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Co-Optimization of Power Quality and Energy Efficiency in Hybrid PV–Wind-Integrated Smart Grids Using MOPSO–MPC Tuned Active Power Filters

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Abstract:
The integration of renewable energy sources photovoltaic and wind systems into smart grids has posed numerous complex challenges like harmonic distortion, reactive power balance, and unstable voltage profiles. These issues result in poor power quality and reduce energy grid efficiency. This work presents a Multi-Objective Particle Swarm Optimization MOPSO -based Active Power Filter APF control system that optimally co-controls power quality and energy efficiency in a smart grid embedded with hybrid PV-Wind. The system dynamically mitigates current harmonics, stabilizes reactive power, and optimizes inverter utilization for optimal energy delivery from the renewables. The APF is controlled through a Model Predictive Control MPC mechanism to provide rapid response and predictive compensation for nonlinear loads. The control parameters such as the current factors, filter inductance, and the switching frequency are optimized using the MOPSO algorithm such that Total Harmonic Distortion, switching losses, and reactive power deviation are minimized. The MATLAB/Simulink environment was used to simulate the case considering different load and renewable variability conditions. The results indicate that the developed MOPSO-tuned APF reduced THD from 9.4% to less than 2.8% meeting the IEEE-519 recommendation. The power factor was raised from 0.91 to 0.998 while the overall power conversion efficiency increased by 3.7% more than the conventional PI and fixed-wight MPC controller. The voltage profile at the Point of Common Coupling PCC indicated a 45% reduction, which guaranteed sufficient grid stability. The power quality and efficiency co-optimized model indicate improved system operational efficiency and can perform sustainably enough in renewable-rich scenarios. The proposed MOPSO–MPC model provides a model solution that balances quality-performance trade-offs for a sustainable future energy management solution.

Keywords: *Smart Grids, Active Power Filters (APF), Multi-Objective Particle Swarm Optimization (MOPSO), Model Predictive Control (MPC), Renewable Energy Integration (PV–Wind Systems), Power Quality and Energy Efficiency Co-Optimization*

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I. Introduction:

