

Enhanced Power Quality in Solar PV-Based Unified Active Power Filters using a High-Gain Boost-Luo Converter with Intelligent Control

K. Natarajan^{*†}, Mohammadha Hussaini M^{**}, Siddheswar Kar^{***}, Krishna Prakash Arunachalam^{****}, Pranita Chavan^{*****}, S. Baskaran^{*****}

^{*}Professor, Department of Electrical and Electronics Eng., Trinity College of Engineering and Technology, Peddapalli, India.

^{**}Assoc. Professor, Department of Electrical and Electronics Eng., Government College of Eng., Erode, Tamilnadu, India.

^{***}Assistant Professor, Department of Electrical Engineering, Medcaps University, Indore, India.

^{****}Departamento de Ciencias de la Construcción, Facultad de Ciencias de la Construcción Ordenamiento Territorial, Universidad Tecnológica Metropolitana, Santiago, Chile, 8330383.

^{*****}Assistant Professor, Pillai HOC College of Eng. and Technology, Rasayani, University of Mumbai, 410207, India.

^{*****}Associate Professor, Department of Electrical and Electronics Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, SIMATS, Saveetha University, Chennai, Tamilnadu, India.

(drknatarajan17@gmail.com, hussaini1008@gmail.com, siddheshwar.kar@medcaps.ac.in, k.prakash@utem.cl, pranitapramod44@gmail.com, baskaran1985@gmail.com)

[†]Corresponding Author; K. Natarajan, drknatarajan17@gmail.com

Received: 14.07.2025 Accepted: 13.03.2026

Abstract- Maintaining high power quality is essential in modern electrical systems, as even minor distortions significantly impact equipment performance, operational efficiency and system reliability. Power Quality (PQ) issues such as harmonic distortion, voltage instability and frequency deviations pose major challenges to smooth operation of electrical networks. The integration of Renewable Energy Sources (RESs), particularly Photovoltaic (PV) systems, further complicates PQ management due to their intermittent nature. To address these challenges, this research proposes a Unified Active Power Filter (UAPF) that combines both series and shunt compensation techniques for comprehensive PQ enhancement. A PV based High-Gain Integrated Boost-Luo Converter is incorporated to power the DC link while an Improved Artificial Rabbit Optimized Proportional-Integral (IARO-PI) controller ensures precise voltage regulation and stable DC-link voltage. Additionally, a Cascaded Fuzzy Controller governs UAPF operation, enabling adaptive responses under nonlinear and dynamic system conditions. The proposed PV-UAPF system is validated through MATLAB simulations, achieving a substantial reduction in Total Harmonic Distortion (THD) to 0.98% and maintaining near-unity power factor. These results confirm that the integration of renewable energy with intelligent PQ management provides a robust solution for delivering stable, efficient and sustainable power distribution.

Keywords - Power quality, renewable energy sources, unified active power filter, high gain integrated Boost-Luo converter, IARO-PI controller, cascaded fuzzy controller.

Cite this article as: K. Natarajan, M. Hussaini M, S. Kar, K.P. Arunachalam, P. Chavan, and S. Baskaran, "Enhanced Power Quality in Solar PV-Based Unified Active Power Filters using a High-Gain Boost-Luo Converter with Intelligent Control" *International Journal of Smart Grid (ijSmartGrid)*, Vol. 10, No. 2, pp. 73-84, June, 2026.

1. Introduction

PQ issues are increasingly prevalent in modern electrical systems owing to the extensive usage of linear and non-linear loads [1]. These issues, as displayed in Figure 1 manifest as disturbances such as voltage sags, harmonics, flicker and unbalanced current, which significantly affect the performance and reliability of sensitive equipment. In order to conquer these challenges, the researchers have developed a number of ways to enhance PQ by utilizing Power Factor Correction (PFC) devices [2-3]. PFC techniques are pivotal in enhancing the efficiency and reliability of electrical systems by addressing inefficiencies associated with low power factors [4]. The large scale projects and installations typically utilize specialized equipment, such as Dynamic Voltage Resistor (DVR), Unified Power Quality Conditioners (UPQC) and distribution Static Synchronous Compensators (D-STATCOM) [5-6]. These devices are also known as Unified Active Power Filter, which is a sophisticated device employed in this developed work to significantly improve PQ by actively compensating for a range of disturbances and harmonics [7]. Conventional filters lacks the ability to adapt to dynamic changes in load characteristics and network conditions, which leads to inadequate power compensation for varying PQ disturbances [8]. These drawbacks are overcome by the UPAF system, which integrates both series and shunt active filter. The UAPF integrates both series and shunt active filters: the series filter regulates voltage by compensating sags and swells, while the shunt filter mitigates harmonic currents in real time. Together, they enhance PQ and improve system reliability. By combining these functionalities, UAPF provides an effective solution to enhance PQ, reduce energy losses and extend the lifespan of load.

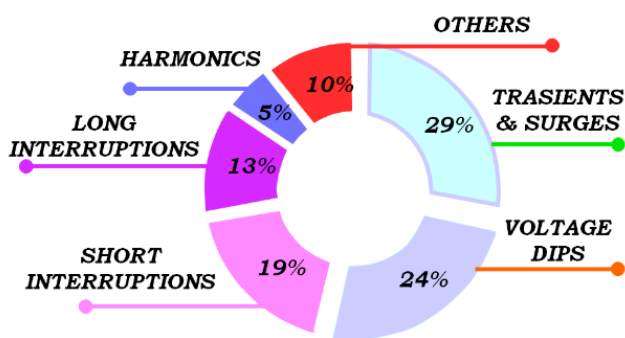


Fig. 1. Major PQ issues studied in Ref [9].

