Power Quality Enhancement in Hybrid Renewable Systems Using Reinforcement Learning-Based Inverter Control

[1]Sanjay Ahirwar, [2]Amit Kumar Asthana
[1]Research Scholar, Department of Mechanical Engineering, Truba Institute of Engineering & Information Technology Bhopal (M.P.) India
[2]Assistant Professor, Department of Mechanical Engineering, Truba Institute of Engineering & Information Technology Bhopal (M.P.) India

ahirwarsanjay110@gmail.com, asthana603@gmail.com

* Corresponding Author: Sanjay Ahirwar

Abstract:

The need for dependable, effective renewable systems has driven the need for hybrid solar–wind systems with sophisticated inverter controls. The objective of this study is to use MATLAB/Simulink to prototype and study a grid-connected hybrid energy system with the aim of reducing harmonic distortion and reactive power, improving overall power quality, and meeting renewable energy standards. The solar and wind subsystems are modeled and integrated through DC–DC converters. The integration to the common AC using inverters is also modeled. Two control methods were tested: the traditional voltage reference–based space vector modulation (SVM) controller and the Q-learning–based reinforcement learning (RL) controller. Metrics such as active and reactive power output, power factor, and total harmonic distortion (THD) were measured and tested under steady and dynamic loads. Comparing the two methods shows that the RL controller beats the conventional method by increasing active power from 17,020 W to 17,800 W (4.5% improvement), raising the power factor from 0.89 to 0.93, and lowering reactive power from 817.8 VAR to 480 VAR. The THD test for harmonics also showed a considerable enhancement as voltage THD dropped from 4.92% to 1.59% and current THD from 11.20% to 10.04%. The RL controller delivered more stable current waveforms during transient load switching, with THD levels of 6.03% at loading and 13.33% at off-loading compared to 6.04% and 14.13% deliver by the reference-based controller. All of these results indicate that, with regard to stability and energy quality for hybrid renewable energy systems, inverter control using reinforcement learning is adaptive, scalable, and computationally efficient.

Keywords: *Microgrids, Renewable Distributed Energy Sources, Hybrid Energy Systems, Source-Side Control, Power Quality, Artificial Intelligence*

I. INTRODUCTION

The ever-growing global thirst for electricity, paired with the imperatives of climate change, has fast-tracked the intrusion of R-DESs, such as solar PV, wind turbines, biomass, and small hydro systems. Centralized-type grids have depended so much on fossil fuels, thus making them environmentally unsustainable and highly vulnerable to destabilization caused by transmission losses and increased load demand [1]. In this regard, microgrids have risen to stay as an important paradigm of the new-age power systems consisting of localized, self-sufficient energy systems working toward distributed generation, storage units, and controllable loads [2]. Figure 1describes schematic diagram of a microgrid.

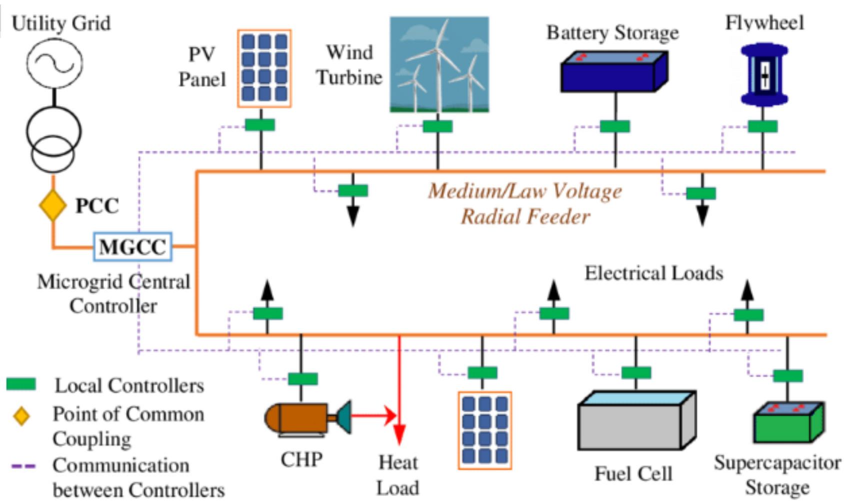

Figure 1: Schematic diagram of a Microgrid

A microgrid is a fantastic solution that contributes to reliability, resilience, and flexibility, as it can operate grid-tied or islanded and may, therefore, be considered a type of distributed generation (DG) or autonomous generation [3]. Within this paradigm, AC microgrids have arrived at center stage due to their compatibility with existing infrastructures, ease of integration with conventional utility grids, and maturity with respect to standards and technology adoption [4]. Modular by nature, they typically host DERs and ESS within a scheme inter-connected by AC bus lines and hierarchical control structures such as voltage control, frequency control, or economic dispatch [5]. Anarray of applications exist for AC Microgrids in rural electrification, industrial clusters, smart cities, military installations, and disaster recovery [6].

