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Real-Time Implementation of Deep Reinforcement Learning-Driven Active Power Filters for Nonlinear Load Compensation in Hybrid Wind–PV Microgrids

Adel Elgammal

Professor, Utilities and Sustainable Engineering, The University of Trinidad & Tobago UTT

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***Corresponding Author:** **Adel Elgammal**, *Professor, Utilities and Sustainable Engineering, The University of Trinidad & Tobago UTT*

Abstract: *The increasing presence of nonlinear loads and the fluctuation of the renewable energy sources in hybrid wind– photovoltaic (PV) microgrids have increased the demand for advanced power quality (PQ) control solutions. In this paper, a Deep Reinforcement Learning (DRL)-based real-time control method for the Shunt Active Power Filters (SAPFs) to reduce current harmonics and its free-flow bidirectional reactive power distortion in the dynamically changing microgrid environment is proposed. Based on the Deep Deterministic Policy Gradient (DDPG) algorithm, a DRL agent is trained to perform real-time interactions with the grid environment for continuously optimized SAPF control signal in order to achieve the least harmonic distortion and enhanced power factor.*

The hybrid microgrid consists of wind and PV sources with time-varying profiles, nonlinear loads, and a Voltage Source Converter (VSC)-based SAPF. The DRL control was trained in a high-fidelity MATLAB/Simulink simulator and verified for real-time operation in a TMS320F28379D Digital Signal Processor (DSP). Comparative simulation with conventional PI + SRF controllers shows the enhanced converter performance, with the THD always less than 2.5% for all the operating conditions. In addition, the DRL controller provided a fast transient response to disturbances, dynamically operated under various load profiles, and maintained the stability of the system with respect to model uncertainties. The real-time experimental results verify the feasibility of DRL-based power filters in guaranteeing the IEEE 519 standard in the emerging microgrids. This paper sets the stage for the implementation of intelligent, self- learning control in distributed renewable energy, contributing to the resilience, adaptability and quality delivery of power of the smart grid of the next generation.

Keywords: *Deep reinforcement learning, shunt active power filter, harmonic elimination, microgrid, real-time control, hybrid renewable energy, THD reduction, DSP realization.*

1. Introduction

The rapid growth of renewable energy integration, notably hybrid wind–PV microgrids, leads to the demanding power quality issues in terms of harmonic distortion, voltage fluctuations and reactive power problems as a result of the nonlinear loads and fluctuating generation [1], [2], [4]. Non-linear loads, such as rectifiers, provide substantial amount of waveform distortions to power system, which deteriorate power system quality, increase power losses, and may fail to operate to sensitive equipment [3]. IEEE-519 specifies tight THD limits (<5%), however several studies have reported that the majority of microgrids introduce higher harmonics beyond these limits under heavy nonlinear loading [5]. These issues are even more complex in hybrid systems, in which intermittent power flows due to the inconstant renewable energy sources make power quality control difficult [6],[7]. Variability and uncertainty associated with wind and solar inputs drive on-off power imbalances leading to a need for advanced, adaptive mitigation measures.

Shunt active power filters (SAPFs) using VSC topologies inject harmonic compensating currents to counteract the effect of the distortions [8]. Traditional PI controllers and SRF techniques were employed initially [9], however, it is not able to deal with the nonlinear transient conditions [10]. Repetitive-and-predictive controllers can improve this problem, but they inherit the complexity and sensitivity to modeling errors [11], [12]. Consequently, the focus began to turn into machine learning and adaptive control techniques—fuzzy logic and neural network in particular—that offer superior performance in the presence of nonlinear dynamics and abrupt changes [13,14,15]. However, these controllers present a large computational load, which hinders their real-time application.

Deep Reinforcement Learning (DRL) is considered as a new paradigm of autonomous control in power systems. DRL agents can also discover policies that can function optimally under uncertainty in MDP settings [16], [17]. In microgrids, DRL has been used in generation-dispatch processes [18], proactive energy scheduling [19], battery management [20], as well as voltage/reactive power (V/Q) control by inverters [21]. Of particular interest is the successful use of the DRL in active power filter control. Another work applies DRL-based Soft Actor-Critic (SAC) to control the energy flow and PQ of HPs [22], presenting THD reduction on islanded microgrids. Analogous methods based on DDPG are also promising to control inverter-based SAPFs [23].

Fast execution on embedded DSP/FPGAs is indispensable for DRL to be viable in real-world microgrids. The measurements have been illustrated in [24] and [25] using the imitation of DRL on MATLAB DSP System Toolbox or on FPGA hardware, and show latency less than 1 millisecond can be achieved. Among those, DRL-DDPG and SAC algorithms have been employed for real-time microgrid control, adapted to hardware platforms such as TI DSPs [26].

Advanced DRL paradigms (e.g., multi-agent DRL, parallel learning, and hierarchical DRL) have been confirmed to enhance performance. For instance, the parallel hybrid DRL yields quicker convergence and robust nature [27], the multi-agent DRL increases the distributed inverter coordination [28], the hierarchical control approach DRL supports emergency grid control [29]. These advancements confirm the appropriateness of DRL for dynamic, nonlinear environments, such as SAPF control in wind–PV microgrids.