Furthermore, the control technique is essential for UAPF to enhance the reliability, efficiency and adaptability of the electrical network, this is also crucial in modern power system where the demand for stable and high quality electrical supply is paramount [10]. The conventional control technique is widely used in UAPF system due to their ability to provide desired performance metrics such as harmonic mitigation and PFC and it is robust in handling linear system dynamics. However, it is limited in handling non-linearity's and sudden changes in system dynamics without additional enhancements [11]. Therefore, the intelligent control technique of fuzzy controller [12] is employed to control the

UAPF system efficiently. This control technique adapt their control actions based on real time inputs, mimicking human decision-making processes. Nevertheless, this method has computational demands, which impact real-time control performance and system responsiveness [13-14]. Henceforth, the proposed work introduced a cascaded Fuzzy controller, which ensuring the UAPF effectively filters out harmonics and regulated PF with high accuracy.

The UAPF interconnected with the DC-link, to power this RES based PV system is utilized for reducing the greenhouse emission, which generate low output voltage owing to its sporadic nature [15]. Therefore, the DC-DC converter is required for maximizing the power of PV system, thus conventional boost, Cuk, SEPIC and Luo converter is developed for enhancing the output voltage of PV with refaces the challenges like switching stress, high complexity, and low efficiency with ripple current [16-17]. Henceforth, the proposed study introduces a novel interleaved Boost-Luo converter for providing high voltage gain with reduced switching stress. This converter enhance the voltage, but it not generate stabilized voltage, thus the control technique needs to be implement [18]. The PI controller generally used to control the voltage and to tune the parameters of this controller, Improved Artificial Rabbit Optimization approach is developed in this study for providing better performance with quick settling time and convergence speed.

Literature Survey:

Surya Prakash *et al* (2025) [19] have presented an Adaptive Proportional Integral Controller (API) for PV based Shunt Active Power Filters (SAPF). The API controller adaptively modify its parameters based on the dc-link error voltage and therefore support low bandwidth disturbance rejection for high speed dynamic response with reduced settling time, while suppressing high-order harmonic currents from the utility grid. However, the performance of the API controller is contingent on its ability to accurately estimate the reference currents.

Sergio Coelho *et al* (2022) [20] have introduced a Unified Power Converter (UPC) for solar PV in microgrid systems. The UPC function in four operating modes and each of these operating modes utilizes Dual Phase-Shifting (DPS) Modulation implemented through a Dual Active Bridge (DAB), which provides galvanic isolation and bidirectional power flow. Nonetheless, the use of high switching frequencies (100kHz), increase the difficulty of accurately calculating components.

Rajendran Boopathi *et al* (2025) [21] have implemented Predictive Direct Power Control (PDPC) approach for PV interfaced shunt active power filter. PDPC method generates reference input signals for three-level NPC inverters, providing effective harmonic reduction, reactive power compensation and active power production from the PV arrays which results in enhanced overall quality of the grid supplied power. Complex algorithm implementation creates increased computational weight that impede real time adaptation of the controller under a highly dynamic non-linear load.

V. Sheeja *et al* (2023) [22] have developed a non-isolated High Gain Boost Converter (HGBC) for compensating reactive harmonics in the grid. The HGBC which employs a sliding mode power flow controller and frequency-adaptive (SOGI) control for effective reactive power compensation and harmonic current compensation. Yet, the HGBC has designed for operation at very low voltages to minimize switch stress.

K. Hemasri *et al* (2024) [23] have designed a fuzzy controller for reducing harmonics in SAPF. The fuzzy logic controller is effective for mitigating harmonics and creates reactive power compensation for unbalanced loads while keeping the THD of the source current within the IEEE-519 limit of 4.74%. However, it relies heavily on the well-designed rule base and finely tuned parameters.

Problem Definition:

In modern electrical systems PQ issues are serious issues such as harmonics, voltage sags and unbalanced currents especially due to the widespread use of nonlinear loads. Typical controllers and filters does not adapt to the dynamic variations of the load, which results in poor compensation and a drop in efficiency. Besides this, PV-based systems are characterized by low and fluctuating voltage outputs, while the use of traditional converters causes switching stress and ripple. Hence, an advanced technique is necessary to accomplish efficient harmonic elimination, stable voltage regulation, and improved grid reliability.

The implemented work foremost contributions are illustrated as below,

- The UAPF plays a vital role in this work for enhancing PQ by addressing harmonic distortions, improving PF and balancing loads.
- Implementing Cascaded Fuzzy controller to effectively manage the operation of UAPF.
- A novel PV based Interleaved Boost-Cuk converter is introduced to ensures the voltage from the PV array matches the requirements of the DC-link.
- Employing Improved ARO optimized PI controller to enhance the voltage control, achieve fast response time with minimized MSE.

Organization:

Section 2 details proposed UAPF system description. Section 3 provides a comprehensive methodology, including all modeling of the UAPF System, fuzzy controller in cascade, PV system, boost-luo converter and improved rabbit optimization technique. Section 3 outline simulation results and performance analysis. Finally, Section 4 provide concluding remarks, including major findings and other contributions.