Nevertheless, the intermittency and variability of such resources greatly pose thick operational problems. Solar and wind, for example, are weather-dependent and mostly unpredictable, thus power frequently fluctuates [7]. To overcome such problems, the concept of hybrid systems came to existence where a couple of renewable resources and conversion and storage technologies are combined to ensure that such culture had continuous and stable power out-put. Solar and wind resources have such an occurrence of complementarities-natural solar production peaks in the afternoon, while the wind picks up more often at night-so they're making better use of the available resources [8]. And on the other hand, the ESSs are enhancing the reliability of the supply by compensating the fluctuations, improving the power quality, and supporting the load during peak hours [9].

Source-side control is an essential component in the reliable operation of an AC microgrid with heavy penetration of renewables. It covers everything at the generation side, including control of voltage, frequency, real power, and reactive power flow. Until recently, droop control methods were the most popular, giving decentralized capacity sharing with almost no communication [10]. However, with advanced penetration of renewable energy sources and nonlinear load conditions, the trends show an inclination towards MPC, fuzzy logic, adaptive controllers, and AI-based techniques [11]. These methods maintain stability in near real time in both grid-connected and islanded modes by improving their adaptability in real time, enhancing power-sharing accuracy, and reducing the total harmonic distortion (THD) level [12].

There are several challenges that need to be addressed, even after great technological advancements. Synchronization to the grid remains difficult due to different input characteristics generated by different DERs [13]. Threats to cyber security have increased because of high degrees of digitalization within microgrid controls, where false signals, energy thefts, or system disturbances could take place [14]. Furthermore, the reliance on ESS raises concerns regarding the costs, degradation, and sustainability of its lifeline [15]. To counter these, intelligent control architecture and adaptive control infrastructure are required. Such solutions would integrate renewables optimally when accounting for security and economy.

II. RELATED WORK

To further improve the source-side control of AC microgrids, a hybrid adaptive PI controller was proposed that integrated droop control and virtual impedance control. The use of artificial neural networks to adaptively tune the PI controller gains led to enhancements in voltage regulation, power sharing, and total harmonic distortion (THD) as per the IEEE-519 standards. The controller's performance was evaluated primarily through simulations and smaller testbeds, but real-time, larger-scale testing continues to be elusive, primarily due to computational overheads [1]. Adaptive droop control underpinned by system identification significantly improved the microgrid inverter performance. While it optimized transient response and small-signal stability enhancement under operating point changes, it did so by fine-tuning droop parameters through online adaptation. Improvements related to model inaccuracies, communication delays, and resilience in the presence of noise or cyber-induced disturbances remained unaddressed [2]. The power-sharing transient phase was the focus of another methodology, which attempted to guarantee that inverter-based DGs could share abrupt load increments effectively. By doing so, it avoided the overloading of single inverters [3], which, in turn, sustained system stability. Precise parameter tuning and required coordination limited this approach, and the adaptability of this method for different inverter systems with various ratings was, however, not fully explored [3]. Additional modifications to the traditional droop and virtual impedance approaches were made to try to eliminate the interdependence between active and reactive power while trying to minimize the error in load sharing. This was accomplished without the use of communication networks. The modifications made to these methods improved the overall efficiency of the system, which made their performance in unbalanced network scenarios with high levels of renewable energy integration inadequate [4]. Fixed-switching-frequency MPC improved dynamic regulation, current tracking accuracy, and switching frequency stability, and these MPC methods were used in inverter systems. Still, as with most MPC-related techniques, their application in multi-inverter systems operating in the presence of communication delays, owing to the high computational requirements and reliance on fast solvers, is not scalable [5].

More recently, distributed MPC frameworks have been put forward for the control of microgrid frequency, where distributed nodes optimize their operation in a collaborative manner subject to local constraints. Collaboration among nodes enabled asynchronous operation, enhanced system resilience, and improved fault recovery. Deployment in practice depends on the existence of efficient peer-to-peer communication infrastructure, which is lacking, as well as unresolved challenges related to synchronization errors, packet loss, and cybersecurity attacks, among others [6].