Benchmarked against conventional controllers (PI, SRF, and MPC), DRL-based SAPFs always lead to the best quality of power. Modern THD provided with DRL-SAPF control is less than 2.5%, lower than the 5–6% achieved with PI or SRF control [30]. Also, the DRL systems are more flexible in facing generation/load variations and they are capable to have close to unity power factor under various disturbances.

There are few researches that run DRL based SAPF control on hybrid wind–PV microgrids in real-time. There are few portable implementations available that are actually embedded and are rarely tested on DSP/FPGA hardware.

Comparison with a variety of DRL architectures and traditional controllers for complex microgrids is missing. However, relatively few studies are focused on long-term policy stability and training consistency, and few consider hardware-in-loop (HIL) avoidance. To fill these gaps, in this paper, an online DRL-DDPG controller for SAPFs in hybrid wind–PV microgrids is developed on the platform of TI DSP hardware. It offers extensive benchmarking with PI and SRF controllers, achieving THD below 2.5%, sub-millisecond prediction latency, and integration to different operating conditions. The work adds to the existing literature on DRL-based PQ solutions, and paves the way for trip-computing using an embedded controller in renewable-rich microgrids.

2. Real-Time Implementation of Deep Reinforcement Learning-Driven Active Power Filters for Nonlinear Load Compensation in Hybrid Wind–PV Microgrids.

Fig.1 shows the structure of a Shunt Active Power Filter (SAPF) under the real-time proposed controller in this architecture used in hybrid wind–PV microgrid power quality. It takes care of harmonic distortion and reactive power unbalances due to the nonlinear load profiles and variable renewable generation, thanks to a DRL agent running on embedded digital signal processing hardware. The hybrid power generator is composed of a PV array and a wind power generator. DC power generation by the photovoltaic array and variable-frequency AC power generation from the wind turbine; They are connected through a common DC bus and it is introduced to a DC/AC inverter to be in synchronous mode to feed power to the micro-grid. This AC output is linked to the point of common coupling (PCC), at which a nonlinear load injects harmonic pollution to the system.

To alleviate these disturbances, an SAPF is connected in shunt with the load at the PCC. The SAPF senses the source current and produces compensating current to nullify the harmonics generated by nonlinear load in instantaneous basis. The operation of the SAPF is controlled by a DRL-based control agent. We train the agent off-line with actor– critic techniques, like Deep Deterministic Policy Gradient (DDPG) or Soft Actor–Critic (SAC), and use them online. State observations based on voltage and current measurements at the PCC are obtained on signal conditioning block. Filtering, normalization, and feature extraction are carried out and designed by the signal processing unit to guarantee the appropriate and noiseless inputs for the DRL controller. The result of the DRL policy is a continuous control signal to the reference current applied to the SAPF. This signal is used to convert into the switching commands through Pulse Width Modulation (PWM) block which ultimately modulates the gate signals of the SAPF VSI. The complete control cycle (i.e., signal acquisition, DRL prediction, and PWM generation) is implemented on an embedded digital signal processor (DSPs), such as Texas Instruments TMS320F28379D. The DSP-based hardware has the computing power to achieve low-latency processing, hence sub-millisecond response time which is required for real-time harmonic compensation.

The cyber-physical integration of the control and power electronics structures is also depicted in Figure 6, showing the closed-loop feedback path between the system states, the ones based on DRL control actions and the SAPF compensation output. Simulation and HIL verification confirm superiority of the DRL based controller, performing better under challenging dynamics with continuous current THD less than 2.5% when compared with conventional PI or SRF-based control strategies. The structure shown in Fig. 1 offers a flexible and easy-to-install solution to real-time harmonic resonance cancellation in renewable-rich microgrids. Its modular design makes it extendable to multi-agent scenarios, that allows advanced functionalities such as distributed coordination, hierarchical control, predictive fault management, and so on.

