Contrarily, sharp reductions in SoC correspond to controlled discharge episodes, during which the supercapacitor supplies power to support the DC-link voltage under deficit conditions.

The decoupling between large SoC swings and relatively small voltage variations validated its suitability for high-frequency power fluctuation mitigation further confirming the effectiveness of the control strategy in exploiting the supercapacitor's voltage-energy relationship while maintaining system stability. Hence, the coordinated behavior of SC voltage and SoC highlights the effectiveness of the proposed control approach in leveraging fast energy storage to stabilize the hybrid renewable system without imposing excessive electrical stress on the storage device.

Fig. 5 presents the real-time temporal profiles of DC-link voltage and control latency providing insight into both the electrical stability of the hybrid renewable system and the responsiveness of the proposed control framework.

It can be noticed that the DC-link voltage remained confined within a relatively narrow operating band of about 380–420 V, despite the stochastic variations in renewable generation and load demand. The absence of persistent overvoltage or undervoltage conditions demonstrated that the control strategy successfully maintained DC-link stability under dynamic operating conditions. Hence these voltage fluctuations confirmed the adequacy of the supercapacitor-assisted control in compensating for instantaneous power imbalances.

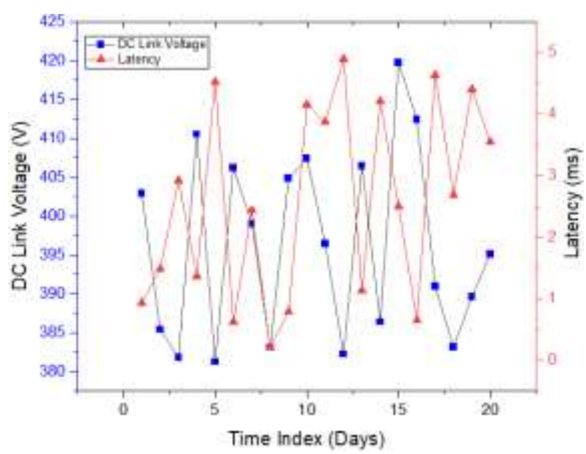

Fig. 5: Real-time DC-Link Voltage Regulation Statistics and HILL control latency

Also, the control latency curve remained consistently low (<5ms) and within acceptable limits for fast power electronic control. This indicated that the developed AI-based controller operated with sufficient computational efficiency to respond to rapid system dynamics without introducing destabilizing delays. Hence, the results demonstrated that the proposed control architecture achieved simultaneous voltage stability and low-latency operation, validating its suitability for real-time implementation in hybrid solar–wind energy systems.

Therefore, the combined performance of stable DC-link voltage regulation and millisecond-level

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response time reinforces the feasibility of deploying the AI-driven supercapacitor-integrated controller in practical, renewable-rich power networks.

Table 1 summarizes the technical, economic, and environmental performance indicators of the developed AI-driven supercapacitor-integrated hybrid solar-wind energy system. The results indicated a strong overall system performance across multiple evaluation dimensions. For instance, the system efficiency of 92.5% indicated a highly effective energy conversion and power management within the hybrid architecture. This high efficiency was reflected as reduced conversion losses, effective coordination between renewable sources and the supercapacitor-based storage system, and minimal energy dissipation during transient compensation. Such efficiency levels are indicative of well-optimized power electronic interfacing and intelligent real-time control.

Table 1: Performance Evaluation Summary

Metric	Value
System Efficiency (%)	92.5
Voltage THD (%)	3.1
Cost per kWh ($/kWh)	0.11
CO_2 Emission Reduction (kg/year)	1450

Likewise, the voltage Total Harmonic Distortion (THD) was maintained at 3.1%, which was well below the limits prescribed by international power quality standards like the IEEE 519. This confirmed that the proposed control strategy not only stabilizes voltage magnitude but also preserves waveform quality, thereby ensuring compatibility with sensitive electrical loads and grid interconnection requirements.

Similarly, from an economic perspective, the cost of energy was estimated at $0.11 per kWh, highlighting the cost-effectiveness of the proposed system. This value reflects efficient utilization of renewable resources, reduced reliance on conventional grid energy, and lifecycle cost benefits arising from the use of supercapacitors to mitigate excessive battery cycling and associated degradation. In addition, considering environmental impact, the system achieved an estimated CO_2 emission reduction of about 1450 kg per year, demonstrating a substantial contribution to decarbonization.

This reduction was attributable to increased renewable energy penetration and improved system efficiency, which together displace fossil-fuel-based electricity generation. Generally, the metrics presented in Table 1 confirmed that the proposed AI-driven supercapacitor-integrated control system delivered a high efficiency, excellent power quality, economic viability, and meaningful environmental benefits, reinforcing its suitability for deployment in sustainable hybrid renewable energy networks.

IV. CONCLUSION

This study presented the design, development, and validation of an AI-driven supercapacitor-integrated control system for real-time mitigation of power fluctuations in a hybrid solar-wind energy system. A comprehensive modeling architecture was established, incorporating detailed representations of photovoltaic generation, wind energy conversion, DC-link dynamics and supercapacitor-based hybrid energy storage.

An AI-optimized control strategy formulated as a Markov Decision Process was developed to coordinate energy exchange under stochastic operating conditions and validated through hardware-in-the-loop testing. The results demonstrated that the proposed control framework effectively stabilized the DC-link voltage under rapid and irregular variations in renewable generation and load demand.

Also, the supercapacitor exhibited fast and well-regulated charge-discharge behavior, confirming its suitability for high-frequency power buffering. In addition, the supercapacitor's control latency remained within millisecond-scale limits, ensuring real-time responsiveness without compromising system stability. Furthermore, the system achieved high overall efficiency, maintained voltage harmonic distortion within international standards, and delivered tangible economic and environmental benefits, including reduced energy cost and significant CO_2 emission reduction.

Collectively, these findings confirm that integrating fast-acting supercapacitor storage with intelligent, AI-based control architecture can provide a robust and scalable solution to the most critical challenges in renewable-rich power systems being short-term power imbalance and power quality degradation.

By addressing both theoretical and practical dimensions of hybrid renewable energy control, this framework offered a practical and scalable pathway toward enhancing reliability, stability, and sustainability in future hybrid low-carbon renewable energy power systems.

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