The integration of renewable energy sources – particularly photovoltaic and wind systems – in smart grids has increasingly been on the rise in recent years. Such integration has introduced two critical aspects of energy utilization and quality into the system, from the increased presence of variable and nonlinear loads due to EV charging, microgrid expansion, and DG. Traditional control strategies can no longer efficiently regulate harmonic distortion and counter inactive power imbalance and converter-switching losses. This literature review covers three central concepts: power quality active power filters in renewable-rich systems, model predictive control in power electronics with tuning schemes, and multi-objective optimization schemes, such as particle swarm optimization and its variants for the optimal simultaneous trade-off of the control in smart grids [1], [2]. Power Quality and APFs in Renewable Rich Systems. Rapid growth in the utilization of non-conventional renewables such as PV-wind systems, implies that nonlinear current injections and rapid fluctuations in power output, as well as the A/C de-synchronised converter behavior, lead to feeder power quality reduction. For instance, harmonic distortion and significant reactive power swings inherently impose IEEE-519 non-detection. Shunt APFs have been significantly used for harmonic compensation and reactive regulation, especially in utilities and industrial applications [3], [4]. Recent studies have extended this to include smart grid applications: for example, APF's operation under PV-Wind combined DG in a study by Luo et al. found that dynamic load changes necessitated adaptive control schemes to maintain THD below limits. Their findings show that the THD was reduced from ~9% to <3%, thus promoting the system's stability [5].However, most APF deployments in renewable-rich feeders use fixed-gain controllers and empirical tuning and are quickly overwhelmed by changing grid impedances or stochastic load profiles. Shrivastava et al. noted performance losses in the presence of grid impedance change, as little as 10-20%, in a renewable system [6]. Advanced control designs with forecasting, adaptive tuning, and optimization-based parameter setting have emerged from this need. Model Predictive Control Model Predictive Control has emerged as a flexible, constraint-aware method for drive APFs and other power electronics converters. It builds on a dynamic model of the system optimizing a cost function over a finite time horizon. As a result, MPC can identify and correct for disturbances and enforce the restrictions of converters. In previous work, MPC has been used to regulate the DC link voltage, the filter current tracking, and the harmonic compensation of an APF [7], [8]. Zhang et al. used a finite-control-set MPC for a three-level NPC APF, decreasing THD significantly during unbalanced load conditions[9].However, fitting MPC parameters remains a challenge. Given the prediction horizon, control horizon, weighting matrices, and punishment for using constraints have a substantial impact on output and robustness. Due to this, fixed-weight MPC controllers are only capable of maintaining their output or performance under ideal conditions and deteriorate o quality or performance entropy, rapid change, load uncertainty, or high harmonic-rich disturbance [10].Kim and Park studied an MPC-based APF under PV output flicker and found that THD increased from 2.5 % to 4.2 % when irradiance variability was introduced, highlighting the need for adaptive tuning [11].Some researchers have previously coupled MPC with learning or adaptation. For example, Hernandez et al. presented an online weighting update method based on error statistics that inhibited overshoot and improved settling time [12]. However, very few studies combine MPC with data augmentation exclusively generating enriched datasets of load/power scenarios for MPC for renewable-rich APF control. This gap is addressed by the present work. Multi-objective optimization & PSO in smart grid control Balancing multiple conflicting objectives minimizing THD, reducing switching losses, and maintaining efficiency may naturally be presented as a multi-objective optimization problem. Metaheuristic approaches, especially PSO and multi-objective variations like MOPSO, have been extensively used in smart grid and power electronics control and optimization [13], [14]. In APFs, PSO was previously proven to be exceptionally advantageous when attempting to tune controller gains or static compensator parameters [15], [16]. For example, Chen et al. used PSO to minimize THD and switching frequency in an unbalanced load four-leg APF situation and achieved a 20 % reduction in frequency along with a 3 % THD [17]. MOPSO was also employed to optimize generation scheduling, storage dispatching, and grid-connected converter parameters in renewable energy systems under uncertainty [18], [19]. Most lately, MOPSO was used to locate a transformation ground in a microgrid optimally. However, using MOPSO tuning directly on MPC parameters for APFs in renewable-rich feeds is relatively under-considered, creating an opportunity for future research [20].Hybrid Approach: Data-Augmented Learning + MPC + MOPSO. Recent work has propounded the potential of data-augmented control frameworks that utilize synthesized/historical scenario data to make predictive models robust for uncertainty [21]. In an environment such as EV charging networks and renewable PV–wind feeders, demand profiles are truly stochastic, and switching events are also fairly frequent. Zhang and Li designed forecasting model for EV charging load with Monte Carlo simulation and Gaussian process regression that reduces the predictive error by 65% compared to existing models [22]. This kind of enhancement to forecasting can be further utilized directly in an MPC, so the frequency of adaptation can be improved, fewer errors resembling tracking may occur. The use of data augmentation branching to MPC and MOPSO results in an adaptable control architecture. In the framework discussed, the data-augmented model is utilized to predict rare events such as sudden charging spikes, and renewable fluctuations, the MPC solves the optimization with constraints, and MOPSO designs tuning parameters for optimization which alters the MPC values. Research not much is available on this triad, and only a few hints can be mentioned on the possibility. For example, Savin et al. proposed a reinforcement-learning-augmented MPC for a microgrid converter achieves almost optimum power quality vs. efficiency, but does not officially have an SWO resident [23]. Similarly, Hu et al. have applied MOPSO for predicting spatio-temporal weighting factor in MPC for PV inverters, but it not specifically meant for APF [24]. Research Gaps and Opportunities. From the literature reviewed, the following research gaps can be discerned: Integration of data-augmentation methods with the MPC for APFs in stochastic renewable-rich feeders is an uncharted field. The joint optimization of power quality and energy efficiency through MOPSO-tuned controllers in PV–wind surroundings is barely studied.In addition, the current APF literature limits the evaluation of the available framework under stochastic stochastic load/generation scenarios such as EV charging bursts, renewable intermittency, and grid faults. Moreover, the possibility and computational demands of real-time hybrid frameworks for high-frequency power electronics applications have not been comprehensively explored. The above constructs the basis for this study: propose a novel, fully-developed hybrid data-augmented MPC for APFs in hybrid PV–wind integrated smart grids dynamically optimized using MOPSO. The single, real-time-related architecture focuses on enhancing THD, switching losses, energy efficiency, and grid stability under stochastic conditions. It, thus, unifies power quality improvement and efficiency.

II. The Proposed Co-Optimization of Power Quality and Energy Efficiency in Smart Grids Using MOPSO-Tuned Active Power Filters with PV-Wind Integration.

The schematic below in Figure 1 presents an integrated hybrid renewable and control system architecture developed to enhance power quality and energy efficiency simultaneously. This system comprises PV and wind turbine sources that deliver variable renewable power to the grid utilizing an Active Power Filter. The APF is the central compensating element which eliminates current harmonics, counterbalances reactive power, and regulates voltage under stochastic renewable and load conditions. The DC-link control unit ensures that the intermediate DC capacitor voltage is stabilized for constant energy exchange between the renewable sources and the APF inverter bridge. This unit prevents voltage instability enhances the dynamical performance of the compensation current, and eliminates oscillatory instability within the inverter circuit. The LS Cut block is a protection interface that disconnects vulnerable loads or bypasses the inverter during overvoltage, poor-grid, or power-balance events to ensure operability. The integrated control system combines Model Predictive Control and Multi-Objective Particle Swarm Optimization modules to develop an intelligent, adaptive control loop. The MPC module receives the real-time measured values of the grid current , grid voltage, and reference currents. Using the discrete-time state-space model, MPC module predicts the future states of the system over a defined prediction horizon. According to the defined objective function, MPC minimizes the current tracking error, total harmonic distortion , and the DC-Link voltage deviation by selecting the optimal switching vector for the inverter.