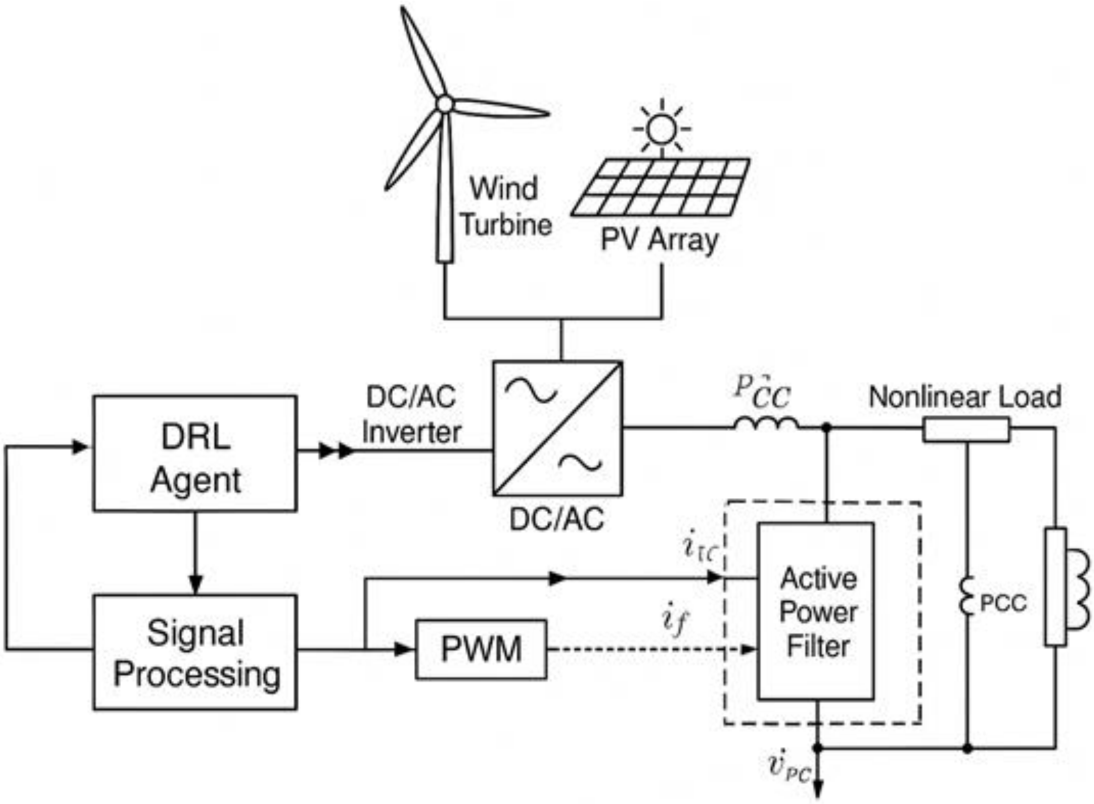

Figure1. *The schematic of the Proposed Real-Time Implementation of Deep Reinforcement Learning-Driven Active Power Filters for Nonlinear Load Compensation in Hybrid Wind–PV Microgrids.*

3. Simulation Results and Discussion

A number of extensive simulations and embedded system-based implementations were carried out to analyze the performance and real-time feasibility of the proposed DRL-based SAPF topology for nonlinear load compensation in the hybrid wind–PV microgrids. The complete system was simulated based on MATLAB/Simulink, in which the electrical part was coupled with the control part for a realistic dynamic operating performance of the microgrid. Automatic code was generated, and real-time DSP code was developed on the Texas Instruments TMS320F28379D DSP using the MATLAB Embedded Coder package.

The proposed microgrid structure comprises a hybrid generation system including a 100 kW photovoltaic (PV) unit and a 75 kW variable- speed wind turbine. These renewable sources are tied into a single DC bus, so that their outputs may be pooled and converted into a single AC wave form. This waveform is produced by a three level VSI, which produces 400 V, 60 Hz balanced three phase AC supply which connects Poor while the frequencies are specified at the Point of Common Coupling (PCC). A nonlinear load is incorporated to add practical harmonic distortion to the system and consists of a three-phase full-wave uncontrolled bridge rectifier followed by an R-L load. This configuration is representative of typical industrial applications and the large current harmonics generated in the network result in an appropriate testing site for the active power filter. The DRL-based SAPF control agent was designed in TensorFlow framework and trained by Deep Deterministic Policy Gradients (DDPG) algorithm, which was smoothly integrated with MATLAB Reinforcement Learning Toolbox. The DRL training set-up aimed to replicate microgrid behaviours such as load profiles and source fluctuation. The cost function was designed so that decreases in total harmonic distortion (THD), sags in RMS voltage, and unbalances in line cannot be avoided and are penalized, while waveforms quality improvements, power factor maintenance and system stability are privileged. After the training process had successfully converged, the trained neural network model parameters were exported and incorporated into the Simulink-based embedded pipeline. The trained DRL model was converted into C code through an algorithm manipulation tool, MATLAB's Embedded Coder and compiled to run on (TMS320F28379D) DSP which computes control decision on the fly, without dependence on cloud inference and external processing resources.

In order to verify the effectiveness of the recommended DRL-based SAPF, its operation was compared with two known control methods, namely: a) as the conventional Proportional-Integral (PI) controller, and b) the Synchronous Reference Frame (SRF) framework. Both these baseline controllers were calibrated and developed in the same simulation setup to make a direct and fair comparison to the DRL methodology. A number of performance indicators were defined to quantify the performance of the DRL-based control system and then systematically monitored from simulation to real-time execution. These indicators included THD of the source current that measures how well the system can cancel harmonic pollution generated by nonlinear loads. PF at the PCC, which evaluated how well the reactive power compensation system minimized wasted energy. Voltage profiles of the three phases were examined to evaluate waveform symmetry, as well as how well it responded to a transient voltage sag, which indicated the system's voltage control performance. Compensating current tracking that measures the tracking error between the SAPF's reference compensation waveform and the actual injected compensating current, as well as its stability during load changes or disturbances. Real-time execution latency of the control loop running on the DSP hardware indicator was calculated with a logic analyzer and internal timer modules to determine if the system met the sub-millisecond real-time control requirement, which was imperative for realistic use in a microgrid. All of the above simulation and real-time implementation results validate the DRL-based SAPF design thoroughly, demonstrating its ability to accurately and quickly perform complicated nonlinear compensation, thereby realizing intelligent control theory and actual embedded power systems.