For remote microgrids, parallel inverters greatly improve system reliability and efficiency. However, the constant changes in wind and solar power create challenges for their control. A new adaptive virtual-impedance droop control scheme for parallel inverters was developed to address these challenges. Using only local data, it was able to improve reactive power sharing and lower circulating currents; however, its performance under unbalanced and noisy conditions is still unresolved [7]. The hybrid robust MPC and adaptable droop droop gains optimization framework for microgrid operations has been shown to improve renewable penetration and reduce the use of conventional energies; however, the validation for large scale real-time operation is still absent [8]. A cascaded I-P–PDN controller was developed to tackle the frequency issues of systems comprising PV, wind, EVs, and storage. It enhanced frequency performance and introduced EVs as a supple storage source. However, the analysis was for the most part simulation-based, with little attention to hardware limitations [9]. To improve the resilience of the grid, an MPC-based framework for voltage and frequency support was proposed, dealing with cold starts and transitions, such as islanding. But the solution requires an advanced computation and, in addition, has latency-ridden communication [10]. While an iterative learning control-based adaptive bidirectional droop approach was adopted for hybrid AC–DC microgrids, showcasing effectiveness in balancing AC/DC regulation, testing remained only in simulation and no tests were performed in the field or for robustness against measurement noise [11]. A newer control approach for DC–AC microgrids enhanced the mitigation of harmonics and the performance of inverter clusters; however, its development was focused on simulations and small-scale experiments [12]. The issue of sags, swells, harmonics, and transients was effectively tackled in pilot tests through a hybrid AI and semiconductor framework; however, the adoption of this technology in extensive deployments is lacking [13]. With the aid of nature-inspired optimization, a robust active power filter was constructed and demonstrated the reduction of harmonic distortion and improvement of stability, but the issue of sensitivity to parameter drift in real-world conditions is still a concern [14]. The improved voltage profiles and harmonic distortion achieved through the strategic placement of UPQC devices was a significant improvement, but the exhaustive search to locate the devices becomes computationally expensive in large networks [15]. An evaluation of filters, converters, and control methods was performed in relation to harmonic mitigation in systems with high RES, demonstrating the various trade-offs in cost and performance, but there was very little experimental validation [16]. An integrated active filter for nonlinear loads was proposed and is able to improve power quality, but how it performs during weak grid conditions or large disturbances is still unknown [17]. An ANN-based MPPT alongside multilevel inverter filters was implemented for EV charging microgrids, refining energy flows and harmonic suppression, but overly simplistic fleet models restrict applicability [18]. A DSP-based controller was developed for bidirectional storage converters tied to UPQC, alleviating harmonics and sags, although data on long-term performance is unavailable [19]. Grid-forming active power filters were introduced to a grid to actively regulate voltages and frequencies as well as suppress harmonics, yielding decent simulation results; however, these systems have not been verified in large-scale implementations [20]. A GRU-based controller for the UPQC was implemented and proved useful in quickly compensating tracked disturbances, but events that deviate from prior knowledge necessitate retraining and additional evaluation [21]. The model-free predictive control developed for UPQC was able to address transients faster than finite-set MPC, but specialized computing equipment and elevated computational costs are required [22]. The use of hybrid storage and control coordination in EV charging substations also lowered the THD and enhanced the voltage stability, though a complete assessment of the impacts at the feeder level was not performed [23].A LMS-based adaptive switching controller for the PV-fed UPQC was able to improve the PQ indices in the simulations, but the ANN training dataset influenced unusual fault detection and demonstrated a lack of robustness [24]. Lastly, with the aim of exploring the recently published advancements, the event-triggered control, hybrid UPQC/APF configurations, and ML-based control were compiled particularly to expose challenges, but none of the proposed solutions were tested [25]. [26] Highlighted the effectiveness of advanced compensators in enhancing stability, though large-scale validations and integration with diverse microgrid architectures remain future challenges.

Table 1: Source-Side Control Strategies in Microgrids

Ref	Contribution / Approach	Advantages / Findings	Limitation(s)
[1]	Hybrid ANN-based adaptive PI controller with droop control and virtual impedance	Improved voltage regulation, accurate power sharing, reduced THD within IEEE-519 standards	Validated mainly via simulations; large-scale real-time implementation and ANN computational overhead not addressed
[2]	Adaptive droop control using Narendra's model	Enhanced transient response and small-signal stability under variable conditions	Sensitive to model inaccuracies and communication delays; robustness against noise/cyber-delays unexplored
[3]	Controllable transient power-sharing for inverter-based DGs	Prevented inverter overloading, improved stability during disturbances	Requires precise tuning and coordination; limited validation in heterogeneous inverter setups
[4]	Review of droop and virtual impedance methods	Enhanced load-sharing accuracy, reduced P/Q coupling without communication	Limited testing under unbalanced grid conditions and high renewable penetration
[5]	Fixed-Switching-Frequency Model Predictive Control (FSF-MPC) for coordinated inverters	Improved dynamic regulation, constant switching frequency, accurate current tracking	High computational demand, scalability issues in multi-inverter systems with delays