2. Proposed System Description

In modern power system, the PQ issues are progressively prominent due to the widespread usage of linear and non-linear loads. Challenges such as voltage fluctuations, harmonics, voltage swell and sag. To address these challenges, the UAPF is developed in this work, which

combines the capabilities of both series and shunt active power filter that efficiently mitigate the harmonic distortions and enhance the overall PQ in the linear and non-linear load. Moreover, to power DC-link of UAPF the proposed work introduced PV fed Interleaved Boost-Luo converter with Improved ARO optimized PI controller. The block diagram of the developed work is illustrated in Figure 2 as follows.

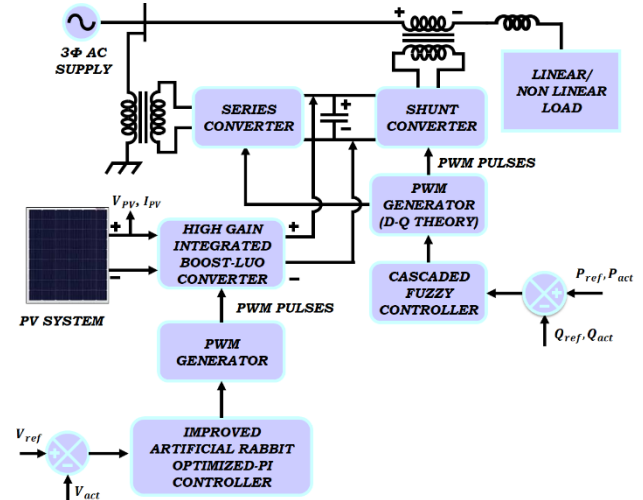


Fig. 2. Block diagram of the proposed work.

The three phase AC supply is linked with the linear and linear load, the UAPF, which is the combination of series and shunt active filters are connected in series and parallel across the PCC to control the voltage and current compensation. The UAPF consist of DC-link capacitor in between the series and shunt converter. To power the DC-link of UAPF, the RES based PV system is employed. The PV system convert the sunlight into electricity, due to the ecological changes it provide low output voltage, to boost low output in to require level it is given to the Interleaved Boost-Luo converter. This converter efficiently enhances PV voltage with high voltage gain and reduced switching stresses. Subsequently, the obtained actual voltage is compared with the reference voltage, which generate an error signal it is fed to the PI controller for error compensation thereby the stabilized voltage is attained. Moreover, to provide the stable output with less settling time, the PI controller's parameters are tuned with the aid of Improved ARO algorithm. The PWM generator is employed to provide the essential pulses for better switching operation of the converter, which is delivered to the DC-link of the UAPF. Subsequently, the UAPF is controlled by the Cascaded Fuzzy controller and to generate the appropriate pulses for the UAPF, the PWM generator (DQ theory) is utilized. Thereby, the reduced THD and stabilized power is delivered to the linear/non-linear load through the UAPF.

3. Proposed System Methodology

3.1. Modelling of UAPF System

In this work, to efficiently mitigate the PQ issues in linear and non-linear load, the UAPF is employed and the Figure 3 illustrates the diagram of UAPF system. The system consists of several key components that work together to improve the

Q delivered to industrial loads. The transmission system generates and supplies electrical power to the utility where the power enters the distribution network of the point of common coupling (PCC) the UPAF system is integrated. This point is crucial as it represents the junction where the utility's power meets the power systems of the industrial loads. The UF system includes two main active filters, the series active filter and the shunt active filter, both of which are interconnected through a DC-link. The series active filter is responsible for mitigating voltage based distortions and compensating for any voltage sags, swells or harmonics that affects the PQ. It ensures that the voltage supplied to the industrial loads is stable and within acceptable quality standards.

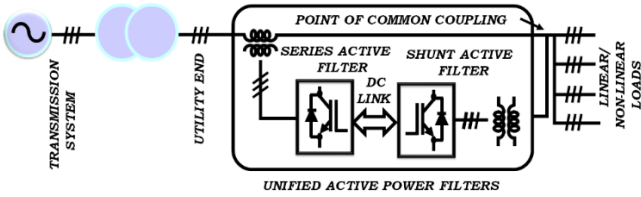


Fig. 3. Structure of UAPF.

Moreover, the shunt active filter is designed to address current based issues, such as harmonics current produced by non-linear loads and reactive power compensation. It aids to maintain a balanced and pure current flow from power compensation. It helps to maintain a balanced and pure current flow from the PCC to the industrial loads. By dynamically adjusting to the load conditions the shunt active filter maximized current distortion and enhance the overall power factor. Together, these filters ensure that the power supplied to the industrial loads is of high quality, free from significant distortions and inefficiencies. The DC-link between the two filters facilitates the exchange of energy, enabling coordinated operation for optimal PQ enhancement. The UAPF helps to sustain a stable and reliable power supply, ultimately benefiting industrial operations by reducing equipment malfunctions and improving energy efficiency.

The power supply, series and shunt APF independently control the power flow and the UAPF's mathematical modelling is examined. The Kirchhoff's law supplies the load is explained in the equation (1) and (2) given as follows,

$$V_{abc} = V_s - L_s \frac{di}{dt} - R_s i_{line} - V_{osr} \quad (1)$$

$$i_{line} = i_L - i_{sh} \quad (2)$$

Here, V_s represents the source voltage, V_{abc} indicates phase voltage of power system, V_{osr} represents the output voltage of series APF, i_{line} indicates the line current, i_{sh} denotes the shunt of APF, i_L specifies the load current respectively.