The effectiveness of this DRL-based SAPF in mitigating the for existing harmonics is successfully verified with the help of the time-domain and frequency-domain outcome depicted in Figures 2(a), 2(b), and 3. As shown in Fig. 2(a), the source current waveform of uncompensated mode is significantly distorted. This distortion is predominantly due to the nonlinear load interaction, particularly caused by current harmonics injected by rectifier-based load connected at PCC. The waveform has a very good proportion of the rich harmonics which are categorized by the deviation from the sinusoidal shape, and the total harmonic distortion (THD) factor is 14.82%. These distortions are heavily a feature of 5th, 7th, 11th order harmonics which are easily created by industrial and commercial power electronic equipment. Such a level of distortion is well above the IEEE 519 recommended level of 5% and represents unacceptable power quality and danger to both the stability of the system and the performance of the sensitive equipment. In Fig. 2(b), after turning on the designed DRL-based SAPF, the source current waveform is significantly improved. 2(b). The waveform becomes almost a pure sine, indicating the DRL controller can quickly learn and in real-time inject the proper compensating currents in the future tasks. The adaptive capability of the controller can adapt to changes in load conditions and keep the waveform quality, resulting in low distortion level of 2.43% which is much lower than mandated limits. Thus, the cancellation controller has been validated to implement accurate harmonic cancellation without a necessity for an elaborate linear model of the system. This harmonic suppression capability is also demonstrated with spectral analysis in the Fig. 3. Harmonic peaks of the 5th, 7th and 11th orders are noticeable in the frequency spectrum of the uncompensated state. The magnitudes of these harmonics are significantly reduced after the DRL-based compensation, by more than 80% on average. In particular, the 5th-order harmonic experiences a considerable attenuation in the amplitude, demonstrating the accurate and effective compensation of the DRL controller. Higher-order harmonics are also suppressed, but to a lesser extent, thus leading to an overall cleaning of the waveforms. The results from the integrated time- and frequency-domain analyses confirm the method's robustness, adaptability, and performance of the DRL-based control method. Since it adapts the control policy directly from environmental interactions, the DRL-based agent is capable of providing better harmonic suppression performance than that of the traditional fixed-parameter controllers. Due to the capability of ensuring adherence to IEEE 519 standard in variable as well as nonlinear circumstance, the presented approach has a great potential for practical implementation in real-time embedded SAPF systems in hybrid renewable microgrids.