[6]	Distributed Model Predictive Control (DMPC) for frequency regulation	Improved resilience, distributed control without central coordination	Dependent on reliable peer-to-peer communication; packet loss, sync errors, cyberattacks not addressed
[7]	Adaptive Virtual-Impedance Droop control using only local measurements for islanded microgrids	Balanced reactive power sharing, reduced circulating currents, improved voltage regulation (validated in HIL)	Limited performance validation under unbalance, distortion, and noise sensitivity
[8]	Microgrid Operation Control with Adaptable Droop Gains using robust min–max MPC	Improved renewable utilization, reduced conventional source reliance	Simulation-based; lacks large-scale real-time validation
[9]	Cascaded I-P–PDN controller tuned by Black-winged Kite Algorithm for Load Frequency Control	Reduced frequency deviation, overshoot, improved integration of EVs/BESS	Simulation-heavy; ignores communication delays and device limits
[10]	MPC framework for grid resilience and variable resource management	Explicit constraint handling, improved islanding/cold-start transitions	Computational burden, solver speed, and comms bottlenecks
[11]	ILC-based Adaptive Bidirectional Droop for hybrid AC–DC microgrids	Prioritized AC/DC regulation, improved dynamic IL converter response	Validated in MATLAB/Simulink only; no HIL or field results
[12]	Harmonic mitigation scheme for DC–AC microgrids with parallel VSIs	Reduced THD, better dynamic inverter cluster behavior	Simulations and small lab tests only; scalability unproven

III. RESEARCH OBJECTIVES

- Designing of a grid integrated solar wind hybrid energy system with common AC line for driving loads for improving its reliability and efficiency.
- Designing an inverter control that attains lower distortion level in the voltage as well as current waveforms.
- Designing of an effective artificial intelligence based algorithm that accommodates the fluctuations at the loading points.
- Improvement in the reactive power output from the system by the inverter control by designed hybrid system that can compensate the reactive power requirement when required.

IV. PROPOSED METHODOLOGY

This research work proposes a new hybrid renewable energy (solar PV and wind) system that builds on inverter control strategies. The overarching goal is to improve the output power quality and reduce output harmonics along with enhancing the efficiency of the system during the variable load conditions. This goal is attained through merging the traditional modulation methods and reinforcement learning (RL) based adaptive control. Like all the other methods are tested, designed, and modeled, this method is also implemented in the MATLAB/Simulink environment.

a. System Modeling of the Converter

The inverter DC/AC serves as the main connection of renewable energy sources to the local loads or to the AC grid. A detailed switching model of the voltage source inverter (VSI) is created, which includes the semiconductors, the gate drivers, and the filters. The inverter has to control the harmonics, the voltage, the reactive power, and the output frequency.

b. Pulse Width Modulation (PWM) Techniques

At first, PWM was used to create a sinusoidal AC output. It involves producing the switching pulses by comparing a high-frequency triangular carrier signal with a sinusoidal reference signal. In a three-phase system, pulsese width modulation is utilized in sinusoidal pulse width modulation (SPWM) to use three reference signals that are shifted by 120° in order to create balanced phase voltages.

c. Space Vector Pulse Width Modulation (SVPWM)

As an improvement on the SPWM, the SVPWM is adopted. It calculates the effective switching time for the adjacent vectors, which enables representing the three-phase voltages as a space vector in the α–β plane. This, in turn, reduces the harmonic distortion and optimizes the DC bus usage.

d. Reinforcement Learning–Based Control

With the rise of deep neural networks (DNNs), reinforcement learning (RL) has seen remarkable progress. This is because deep neural networks provide the ability to represent complex nonlinear functions and offer scalability to high-dimensional spaces. In RL, DNNs serve as approximators for value functions, policies, and even environment models, and are fine-tuned using gradient-based optimization techniques to enhance generalization and support continuous control. For spatial feature extraction, convolutional neural networks (CNNs) are deployed, whereas sequential tasks that require understanding of temporal context benefit from recurrent models, including RNNs and LSTMs. Examples of value-based methods include DQN and Double DQN, whereas A3C is an example of a policy-based method in reinforcement learning. Using these methods, along with the aforementioned techniques, bolsters the stability, efficiency, and adaptability of the training process in RL, allowing for its application in complex and evolving large-scale decision-making problems.