The following equations (3) and (4) indicates the voltage injected by series APF,

$$V_{inj, sr} = V_{Lref} - V_t = -V_L K < 0 \quad (3)$$

$$K = \frac{V_t - V_L}{V_L} \quad (4)$$

Here, to regulate voltage swell and sag, the APF are used, $V_{inj, sr}$ specifies the injected voltage from series APF, V_{Lref} indicates the reference load voltage, the oscillation of source voltage indicated as K , V_t denotes the terminal voltage and $\cos\phi_L$ represents the power factor load as computed in equation (5).

$$i_s = \frac{i_L}{1+K} \cos\phi_L \quad (5)$$

The equation (6) and (7) expressed the power absorbed by the series and shunt APF,

$$S_{sr} = P_{sr} + jQ_{sr} \quad (6)$$

$$S_{sh} = V_L * i_{sh} \quad (7)$$

Here, $P_{sr} = V_{sr} * i_s * \cos\phi_s$

$$Q_{sr} = V_{sr} * i_s * \sin\phi_s \quad (8)$$

From equation (8), i_{sh} indicates difference between the current source and load current, Q_{sr} and P_{sr} represents the reactive power and real/active of the series APF. The following section discusses about the Cascaded Fuzzy controller for regulating the UAPF.

3.2. Modelling of Cascaded Fuzzy Controller

A cascaded Fuzzy controller is a sophisticated control system utilized for managing UAPF, which is crucial in PQ enhancement applications. The cascaded controller enhances the UAPF's performance by dynamically adjusting its parameters based on real time conditions, thereby ensuring effectual operation under varying load and network conditions. The developed controller typically consists of two main control loops such as inner and outer loops. The outer loop responsible for producing the reference currents or voltages based on the desired performance criteria such as harmonic suppression or PFC. The inner loop then adjusts the control signals to achieve these reference values.

The control signal is expressed in equation (9),

$$\Delta u(t) = \sum_{i=1}^N \Delta u_i(t) \quad (9)$$

Where, $\Delta u_i(t)$ indicates the change in control signal for each fuzzy rule i .

By utilizing the fuzzy logic, each $\Delta u_i(t)$ is calculates in equation (10),

$$\Delta u_i(t) = \frac{\sum_{j=1}^M \mu_{i,j}(e(t)) \cdot \Delta u_{i,j}}{\sum_{j=1}^M \mu_{i,j}(e(t))} \quad (10)$$

Here, error signal is $e(t)$ and membership function is $\mu_{i,j}$.

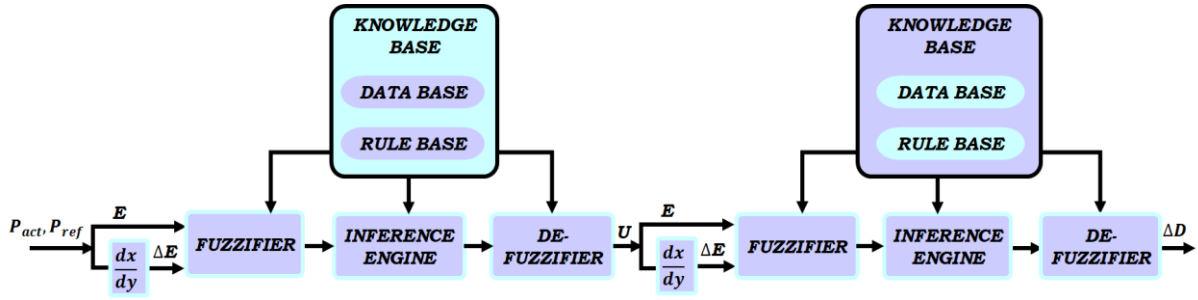


Fig. 4. Cascaded fuzzy controller.

Moreover, the fuzzy logic enables the cascaded fuzzy controller to handle the complex, non-linear dynamics of power systems effectively as illustrated in Figure 4. The following points explain how the fuzzy logic is applied in the context of controlling the UAPF's.

- **Fuzzy Rule base:** A set of linguistic rules is defined to map the input error signal and other system parameters like load conditions to appropriate changes in the control signals.
- **Membership Functions:** this quantifies the degree to which belongs to each linguistic variable defined in the fuzzy rule base. These functions capture the uncertainty and vagueness inherent in real world measurements and system responses.
- **Defuzzification:** after evaluating the fuzzy rules, the output fuzzy sets are combined to determine the crisp control action. This process ensures that the controller's decision are clear and actionable within the physical constraints of the UAPF.

Subsequently, the PWM generator (DQ theory) receives the control signals from the cascaded fuzzy controller to generate the appropriate PWM pulses for the UAPF. Furthermore, to power the dc-link of UAPF, the PV system is employed, which converts sunlight into electricity as described below.

3.3. Modelling of PV System

The PV array model is made up of parallel strings of modules, each string consisting of modules linked in series combination. The equivalent circuit of PV system is represented in Figure 5.