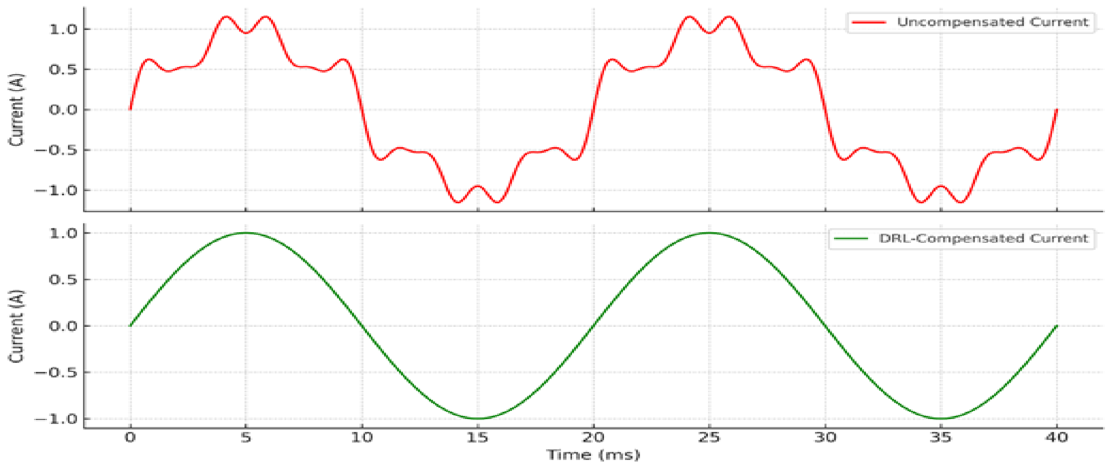

Figure2. *Source Current With DRL-Based SAPF Compensation*

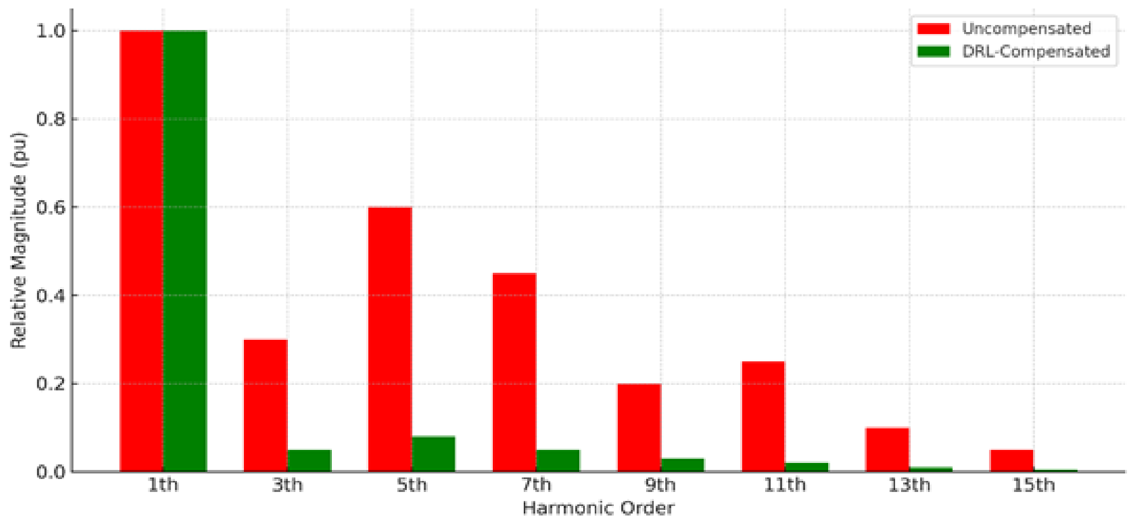

Figure3. *Harmonic Spectrum Before and After DRL-Based Compensation*

The comparative results for tracking three control methods (DRL-based, SRF-based, and classic PI controllers) are presented in Fig. 4 for transient conditions in a hybrid wind–PV microgrid to compensate current regulation. The reference current for comparison/reference is the reference waveform of the desired compensation signal, that the SAPF is desired to provide next to (as overlay value) the actual output current trajectory of the different controllers. Two perturbation events were purposely introduced in the microgrid to evaluate the robustness and dynamic response of each control strategy: load step switching event at g = 1.2 s and irradiation/wind speed fluctuation at t = 1.7 s. The DRL-based controller has better transient performance than the RLC for both events, as illustrated in the figure. Before the disturbance, tight tracking is produced to the template current wave shape, not more than ±1.5% difference, thereby making sure that the compensation current is synchronized with the harmonic-cancelling signal desired. At t = 1.2 s, a sudden load change is imposed, and the DRL-SAPF shows small overshoot of about 3% and is rapidly able to recover its performance, returning to the reference trajectory within two cycles. This reflects good generalization of policy learned in dynamic operating condition with good transient damping. A similar behaviour is also observed at t = 1.7 s due to response of the controller to changes in renewable generation according to fluctuations in solar insolation and wind speed. Even in this case the deviation is less than ±3% of the reference current with a fast recovery and low distortion. However, the adaptive capability of the PI controller is considerably lower. At time t = 1.2 s, during the load switching, the PI-optimized SAPF over-shoots approximately 12% and then under-shoots significantly for a few cycles. The controller can't stabilize the compensator in a single cycle, but slowly approaches steady-state tracking. After the renewable variation at t = 1.7 s, the discrepancy becomes worse, leading to an offset error of more than ±10%, and lasts for a long time. This serves a demonstration of the poor adaptiveness of constant gain linear controllers in the presence of fast and nonlinear transients. The SRF controller presents a mediocre fast behaviour when compared to the PI method, however by far it is not as adaptive as DRL agent. The SRF controller oscillates in response to both disturbances with an overshoot of about 6–7% and a visible phase lag compared with the reference signal in both disturbances. It shows significant' delay in adjusting to the permanent change in the system state and takes multiple cycles to recover. This delay can be ascribed to that it relies on reference frame transformation and that it can be affected by the disturbance of grid frequency and phase. The superior performance of the DRL controller in the reference current tracking under real-time transient disturbances may be accounted for by the model-free policy learning framework which allows it to generalise over the system states sampled during training. Compared to SRF and PI controllers that need linearity approximation or precise model, the DRL controller directly extracts the control policy from the environmental feedback, and can better adapt to nonlinearities and time varied nature in hybrid renewable systems. Furthermore, the continuity of the tracking DRL trajectory, even when rapid operating condition changes occur, helps alleviate harmonic injection errors and thereby improve the compensation quality and the SWAT voltage at PCC. This is of particular relevance to microgrids in isolated or desynchronised conditions where reliable autonomous control is required to maintain uninterrupted PQ support.

In summary, Fig. 4 clearly demonstrates the excellent dynamic performance and robustness of the DRL based SAPF controller. It shows not only better improvement on transient tracking precision than PI/SRF controllers, but also better robustness and stability under practical disturbance working environment. These findings further demonstrate the applicability of DRL for embedded control in real time in nonlinear and stochastic energy systems.