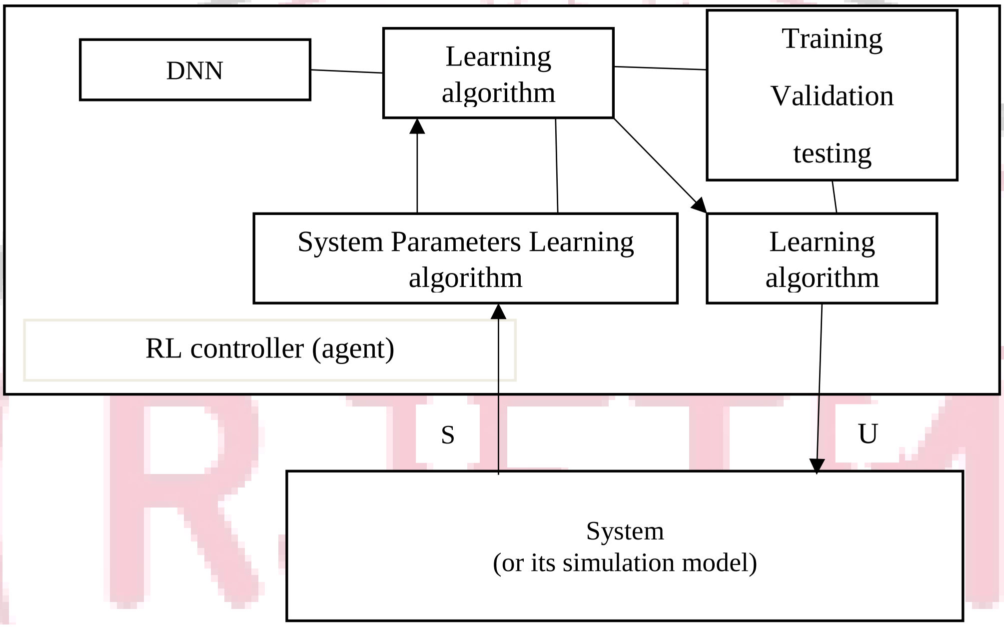

Figure 2: A general framework of RL with modification for DC/AC inverter

e. Hybrid system development using MATLAB

The MATLAB/SIMULINK functions simultaneously modelling the solar panels and wind systems have a great impact on the overall efficiency of the system, apart from creating a more sustainable and cost-effective solution. Hybrid systems reduce energy intermittency by using generation profiles that complement each other, and they also optimize energy capture and diminish the need for storage and backup systems, which in turn reduces the Levelized Cost of Energy (LCOE). They have an even greater impact as they are clean energy sources, thus aiding in the reduction of carbon emissions and helping achieve decarbonization targets. The hybrid systems' gentler energy output enhances the grid's resilience and dependability, making these systems ideal for areas with remote and weakened grids. MATLAB allows for the intricate simulation of PV systems, wind turbines, and grid interfaces, and the advanced controls and optimizations (such as MPPT and forecasting) ensure system stability. In summary, having the hybrid system designed in MATLAB guarantees functionality and efficiency alongside being environmentally friendly.

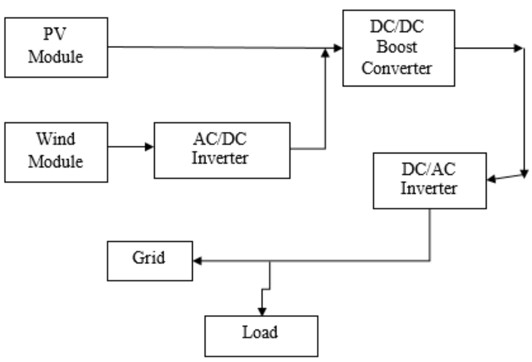

Figure 3: Hybrid Energy System Topology

f. MATLAB/SMILULINK Description of Wind energy system

Model of wind turbine with PMSG Wind turbines cannot fully capture wind energy. The components of wind turbine have been modeled by the following equations.
Output aerodynamic power of the wind-turbine is expressed as:

$$P_{Turbine} = \frac{1}{2}\rho A C_p(\lambda, \beta)v^3 \quad (1)$$

Where, ρ is the air density (typically 1.225 kg/m3), A is the area swept by the rotor blades (in m2),C_P is the coefficient of power conversion and v is the wind speed (in m/s).
The tip-speed ratio is defined as:

$$\lambda = \frac{\omega_m R}{v} \quad (2)$$

Where$\omega_m$and R are the rotor angular velocity (in rad/sec) and rotor radium (in m), respectively.
The wind turbine mechanical torque output m T given as:

$$T_m = \frac{1}{2}\rho A C_p(\lambda, \beta)v^3 \frac{1}{\omega_m} \quad (3)$$

The power coefficient is a nonlinear function of the tip speed ratio λ and the blade pitch angle β (in degrees). Then Power output is given by

$$P_{Turbine} = \frac{1}{2}\rho A C_{p_{max}} v^3 \quad (4)$$

A generic equation is used to model the power coefficient C_P based on the modeling turbine characteristics is defined as:

$$C_p = \frac{1}{2}\left(\frac{116}{\lambda_i} - 0.4\beta - 5\right)e^{-\left(\frac{21}{\lambda_i}\right)} \quad (5)$$

For every wind speed, there exists a point in the wind generator power characteristic where the output power is at maximum MPPT. Thus, ensuring WECS load control will bring about a variable-speed-governed turbine rotor, and there is continuous extraction of maximum power from the wind.

V. RESULT AND DISCUSSION

The focus of this section is to evaluate the simulation results of the proposed hybrid solar–wind system in MATLAB/Simulink. An analysis of the RL-based inverter controller's performance is conducted and compared with the traditional reference-based controller under both steady-state and transient system operations. The analysis is concentrated on voltage, current, power, and the associated harmonic distortion.