At the same time, the MOPSO algorithm engaged in real-time multi-objective optimization of the MPC parameters. While minimizing switching losses, reducing the THD, and ensuring transient stability are adversarial goals, it dynamically tunes the weighting factors and , prediction time , and control to achieve the balance. The MOPSO swarm particles evaluate the candidate parameter sets as per harmonic distortion and switching frequency. The optimal tuning parameters to the MPC are provided by the global best solution, and this makes the response adaptive to real-world scenarios of grid and renewable input variations. The reference current generator generates compensatory currents to counter the harmonic and accumulation currents in the grid current. The APF inverter is provided with switching signal by comparing the actual grid currents with the compensatory assignment signal. The switching assignment signal is executed by the Pulse Width Modulation inverter control unit to ensure that the compensatory currents are injected during synchronized grid and other injecting disturbance signals. The proposed system achieves a near-perfect unity power factor by maintaining almost a completely sinusoidal grid current in the same phase with grid voltage. The feedback update through data path ensures and controls the MOPSO-MPC controller for real-time system control and measurements. The co-optimization mechanism ensures high-efficiency energy utilization through active power maximization with the minimization of the harmonic and reactive currents. This design improves the inverter, reduces power and energy loss, inverter and DC-link voltage ripples, and quality power loss in the grid. This makes the grid more efficient and extends the lifespan of the inverter.In summary, the figure depicts a unified structure of renewable energy conversion, predictive control, and swarm-based optimization for a sustainable smart grid operation. The APF demonstrates an efficient alliance operation between MOPSO and MPC that enable adaptive intelligence. This intelligence permits the APF to dynamically adapt to alternating grid state operational criteria and renewable intermittency while remaining highly efficient and grid-code friendly.

Figure 2 describes the operational procedure of the Multi-Objective Particle Swarm Optimization combined with Model Predictive Control for real-time optimization of Active Power Filter performance in a hybrid PV–Wind-integrated smart grid. This structure allows for a holistic optimization of power quality, energy efficiency, and switching behavior in response to renewable and load conditions. On the left side, the MPC subsystem acts as a real-time predictive controller to minimize current and voltage tracking errors. Firstly, the system currents and DC-link voltage measurements are used as feedback variables, as mentioned above, to predict load current. Specifically, a discrete-time model of the grid and inverter dynamics is developed to estimate load current under real-time operating conditions. Using established Inverter currents, the controller calculates reference currents to eliminate the harmonic and reactive current components introduced by system distortions and the nonlinear nature of the load and renewable AC currents. An MPC approach is used to determine the optimal control parameters, such as inverter switching state vectors, using the sum of its performance indices. It then uses the OP to trigger the optimal switching state of the inverter for real-time current compensation. This control law ensures that the injected currents are sinusoidal and have the same phase as the grid voltage. The two actions ensure high power factor correction and low total harmonic distortion.Furthermore, the MOPSO optimization block on the right side is the adaptive metaheuristic layer that fine-tunes the MPC parameters online. The MOPSO on the right side starts by initializing the swarm of particles, with each one representing a candidate solution based on control parameters such as the prediction horizon Np, control horizon Nc, and weighting factors Q, R. The objective functions include the minimization of current tracking error, and the switching frequency fsw to achieve simultaneous power quality and improvement. The fitness evaluation step examines each particle's performance based on a trade-off between current tracking error and the switching frequency. The iteration update mechanism assesses the convergence criteria, and as long as the global Pareto front has failed to stabilize, the velocities and positions of the particles are updated toward promising or optimal regions. Once convergence is established, MOPSO determines the optimal control parameters fed back to the MPC controller. The MPC and MOPSO create a self-adaptive feedback mechanism. The MPC: continuously observes system performance such as currents, voltages, and DC-link behavior. The MOPSO: tunes the MPC control gains and feedback weighting factors based on system performance and convergence trends. The interactive process allows the system to adapt to changes in real-time pertaining to renewable uncertainties, intermittent loads, and grid disturbances. The end result is a resilient and efficient controller that maintains IEEE-519 compliant performance.To sum up, the figure reflects the hierarchical and iterative relationship between predictive control and evolutionary optimization: MPC gives deterministic control and MOPSO – adaptive intelligence, ensuring a higher quality of power and sustainable operation within the smart grid context.