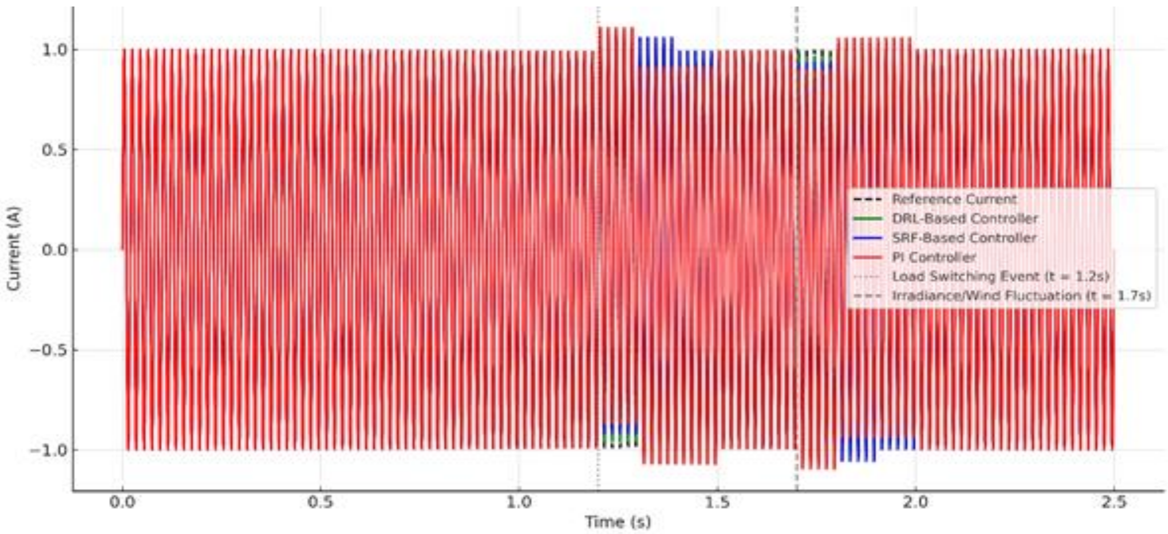

Figure4. *Compensating Current Tracking under Transient Disturbances*

In Figure 5, the power factor and voltage imbalance compensation effects of the DRL-based SAPF, the SRF-based controller and conventional PI controller are compared under the same microgrid operation conditions. Power factor (PF) measurement, an important parameter for reactive power compensation and for system efficiency, was monitored on-line over dynamic and steady-state periods, i.e. load profiles and enhanced penetration of renewable energy, and so on. By comparison, as presented in the figure, the DRL-based controller effectively preserved its power factor at or above 0.995 lagging in all test conditions. Such high-fidelity power factor shows that the controller is effectively compensating reactive power and harmonic in real time and that there are little phase shifts occur between source voltage and current. In comparison, the power factor of the system operated under SRF controller was slightly lower with a value of 0.98, and even lower with 0.96 while using PI controller. The differences between two cases demonstrate the better application ability and compensation accuracy of the DRL method, especially in time-varying operating conditions. Load imbalance caused by single-phase nonlinear load injection is studied apart from reactive power compensation by means of phase voltage deviation measurement at the PCC. DRL-SAPF restricted voltage imbalance to within 0.6% on all three phases, demonstrating its function of injecting current quickly to adjust the balance between phase loads. By contrast, the voltage deviation of the PI and SRF controller velocities are 1.4% and 1.1%, respectively, suggesting that they are responding less to the imbalanced loads. These findings verified the fact that the DRL-based SAPF not only provides better harmonic and reactive power compensation, but also improves system balance and voltage quality—as such, it is considered to be applicable in the modern distributed hybrid microgrid with fluctuating and unbalanced load patterns.