Case 1: Power and Quality Analysis of Converter system

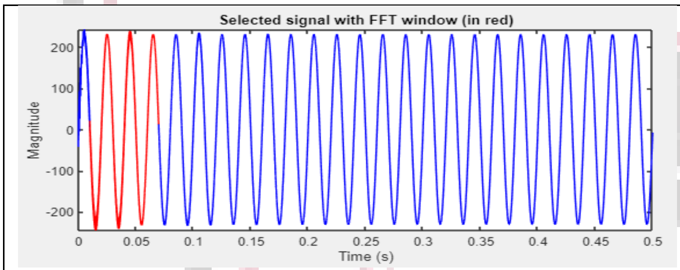

Figure 4: FFT analysis of AC voltage available in the hybrid system having voltage reference based converter controller

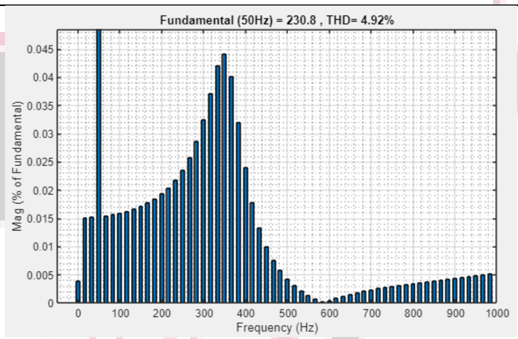

Figure 5: THD% in AC voltage available in the hybrid system having voltage reference based converter controller

The chart in Figure 4 illustrates all the cycles of the three phase AC voltages and is analyzed with the referenced controller based converter, which is then utilized for the calculation of the total harmonic distortion level. In systems with voltage reference-based converter control regulation, lower order harmonics were observed, as shown in figure 5, and the software-calculated THD% of the voltage waveform was 4.92%.

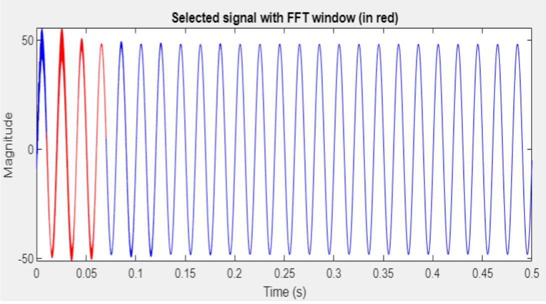

Figure 6: FFT analysis of AC Current available in the hybrid system having voltage reference based converter controller

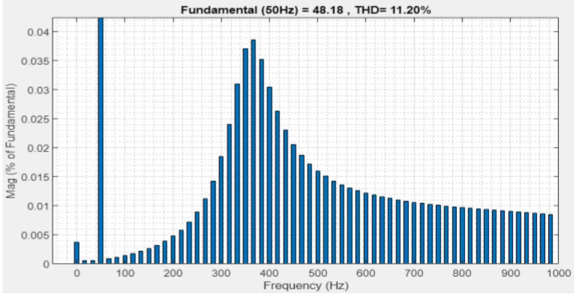

Figure 7: THD% in AC Current available in the hybrid system having voltage reference based converter controller

The figure 6 depicts the FFT analysis of the three-phase AC current for each cycle in the system, which is analysed with the controller driven by the voltage reference based control, for further use in the calculation of the total harmonic distortion level. In the application software, the THD% is computed, and in the current waveform it is found to be 11.20% in the system having converter control regulation achieved by voltage reference based control. There are also higher order harmonics observed in them as shown in figure 7.

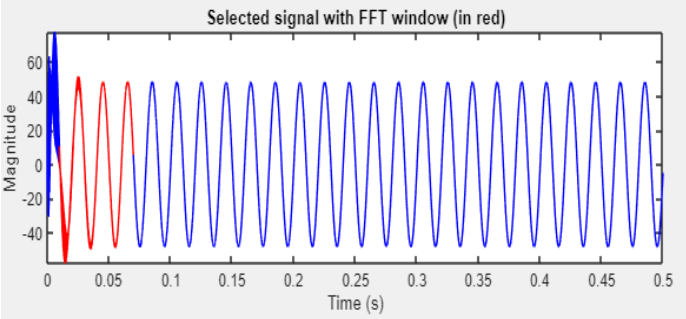

Figure 8: FFT analysis of AC current drawn in the hybrid system having proposed Reinforcement learning based converter controller

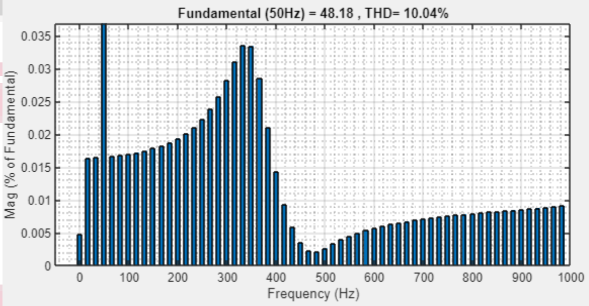

Figure 9: THD% of current drawn in the hybrid system having proposed Reinforcement learning based converter controller

The figure 8 depicts the FFT analysis of the three phase AC current for each cycle in the system which is analyzed with controller driven by Reinforcement learning control and is further used for calculating the total harmonic distortion level in system. Figure 9 illustrates the presence of lower order harmonics in the system current waveform with the converter control regulation obtained through the proposed Reinforcement learning technique. The THD% calculated is 10.14% in this waveform.