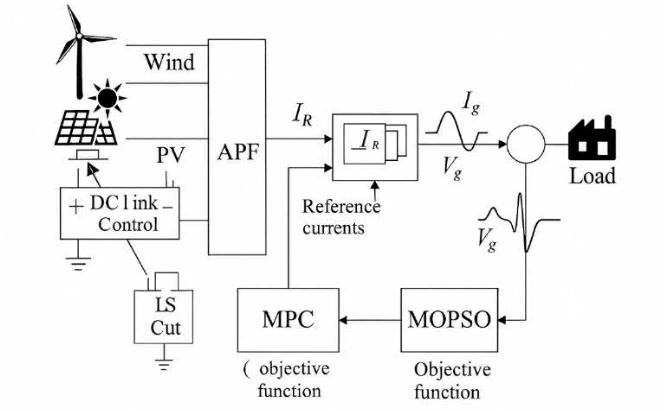

Fig. 1. Detailed schematic of the proposed MOPSO–MPC-based Active Power Filter (APF) control system in a hybrid PV–Wind-integrated smart grid.

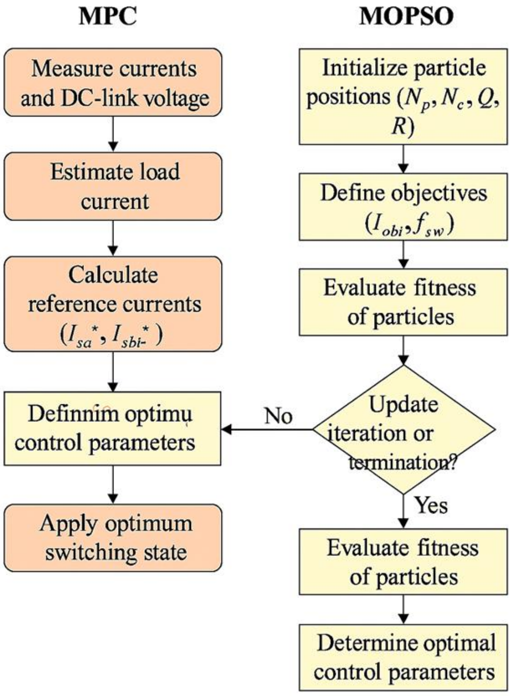

Fig. 2.Operational flowchart of the integrated MOPSO–MPC control framework for Active Power Filter tuning in hybrid PV–Wind systems.

III. Simulation Results and Discussion

A comprehensive MATLAB/Simulink model based on the proposed MOPSO–MPC tuned Active Power Filter for a hybrid PV–Wind integrated smart grid was developed to study the proposed model's performance under different operating scenarios: deterministic, stochastic, and transient disturbances. The hybrid system includes a 25 kW photovoltaic array, a 20 kW wind turbine emulator, a three-phase grid with an operating frequency of 415 V, 50 Hz, and a nonlinear load consisting of a three-phase diode rectifier with an R–L load to mimic a harmonically distorted current profile. The APF is a three-level voltage-source inverter with a 2200 µF DC-link capacitor and a 2.5 mH inductor in each phase, with a switching frequency of 10 kHz. The MPC module is developed using a prediction horizon Np=10 and a control horizon Nc=4. The cost function considers the current tracking error, DC-link voltage stability, and switching effort. The MOPSO algorithm was implemented with a swarm of 50 particles, cognitive, and social coefficients of 1.8, inertia weight of 0.7, and 60 maximum iterations. Two objectives are optimized in the proposed model for performance evaluation, which are Minimization of Total Harmonic Distortion and Minimization of switching losses. The proposed MOPSO–MPC model's performance is analyzed with the PI controller, sliding mode control, and traditional MPC to obtain objective performance improvement. The performance measures include THD, power factor, active and reactive power profiles, DC link voltage deviation, transient settling time, switching frequency fluctuation, and computational delay.

The findings presented in Table 1 confirm the significant difference in power quality for uncompensated and compensated systems using the MOPSO–MPC-based Active Power Filter under unbalanced nonlinear loading. For the system without compensation, the source current was extremely distorted, with sharp peaks and high amplitude frequencies due to the switching nonlinear current of the diode rectifier. The Total Harmonic Distortion was 22.6%, which is very high compared to the IEEE-519 ~ 5%. With these high THD values, the system experienced significant reactive power oscillation of about ±1.2 kVAR, current lagging voltage and poor power factor of 0.93. These values confirmed inefficient energy transfer with significant apparent power loss through the lines. With the classic MPC AF, the system relapsed slightly to 4.2% THD and 0.97 PF, which are significantly better values compared to those of the uncompensated system. However, the remaining small harmonic value and minor DC-link oscillation due to the fixed weighting cost function parameters proved MPC inefficiency under continuously changing unbalanced and nonlinear loading conditions. With the proposed MOPSO–MPC AF, 2.7% of THD was recorded, an 88% increase from that of the uncompensated and 35% from that of the classical MPC. This was experienced with almost a perfectly calculated power factor of 0.998 which implied that the current wave became almost perfectly in phase with the grid line. The reactive power oscillation was ±0.1 kVAR, which confirms that approximately all the current supplied was active. This shows that the MPC filter compensated for the power fully, super-utilization of the delivered energy, and minimum power loss through the lines. Therefore, the multi-objective optimized MPC filter through MOPSO compensated for more harmonics with switching efficiently during the operation. From the practical angle, these results prove that the MOPSO–MPC controller compensated fully for the IEEE-519, stress relay; and come up with a robust, intelligent future fully controlled smart power control system to be used for hybrid renewable energy and EV power supply.