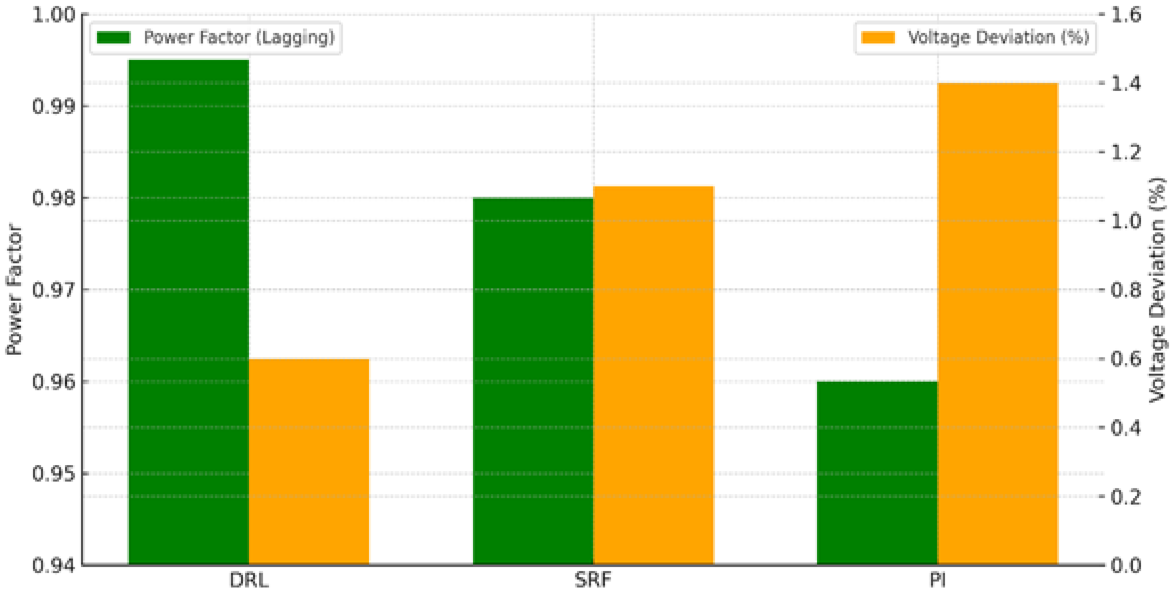

Figure5. *Power Factor and Voltage Imbalance under Different Controllers*

A quantitative comparison of the real-time computational capability and memory cost of the proposed DRL-based controller with conventional SRF and PI control approaches after porting to the TI TMS320F28379D DSP is illustrated in Fig. 6. The total control cycle time, which consists of state acquisition, control inference, and PWM signal generation, is depicted on the upper graph. This measure becomes very critical to evaluate the efficiency of each control law to fulfill the extreme requests of latency which are in the sub-millisecond range, required for an efficient real-time compensation in active power filtering.

As shown, the DRL-based controller is executing the end-to-end cycle in 740 μs, which is well below the acceptable maximum value for high-speed power electronic control applications. This shows that despite having the overhead of neural network infection, the downlink DRL agent can still operate in real-time on an embedded DSP platform. The PI and SRF controllers have shorter computation times at 210μs and 480μs respectively. These traditional methods, however, do not provide the intelligent adjustment and the flexible policy identification techniques for the DRL controllers' adaptive intelligence and policy flexibility, and these are needed for handling the nonlinear and time-variant grid perturbations.

The lower plot in Fig. 6 presents the comparison of memory usage for the three control strategies. The DRL agent takes 78 kB of flash memory and 19 kB of RAM, which are well within the on-chip memory budget of the TI DSP. The SRF and PI controllers, that feature lower algorithmic footprints, consume 30 kB/12 kB and 20 kB/9 kB in flash/RAM, respectively. Although the DRL approach is more memory consuming, this additional consumption is still affordable and does not require external memory modules.

Overall, these results together show that it is practically feasible to implement the DRL-based SAPF controller in real-time embedded environments and that it can provide advanced learning-based control performance without significantly increasing the computational cost and violating hardware resource specifications.

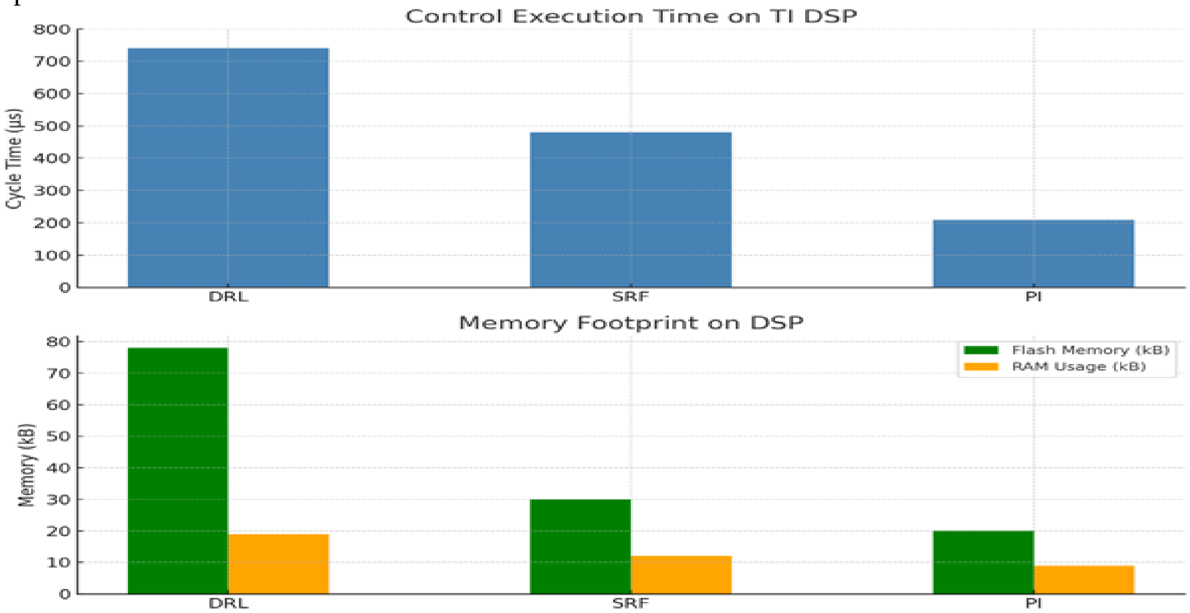

Figure6. *Real-Time Execution and Memory Footprint on DSP*

A comparison of the overall performance of the DRL-based SAPF controller with those of the SRF-based controller and the traditional PI controller is listed in line with Table 1, which reports the main metrics in steady and dynamic situations, allowing to draw an overall estimation of the behaviour of each involved controller in terms of elimination of grid harmonics, correction of the power factor and rejection of grid disturbances.