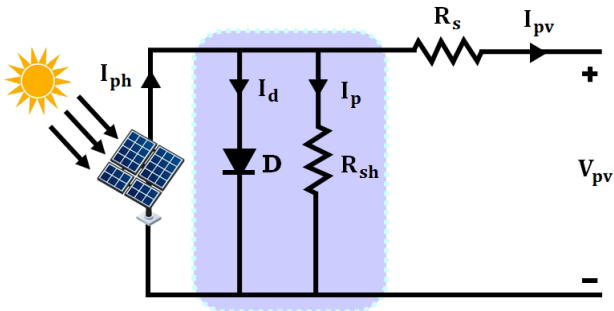


Fig. 5. Circuit diagram of PV system.

The PV system's mathematical model is provided via the equations (11), (12) and (13),

$$I_p = G I_{hg} - i_o \exp \left(\frac{q}{n T K_b} (V_p + I_p R_{sg}) - 1 \right) - \left(\frac{V_p + I_p R_{sg}}{R_{shg}} \right) \quad (11)$$

$$i_{ph} = (i_{sc} + k_i (T - T_r)) \quad (12)$$

$$i_o = \exp \left[\frac{q E_g}{A k_b} \left(\frac{1}{T_r + 273} - \frac{1}{T + 273} \right) \right] \left(\frac{T + 273}{T_r + 273} \right)^3 i_r \quad (13)$$

Here, G specifies SI in W/m², number of panels are denoted as n, K_b specifies the Boltzmann constant, R_{sh} and R indicates resistances, q specifies the charge of electron, T and T_r represents the temperature's, E_g denotes the saturation current, and the i_{ph} indicates the hot-generated current. Moreover, to maximize the output power of PV system, the proposed work introduced a novel high gain integrated Boost-Luo converter.

3.4. Modelling of Boost-Luo Converter

The integrated high gain Boost and Luo converter is type of DC-DC converter that combines the topologies of a boost converter and Luo converter as illustrated in Figure 6. This integration allows the converter to achieve high voltage gain from with reduced switching stress. Moreover, there is a reduction in the input filter capacitors current stress and magnitude. There are two modes in this converter as demonstrated in Figure 7. The proposed converter has s switch, 4 diodes, capacitors and an inductor.

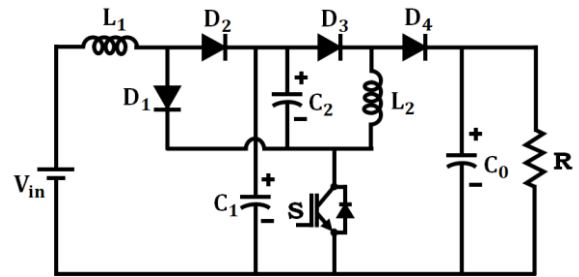


Fig. 6. Circuit diagram of high gain Boost-Luo converter.

Mode 1: When the switch conducts in the first operation mode Figure.7. (a), the forward bias of the first and third diodes become active. In the meantime positive voltage of the magnetized inductors are reset. Due to their negative current, the converter's first and output capacitors are discharged, while its second capacitor has been charged as a result of its positive current.

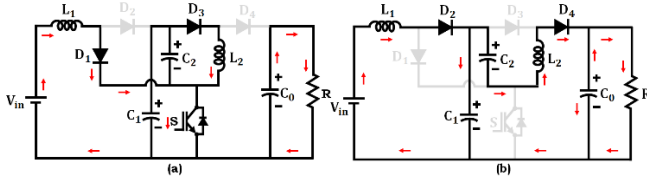


Fig. 7. Modes of operation for integrated Boost-Luo converter (a) Mode 1 and (b) Mode 2.

Mode 2: The switch is on OFF position in this mode, the first and third diodes are biased in the other direction. Conversely, the current begins to flow via the second and fourth diodes. This converter's circuit is shown in Figure 7(b), inductor get a negative voltage. The result is a demagnetized of inductors. Both the input and output capacitors currents are now positive and charging.

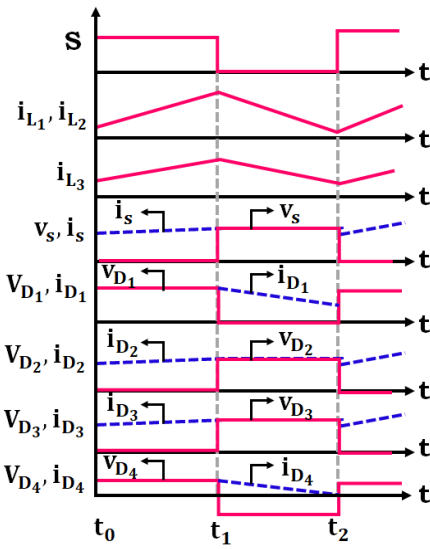


Fig. 8. Switching waveform of Boost-Luo converter.

The equation (14) describe the capacitor current and inductor voltage,

$$\begin{cases} L_1 \frac{di_{L1}}{dt} = v_{in}D + (v_{in} - v_{c1})(1-D), L_2 \frac{di_{L2}}{dt} = v_{c1}D + (2v_{c1} - v_o)(1-D) \\ C_1 \frac{dv_{C1}}{dt} = -(i_{L1} + i_{c2})D + i_{L1} - i_{c2})(1-D), C_2 \frac{dv_{C2}}{dt} = i_{c2}D - i_{L2}(1-D) \\ C_o \frac{dv_{C_o}}{dt} = -i_oD + (i_{L2} - i_o)(1-D) \end{cases} \quad (14)$$

The equation (15) for the average voltage of the capacitors and average current of the inductor is given as below.