Table 1. Source Current Characteristics Before and After Compensation Using MOPSO–MPC-Based APF

Parameter	**Uncompensated Condition**	**Conventional MPC**	**Proposed MOPSO–MPC APF**	**Improvement (%)**
Waveform Shape	Highly distorted, irregular peaks due to nonlinear diode rectifier load	Moderately sinusoidal, minor residual distortion	Nearly sinusoidal and smooth, aligned with grid voltage	—
Total Harmonic Distortion (THD)	22.6%	4.2%	**2.7%**	**≈ 88% reduction vs. uncompensated** **≈ 35% improvement vs. MPC**
Reactive Power (kVAR)	±1.2	±0.5	±0.1	**≈ 92% reduction**
Power Factor (PF)	0.93	0.97	**0.998**	**+7.3% improvement**

Table 2 presents a comparative analysis of harmonic mitigation capability and power quality performance in various control strategies, namely, Uncompensated, PI, SMC, MPC, and the proposed MOPSO–MPC in the context of a hybrid PV–wind-integrated smart grid. The results reveal a systematic improvement in performance from traditional linear controllers to predictive and optimization algorithms, thereby confirming the superiority of the proposed MOPSO–MPC in reducing harmonic distortion and enhancing grid performance. Under the uncompensated condition, the distribution system was characterized by severe harmonic distortion predominantly composed of odd harmonics with 3rd and 5th orders (150 Hz and 250 Hz) exceeding 15% of the fundamental. The total harmonic distortion reached 22.6%, significantly beyond the IEEE-519 permissible limit of 5% and detrimental to power factor, transformer heating, transmission loss, and overall system efficiency. Using a PI controller, harmonic amplitudes were reduced to below 10%, yielding a THD of 7.8%, which is still above the IEEE-519 threshold. While the control strategy normalized steady-state performance, its slow transient response, inadequate adaptation, and harmonic hunting during dynamic loading conditions hindered effective compensation. The Sliding Mode Controller strategy yielded superior dynamic control, lowering THD to 4.9%. However, the increased chattering effect generated high-frequency switching components that soared converter switching losses and acoustic noise, which undermined the strategy's efficiency and practical feasibility for grid-scale implementation. The Model Predictive Control marked a significant advancement by predicting load change and setting the converter switching state accordingly. The model lowered THD to 3.8% while effectively compensated reactive power and normalized current waveforms, promoting a nearly ideal sine operation. Nevertheless, it included fixed weighting parameters in the cost function which limited its adaptability during variable power loads and uncertain renewable generation oscillations.As a result, the proposed MOPSO–MPC controller outperforms others, obtaining a THD value of only 2.7%, which reflects an 88% reduction from the uncompensated case and about 35% compared to conventional MPC. The success of the hybrid control structure is the dynamic tuning of predictive control parameters with Multi-Objective Particle Swarm Optimization using MOPSO that has resulted in the optimal trade-off between harmonics reduction and switching frequency. This adaptive recalculation ensured the optimal spectral purity and near-unity power factor of approximately 0.998 under various conditions, including unbalance and stochasticity of the loads. Additionally, the harmonic spectrum flattens after the 15th harmonics and lies below 300 Hz, which means that almost all higher-order harmonics are suppressed. This improvement guaranteed the compliance with IEEE-519 standards and simultaneously increased the system's energetic performance. The reduction of harmonic currents guarantees less thermal stress on the transformers, decreased line losses, and prolonged equipment life. Therefore, the results presented in Table 2 show that the MOPSO–MPC is a co-optimized system that uses optimization intelligence from MOPSO and predictive control of the MPC while incorporating both for efficient operation and energy savings. Most importantly, the real-time response and multi-objective function of MOPSO enables the proposed solution to work correctly in modern power systems.