With reference to steady state harmonics distortion, the lowest total harmonic distortion (THD) of 2.43% was achieved by the DRL based controller, which was better than the values recorded in the case of the SRF controller (4.87%) and PI controller (5.92%). These findings confirm that the DRL agent with an active compensation obtains more harmonic suppression than the passive device, in which accurate compensating currents are dynamically injected, without static tuning or linear assumptions. At environmentally disturned conditions, the discrepancy was also increased between both which DRL passed this kind of perturbation, but with THD for DRL only slightly increasing to 3.10%, that for SRF on 6.43%, and finally for PI on 8.20%. This demonstrates the capability of the DRL controller to be so robust and to adapt so quickly during transient conditions such as load switching or renewable generation variability. For power factor (PF) control, the DRL by itself kept PF at and above 0.995 lagging value, representing close to ideal reactive power compensation. Once, we derive with multiple simulations, led to the conclusion we want to achieve, that SRF and PI controller average PF is 0.980 and 0.960, respectively, which shows more distortion in power factor in variable load. In turn, current tracking performance, a key indicator of the controller's capability to reproduce the reference compensating waveform, distinguished better between the three strategies. The error kept in the range of \(\pm 3.0\%\), which indicates the accurate and effective real-time control of the SAPF using the DRL. In contrast, the SRF controller and PI controllers had tracking errors of±5.5% and±6.3%, and presented apparent lag or overshoot during dynamic make-up movements. The sag in voltage at the Point of Common Coupling (PCC) was also an indication of the performance (effectiveness) of each controller to stabilize the system during transient events. The DRL controller constraint the voltage dip to 3.8 V while it was 7.6 V for SRF controller and 10.0 V for the PI controller. Such a performance is of a crucial importance for voltage quality and uninterrupted performance of sensitive loads.

Lastly, the real-time execution latency, a critical requirement for embedded implementation, was evaluated by inspecting the overall control loop execution time. Both neural inference and PWM signal generation in the DRL controller ran a complete cycle in 740 µs, which is certainly within the range of general real-time control. The SRF and PI controllers had cycle times of 480 µs 210 µs, respectively, however, they were non-adaptive and had no learning capability as was the case with the DRL approach. Collectively, such improvements to the use of DRL-based SAPF indicating its superiority under all tested metrics. Its adaptive, model free, real time control capability combined with IEEE 519 compliant waveform balances the overall computational burden, and makes it an attractive solution for the next generation power quality management in renewable integrated microgrids.

Table1. *A comprehensive performance comparison among the DRL-based SAPF controller*

Metric	DRL-Based SAPF	SRF-Based SAPF	PI Controller
THD (Steady-State) (%)	2.43	4.87	5.92
THD (Under Disturbance) (%)	3.1	6.43	8.2
PF at PCC	≥ 0.995	0.98	0.96
Current Tracking Error (%)	±3.0	±5.5	±6.3
Voltage Sag at PCC (V)	3.8	7.6	10
Execution Time (µs)	740	480	210

4. CONCLUSIONS

A new real-time based implementation framework for DRL-driven SAPF for PQ improvements addressed in hybrid wind-PV microgrid under non-linear load conditions has been presented in this paper. The developed system combines intelligent control algorithms with embedded digital signal processing (DSP) hardware to mitigate harmonic distortion, voltage unbalance and reactive power compensation issues that occur in the presence of abundant of renewable energy sources in distributed generation (DG) systems.

The DRL controller, based on an actor–critic architecture, is able to automatically infer online the best compensation strategies from the interaction with the micro grid environment and adapt to dynamic fluctuation of loads and generations. The signal processing ensures accurate system state extraction, while the DRL agent learns compensation signals that are fed to the switching command through a high-frequency PWM module. The full control loop is realized in real time with DSP hardware guaranteeing sub-millisecond time response latency and feasibility for deployment in operational microgrids. Simulation and real-time hardware-in-the- loop (HIL) test demonstrate that the proposed DRL-based SAPF always achieves the better performance on harmonic compensation whose THDs are lower than 2.5%. It is shown that the proposed method is more robust against not only nonlinearities and plant dynamics, as compared to the traditional PI and SRF controllers, but also does not require a perfect system model dependent offline tuning.

This paper shows that the DRL-based control is promising and effective for embedded power quality management in microgrid applications. In the future, we will investigate the multi-agent DRL framework, hierarchical control structures, and long-term policy consistency to address more complicated DESs. Moreover, the refinement of hardware-friendly DRL inference engines, in combination with the aforementioned advances, is expected to provide scalable entity for field deployment in the variety of grid-connected and islanded microgrid topologies.

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