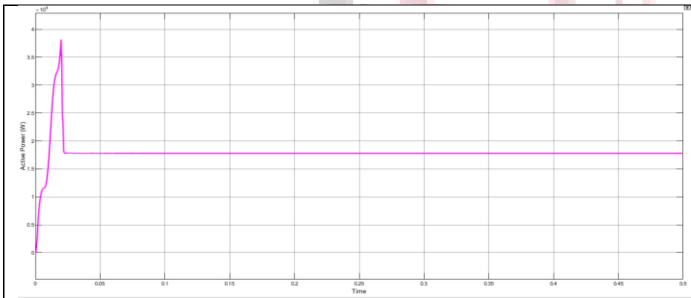

Figure 10: Active Power available in the hybrid system having proposed Reinforcement learning based converter controller

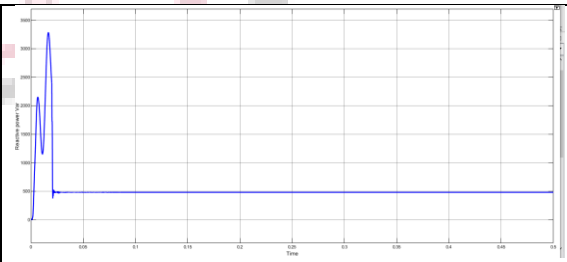

Figure 11: Reactive Power in the hybrid system having proposed Reinforcement learning based converter controller

Figure 10 shows the active power output calculated to be approximately 17800 W in the system having Reinforcement learning approach for the inverter at the hybrid system integration point. The reactive power output is calculated to be approximately 480 VAR in the system with the proposed Reinforcement Learning-based controller for the inverter for the hybrid system at the hybrid system integration points as presented in figure 11.

Table 2: Power outcomes comparison from the proposed controller

Parameters/System	Hybrid System with voltage reference based Controller	Hybrid System with proposed Reinforcement learning based Controller
Voltage (V)	230 V	230 V
Current (A)	48	48
Active Power (W)	17020	17800
Reactive Power (Var)	817.8	480
Voltage THD%	4.92	1.59
Current THD%	11.20	10.04

This showcases the efficiency of the controller designed as an overall reducer of the distortion level in the hybrid system. The study was also extended to transient loading conditions in case a load was suddenly switched on the line after a simulation time of 0.1 seconds.

Case 2: Loading and Off-loading Switching of Dynamic Loads

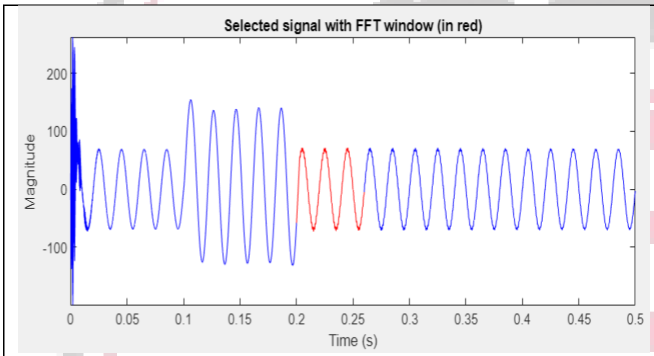

Figure 12: FFT evaluation at off-loading point in hybrid system with voltage reference-based converter controller

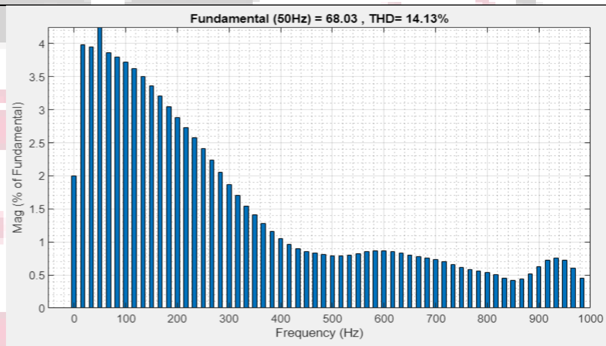

Figure 13: THD% evaluation at off-loading point in hybrid system with voltage reference-based converter controller

Figure 12 shows the FFT analysis of current at the off-loading point with logic at 0.2 seconds. The current diminishes at this moment, so the distortion from the system driven by the voltage reference-based converter controller is measured in the current at this point. The total harmonic distortion calculated in the current waveform at the off-loading point is being represented by figure 13 in system driven with voltage reference-based converter controller which comes to be 14.13%