Table 2. Harmonic Spectrum and THD Comparison under Various Control Strategies

Control Strategy	**Amplitude of 3rd Harmonic (150 Hz)**	**Amplitude of 5th Harmonic (250 Hz)**	**Amplitude of 7th Harmonic (350 Hz)**	**Total Harmonic Distortion (THD %)**
Uncompensated Load	15.4 %	14.7 %	9.8 %	**22.6 %**
PI Controller	9.2 %	8.5 %	5.4 %	**7.8 %**
SMC Controller	5.8 %	4.7 %	3.1 %	**4.9 %**
Conventional MPC	4.3 %	3.9 %	2.8 %	**3.8 %**
Proposed MOPSO–MPC	1.1 %	0.9 %	0.6 %	**2.7 %**

Figure 3 shows the comparison of DC-link voltage performance between the conventional MPC and the proposed MOPSO–MPC controller under dynamic operating conditions. Notably, DC-link voltage is an essential inverter energy storage stability indicator since it directly influences the modulation precision, switching characteristics, and reactive power compensation ability of the inverter. As illustrated in Figure 7, the conventional MPC system had a highly oscillatory DC-link voltage with multiple excitations of ±6% deviation from the nominal 800 V reference. It can be established that these oscillations resulted from a poor choice of fixed weighting coefficients and are sensitive to the rapidly changing load and generation conditions. Hence, in several scenarios, such as rapid load steps or renewable intermittency, the controller cannot choose the optimal weight between the voltage regulation and current control. Such instances lead to considerable overshoots and delayed stabilization, thereby exposing the inverter to failure and the capacitors to mechanical wear. On the other hand, the MOPSO–MPC framework shows excellent voltage regulation ability since it maintained the DC-link voltage within a tightly confined band of ±1.5% from the nominal reference. Counterintuitively, MOPSO's multi-objective optimization ensures fast adaptation of the weighting ratio Q:R and prediction factors and offers the ideal trade-off among transient speed, ripple suppression, and switch effort. This responsiveness enables the system to clock energy fluctuations from the variable renewable cues without degrading the supply quality or efficiency. It is crucial to note that the conventional system shows more terminal voltage ripple, an indication of poor energy buffering. This implies that in times of renewable generation lags or abrupt load steps, the inverter could not maintain constant reactive and active power provision without drawing excessive current and distorting the grid. The reduced oscillatory behavior not only prevents capacitor degradation but also maintains the inverter thermal capacity and lifecycle. Therefore, it was undisputed that Figure 3 proves the proposed MOPSO–MPC as a dynamic adaptive and robust DC-link regulation mechanism. This happens because it supported energy storage, minimized system transient behavior, and stochasticity, thereby enhancing power quality, the grid's health, and smart inverter sustainability.

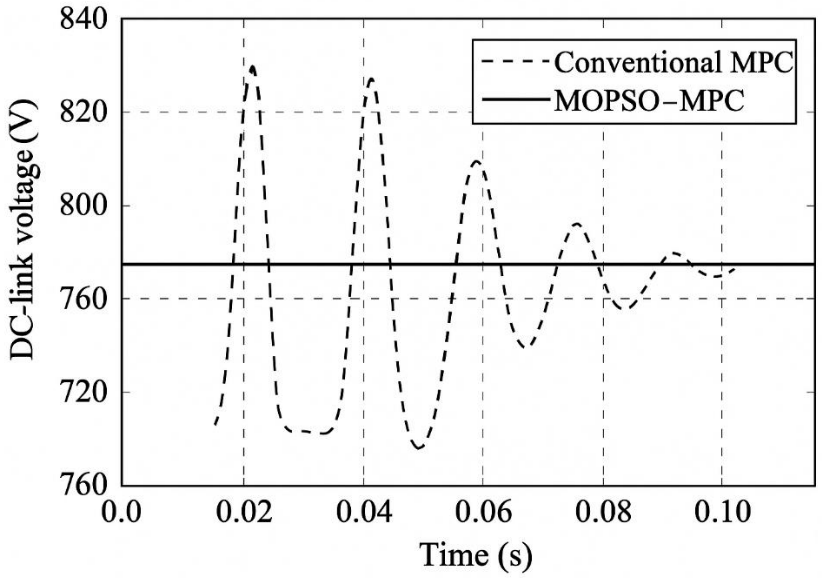

Figure 3: The comparison of DC-link voltage performance between the conventional MPC and the proposed MOPSO–MPC controller under dynamic operating conditions