$$\begin{cases} V_{C1} = \frac{v_{in}}{1-D}, V_{C2} = \frac{v_{in}}{1-D}, V_{C_o} = \frac{(2-D)v_{in}}{(1-D)^2} \\ I_{L1} = \frac{(2-D)}{(1-D)^2} I_o, I_{L2} = \frac{1}{1-D} I_o \end{cases} \quad (15)$$

The current flowing through the inductors when the semiconductors are in their active models causes the current stress in the switch as well as diodes. The capacitors voltage and the semiconductors inactive mode is the cause of voltage stress on the semiconductors. The relationship between the input voltage, output current and duty cycle used to express the voltage/current stress of semiconductors are related in equation (16),

$$\begin{cases} IS_1 = \frac{(1+D-D^2)I_o}{(1-D)^2}, ID_1 = \frac{D(2-D)I_o}{(1-D)^2}, ID_2 = \frac{(2-D)I_o}{1-D}, ID_3 = ID_4 = I_o \\ VS_1 = VD_3 = VD_4 = \frac{v_{in}}{(1-D)^2}, VD_1 = \frac{Dv_{in}}{(1-D)^2}, VD_2 = \frac{v_{in}}{1-D}, \end{cases} \quad (16)$$

Timing diagram of proposed high gain-boost luo-converter is displayed in Figure 8. By utilizing this converter, the output voltage of PV is efficiently boosted with better voltage gain and reduced switching stress. Moreover, to stabilize the voltage with better convergence rate, the improved artificial rabbit optimized PI controller is utilized as discussed below.

3.5. Modelling of Improved Artificial Rabbit Optimization

The improved ARO is developed for tuning the parameters for PI controller. This optimization method enhances the traditional ARA by incorporating an adaptive exploration and exploitation mechanism, which dynamically balances the search of new optimal solution and the refinement of existing ones. In this work, to enhance the efficiency of the conventional ARA. The Adaptive Local Search (ALS) and Experience Based Perturbation Learning (EPL) are the foundation of the enhanced IARO. When a rabbit is in the exploration phase, it follows the rabbit in the population. Invasive diversification patterns result from this update schedule. In order to enhance the exploratory search the EPL is incorporated to find the locations inside the workable search space. Specifically, the EPL begins by computing the mean Δ^{it}_{mean} and deviation Δ^{it}_{dev} of every randomly selected solution in relation to the best solution Δ_{best} . Subsequently, the modified answer is made based on the development with the distributed term. As a result, the improved solution is expressed in equations (17)-(21),

$$\Delta^{it}_{mean} = (Z_{best} + z^{it}_i)/2 \quad (17)$$

$$\Delta^{it}_{dev} = abs(Z_{best} - z^{it}_i) \quad (18)$$

$$\Delta^{it}_c = \Delta^{it}_{mean} + rand_1 \cdot \Delta^{it}_{dev} \quad (19)$$

$$z^{it}_{new} = \Delta^{it}_c + rand_2 \cdot (Z_{best} - \Delta^{it}_c) + 0.95^{it} \cdot (rand_3 - 0.3) \cdot abs(z_{max,j} - z_{min,j}), z_{max,j} \quad (20)$$

$$= max_j\{z^{it}_i\}, z_{max,j} = min_j\{z^{it}_i\} \forall I \quad (21)$$

Where, Δ^{it}_i specifies the arbitrary solution select at random, $rand_1, rand_2, rand_3$ denotes the random numbers based on the interval [0, 1].

An ALS strategy is said to be a guidance system based on shared information over elite group within the rabbits along with their best individual Z_{best} and the worst be individual Z_{worst} , with the goal of reducing the loss of accuracy at the iterative process as well as enhancing exploitation near the promising space. Specifically, the method that determines the best and worst role with in this group and the elite group based on fitness function (z^p and z^w). The updating stage is then carried out using three different sorts of the movement's using z^w in the direction of z^p and pushing z^w in the direction of medium of z^p and Z_{best} . These activates are done after the other in a

sequential manner, which ending when a particular person reaches a higher level of fitness. The equation (22) is an expression of this strategy's updating phase,

$$Z^{ALS}_1 = 2 \times r_1 \times (z^p - z^w) + z^w \quad \text{if } f(Z^{ALS}_1) \leq f(Z^{it}_1)$$

$$Z^{ALS}_2 = 2 \times r_2 \times (Z_{best} - z^w) + z^w \quad \text{else if } f(Z^{ALS}_2) \leq f(Z^{it}_1)$$

$$Z^{ALS}_3 = 2 \times r_3 \times (z^p + Z_{best})/2 - z^w + z^w \quad \text{otherwise}$$

(22)

Here, z^{it}_1 and Z^{it+1}_1 denotes the current and improved solutions of i th solution in an elite class. The flowchart for this improved ARO is represented in Figure 9 as follows. The developed Improved ARO algorithm efficiently tuned the PI controller with precise voltage regulation and rapid convergence speed.