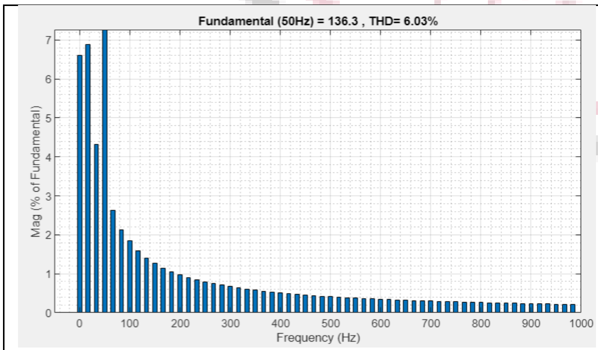

Figure 14: THD% evaluation at the loading point in hybrid system with proposed Reinforcement learning based converter controller

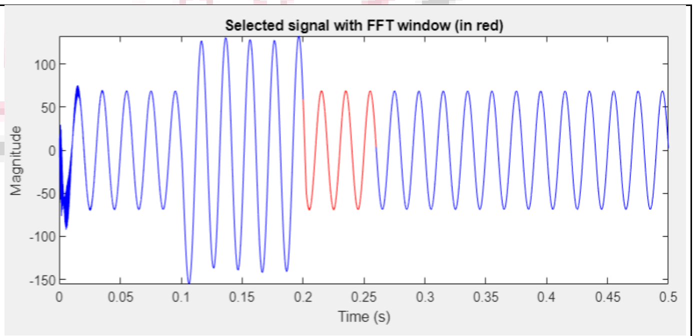

Figure 15: FFT evaluation at the off-loading point in hybrid system with proposed Reinforcement learning based converter controller

Figure 14 illustrates the total harmonic distortion in the current waveform at the loading point. It is observed that the system driven by the proposed Reinforcement learning-based converter controller results in 6.03% distortion. The FFT analysis of current at the point where the off-loading is done at 0.2 seconds and the current decreases at this point is represented by Figure 15 for each cycle and then the distortion is measured in the current at this point in system driven with proposed Reinforcement learning based converter controller.

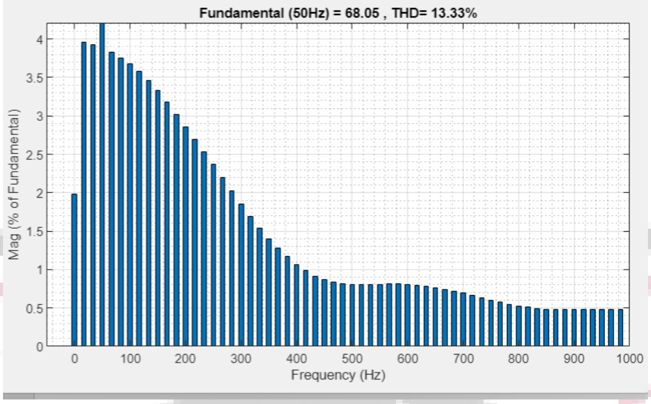

Figure 16: THD% evaluation at the off-loading point in hybrid system with proposed Reinforcement learning based converter controller

The proportion of the harmonics present in the load current waveform is given in figure 16 for the system which is controlled by the proposed reinforcement learning based converter controller. This proportion amounts to 13.33 %.

Table 3: Comparative quality analysis during transient switching of loads

Transient loading comparison		
Parameters	**Hybrid System with voltage reference based Controller**	**Hybrid System with proposed Reinforcement learning based Controller**
THD% in current (loading point)	6.04 %	6.03%
THD% in current (off-loading point)	14.13%	13.33%

VI. CONCLUSION AND FUTURE WORK

The use of AI techniques such as machine learning for the development of control algorithms for the DC/AC converter in hybrid renewable energy systems is well justified due to the remarkable improvements it can bring to system reliability, stability, and performance. This research demonstrated the effectiveness of AI-based control strategies, particularly reinforcement learning, for DC/AC converters in hybrid renewable energy systems. By replacing the conventional space vector modulation with a Q-learning controller, significant improvements were observed in key performance metrics—active power increased by 4.5%, the power factor improved from 0.89 to 0.93, and reactive power was reduced by nearly 40%. Harmonic analysis further revealed a marked reduction in voltage and current distortions, ensuring higher quality power delivery under dynamic load variations. These results confirm that AI-enabled modulation strategies are not only more efficient but also simpler to compute, scalable, and adaptable to multilevel inverter configurations, making them ideal for hybrid solar–wind systems facing variable input conditions. Moving forward, future research should focus on hybrid AI algorithms that integrate reinforcement learning with optimization techniques, alongside large-scale hardware-in-the-loop (HIL) and real-world validations. Additionally, lightweight AI models must be developed to minimize computational complexity, ensuring wider adoption in cost-sensitive renewable deployments. Such advancements will enable more robust, adaptive, and sustainable inverter control frameworks, bridging the gap between simulation studies and practical implementation in next-generation microgrids.

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