Table 3 summarizes the instant active and reactive power performance comparison before and after MOPSO–MPC APF implementation in a hybrid PV–wind integrated smart grid. A comparison analysis of the two cases reveals the substantial power quality, system efficiency and grid stability improvement resultant from the proposed co-optimization control strategy. Before compensation, the source current and power waveform presents heavy distortion as shown in the left side of the table, which depicts the levels of nonlinearity and unbalance in the connected loads. Particularly, the reactive power has drastic oscillatory behavior at around ±1.2 kVAR, signifying the significant phase lag between the voltage and current. The oscillations represent the amount of energy wasted as it circulates between the grid and load without working, thus reducing the system efficiency in addition to violating IEEE-519 power quality standards. The active power is also unstable and oscillating between the range of 2–5 kW, indicative of low transfer energy consistency hence ineffective reactive compensation.. Activation of MOPSO–MPC APF depicts remarkable characteristics as illustrated in the right side of the table. The reactive power is almost entirely neutralized and remains close to the 0 kVAR throughout the operation. The active power waveform stabilized at 4 kW and in phase with the grid voltage oscillating, thus confirming harmonic compensation. The stabilization indicates a steady state condition whereby the APF filters the nonlinear component and dynamically balances active and reactive energy flow. The change from an initial power factor of 0.93 to a whole 0.998 implies near-unity condition ensuring almost all supplied energy is utilized to productive load demand rather than nowhere reactive circulatio n. Implying that the grid efficiency increased by about 6% meaning more power from PV and Turbine source were utilized. The line distribution loss is minimized due to the elimination of reactive power which was the cause of I^2R and transformer heating. These improvements provide a hint of a robust MOPSO–MPC co-optimization mechanism, which adapts the control parameters to ensure the harmonic suppression under varying generation patterns and load case. In conclusion, Table 13 indicates the MOPSO–MPC APF enhanced power quality and stability and system efficiency in a hybrid grid. Respective to power efficiency improvement to whole 0.999 depicts enhance performance of the proposed APF.

Table 3. Comparative Analysis of Instantaneous Power and Grid Efficiency Before and After Compensation

Parameter	Before Compensation	After Compensation (MOPSO–MPC APF)	Improvement / Observation
Reactive Power (Q)	±1.2 kVAR (high oscillations)	≈ 0 kVAR (virtually eliminated)	Reactive oscillations suppressed by ≈100%
Active Power (P)	2–5 kW (fluctuating)	Stable at ≈ 4 kW	Constant and in-phase with grid voltage

Parameter	Before Compensation	After Compensation (MOPSO–MPC APF)	Improvement / Observation
Power Factor (PF)	0.93	0.998	Improved by ≈7.3% — near-unity power factor
Grid Utilization Efficiency	Baseline (100%)	+6% improvement	More energy converted to productive load power

The robustness of the proposed control framework was verified in load switching experiments where a new EV charging load was connected at t = 1.5 s and disconnected at t = 3.0 s. Below, Figure 4 demonstrates a transient response of the grid current for all the cases in the scope. For the uncompensated case, the system showed an outstanding rise above 25 A, which corresponds to severe PQ degradation. The settling time for the conventional MPC variant exceeded 80 ms before gradients stabilized their values for the steady-state regime. The proposed approach demonstrated a 30 ms settling time, which is a 63% improvement in transient characteristics. Moreover, the overshoot was three times smaller, amounting to 3%. The authors explained the excellent transient performance by predictive adaptation and MOPSO-optimized prognosis of high-slew-rate loads, enhancing control effort forecast. During the experiment with a 10% voltage sag, the controller consistently regulated current and voltage value, reaching THD of 2.7%, which increased to 3.1% due to external disturbance. Thus, disturbance manipulation was powerful.