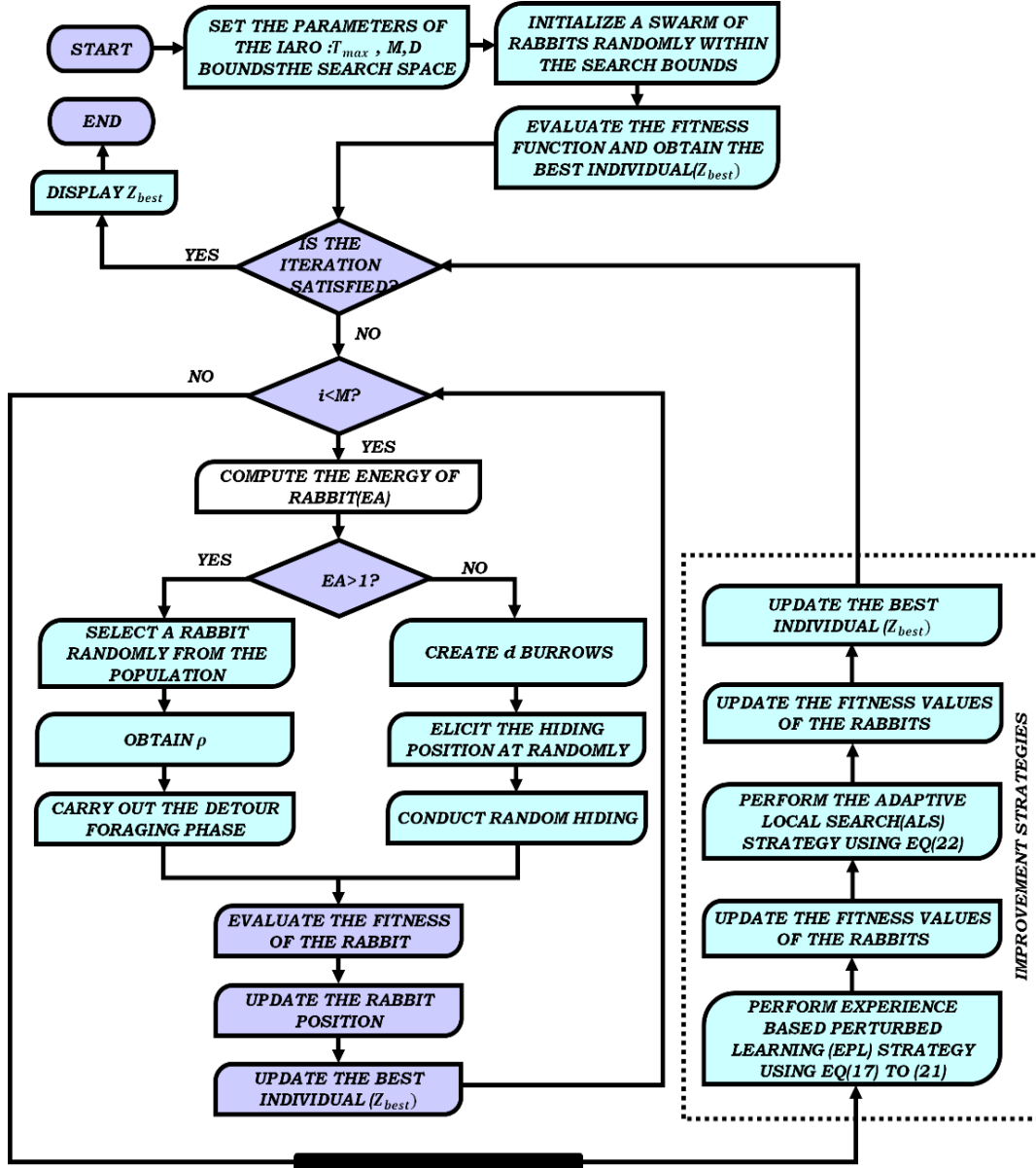


Fig. 9. Flowchart of improved ARO.

Consequently, the stabilized voltage is deliver to the PWM generator for producing pulses for the better switching operation of the converter. Finally, the enhanced and stabilized voltage is given to the linear and non-linear load via the UAPF system.

4. Results and Discussion

High PQ is crucial for maintaining the operational efficiency and longevity of electrical equipment. Thus, the

UAPF is employed in this work, which mitigate PQ issues in linear and non-linear load system by combining the functionalities of series and shunt APF. The cascaded Fuzzy controller is used to enhance the effectiveness of UAPF for enabling adaptive and predictive control responses, thereby the harmonic compensation, reactive power control and voltage regulation is attained. Furthermore, the PV system with integrated Boost-Luo converter based Improved ARO based PI controller power the DC-link of UAPF, which

provides enhanced power supply require for the linear and non-linear load. To evaluate the performance of the developed system, MATLAB/Simulink is deployed. The outcomes obtained for the developed work is illustrated in this section with the comparative analysis. Table 1 specifies the parameter specification for the developed work.

Table 1 Parameter specification

Parameter	Specification
AC Source	
Load Resistance	100Ω
Load Inductance	10mH
PV system	
Open circuit voltage	22.6V
Short circuit voltage	12A
Integrated Boost-Cuk converter	
L_1, L_2	1mH
C_1, C_2	4.7μF
C_0	2200μF
Switching Frequency	10kHz

a) Case 1 with step magnitude -0.2

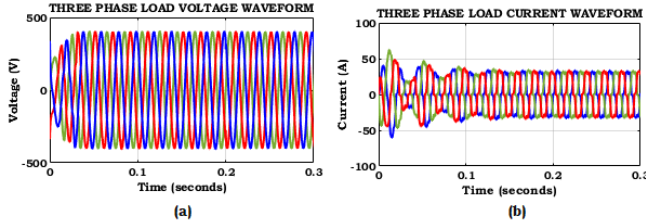


Fig. 10. Three phase load waveform.