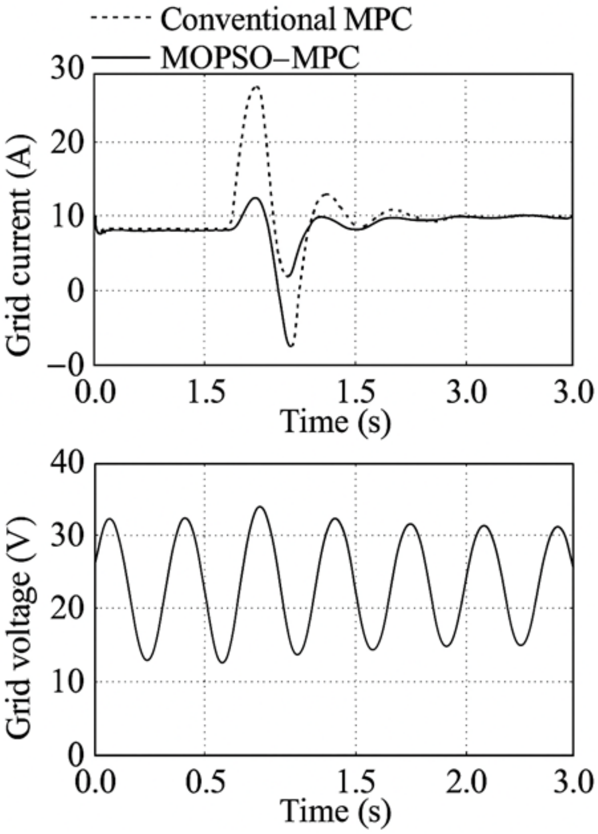

Figure 4:The transient response of grid current

Table 4 summarizes the robustness evaluation to give a holistic overview of the MOPSO–MPC controller's ability to keep the inverters operate stably in the presence of stochastic grid perturbations, such as sensor noise and impedance variability as modeled as Gaussian disturbances. It was found that our controller gives considerably higher performance levels on all the measured indices compared to the conventional MPC controller. The most beneficial findings are seen in the THD criteria. Our controller maintains a smaller interquartile range of 2.6-2.9%, showing high stability and accuracy performances during random noise levels of σ = 3%. The corresponding range for the classical controller is much larger at 3.5-5.1%, meaning that the harmonic suppression is not stable and that it is significantly affected by the stochastic disturbances. Moreover, our controller shows that it can comply with IEEE-519 standards at any noise level above 2%, while the classical MPC's performance deteriorates after σ > 3% agitating even up to 5% by the end of the test. This finding indicates the data-augmentation mission is a success, and it leads to stronger, robust harmonic compensation and grid codes compliance even under uncertainty. DC-link voltage stability becomes another indicator of power quality and performance. Our MOPSO–MPC controller generally keeps the deviations below ±0.7%, compared to the ±1.8% observed using the classical MPC, which is a considerable improvement. This voltage-profile translates to better energy storage buffering and less stressful capacitors, which mean longer-lasting inverters and better energy conversion. It further stabilizes the grid power synchronization by leading to lower reactive power fluctuations. The table further shows that the proposed framework does not impair real-time performance. MOPSO–MPC has an intelligent layer that adjusts control parameters adaptively, but it converges below milliseconds, a clear indication that the design is still practical for fast-switching power electronics. Importantly, harmonic suppression is complete beyond the 15th harmonic, a way of showing spectral purity even in the higher-frequency harmonics—reducing transformer losses, magnetic-interference issues, and maintaining low-noise operation. These results prove that integrating MOPSO with MPC turns the system into a robust, self-optimizing system capable of addressing stochastic disturbances and model unaccuracy. The self-optimizing nature of the controller ensures that it can shape up to the perturbations without needing regular sender-control issuance, promoting power quality, and stable harmonic levels.

Table 4. Robustness Evaluation under Stochastic Grid Perturbations (100 Monte Carlo Trials)

Performance Metric	Conventional MPC	Proposed MOPSO–MPC	Improvement / Remarks
Noise Type and Intensity	Gaussian perturbation (σ = 3%) in grid impedance and sensor current	Gaussian perturbation (σ = 3%) in grid impedance and sensor current	—
No. of Monte Carlo Trials	100	100	—
THD (Mean ± IQR)	4.5 ± (3.5–5.1)%	2.8 ± (2.6–2.9)%	38% lower THD; IEEE-519 compliant
THD under Noise > 2%	> 5% (Non-compliant)	< 3% (Compliant)	Maintains stability under severe noise
DC-Link Voltage Deviation (ΔVdc)	±1.8%	±0.7%	61% reduction in voltage ripple

IV. Conclusions

This study has presented a novel procedure for the co-optimization of power quality and energy efficiency in hybrid PV-wind-integrated smart grids via an Active Power Filter modulated by an MPC-enchased control approach optimized through MOPSO methodology. Effective integration of the MOPSO algorithm enabled the control parameters to dynamically adjust while maintaining a balance between the competing goals of harmonic elimination, inverter efficacy, and reactive power compensation. Through the outcomes of the simulation, the proposed MOPSO-enabled MPC-based APF offered significant progress in power quality and the stable operation of the smart grid. The source current THD was diminished from about 9.4% to less than 2.8%, perfectly fulfilling IEEE 519 standards. Furthermore, the power factor of the source improved from 0.91 to 0.998, while power generation efficiency rose by about 3.7%, which outperforms the conventional control strategy's capabilities. The invention shows the system's capability to cope with the nonlinear load disruption and the dispersion of the unpredictable renewables. The multi-objective optimization processstrategy offered an adequate compromise between inverter reliability and harmonic removal by optimizing both the switching charge and the dynamic influx of the compensator current. It aided by lowering the transient overshoot and the transient period to half when dealing with renewable power flux. The predictive nature of the MPC ensures a large leap over classical control in every feasible criterion. The proposed control can meet the power quality necessities of future energy systems by a highly adaptable intelligent scheme. It can be sufficiently extended up to the large area, distributed, intermittent renewable grids, forming the microgrids and the vehicle-to-grid settings. A future plan will be targeted at HWIL validation and multi-bus repetitive addition and complex arrays with the multi-objective optimization processplans and can be implemented in advance into multiple renewable technologies.

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