The three phase load voltage waveform is illustrated in Figure 10(a) and (b), which indicates that the voltage and current fluctuates initially and after it constantly stabilized at 415V and 30A. The UAPF quickly respond to the sag event by compensating for the drop in voltage and ensures the current supplied to the load remains stable and free of significant distortion.

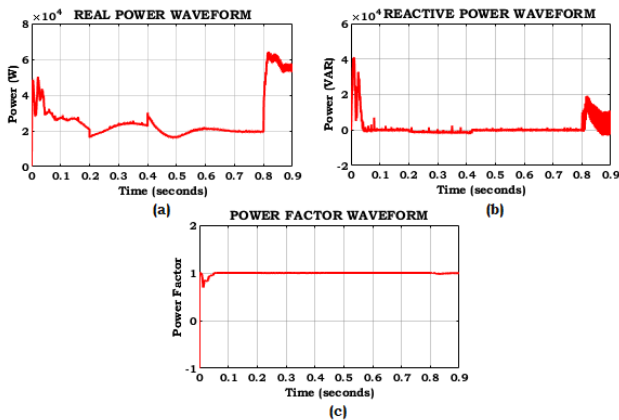


Fig. 11. (a) Real power (b) Reactive power and (c) Power factor waveform.

The real and reactive power waveform illustrated in Figure 11(a) and (b) indicating active compensation and management to handle varying load conditions, the reactive power is actively managed by compensating device such as UAPF. Additionally, the power factor waveform demonstrates that the system's ability to preserve efficient power utilization and it remains close to 1 for the time interval with minor oscillations as specified in Figure 11(c).

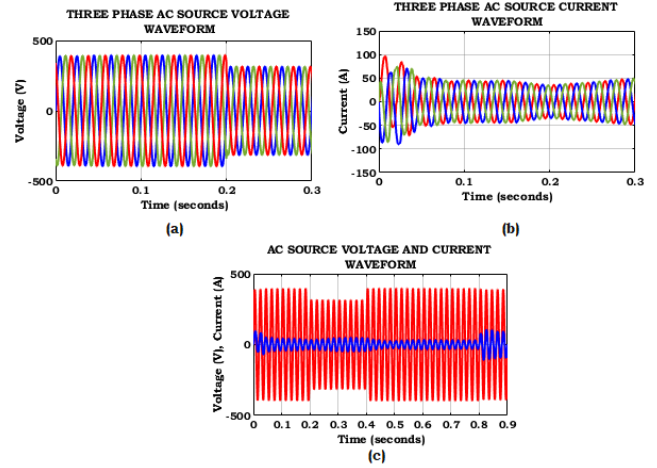


Fig. 12. Three phase AC source waveform (a) Voltage (b) Current waveform and (c) Voltage and current waveform.

The three phase AC source waveform for the voltage is represented in Figure 12(a), which provide the stabilized voltage of 415V and the current waveform in Figure 12(b) specifies that current gets highly oscillated in initial period and after 0.25s it constantly stabilized at 45A. Moreover, the in phase waveform for the AC source is specified in Figure 12(c), the voltage and current is stabilized without any distortions respectively.

The DC-link voltage waveform is illustrated in Figure 13, in which the blue line indicates the reference voltage, which exhibits fluctuations, likely due to the changes in power demand or load conditions. Similarly, the red line indicates the actual voltage waveform observed on the DC link, which closely tracks the reference waveform, with some deviations it gets constant voltage at 850V respectively.

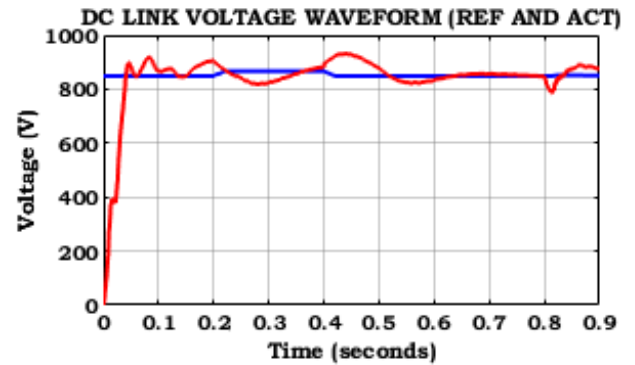


Fig. 13. DC-link voltage waveform.

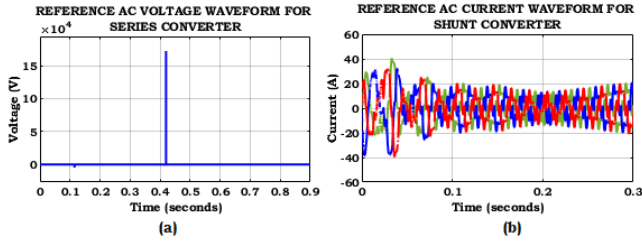


Fig. 14. Reference AC waveform (a) voltage for series converter and (b) Current for shunt converter.

Fig. 14 demonstrates the reference AC voltage and current waveform for the series and shunt converter. The series converter waveform represents that the voltage of the converter as displayed in Figure 14(a) achieve the desired power flow. The Figure 14(b) represents the AC current waveform for the shunt converter. By coordinating the operation of these two converters, the UAPF approach achieve efficient and flexible power flow management.

b) Case 2 with step magnitude -0.2

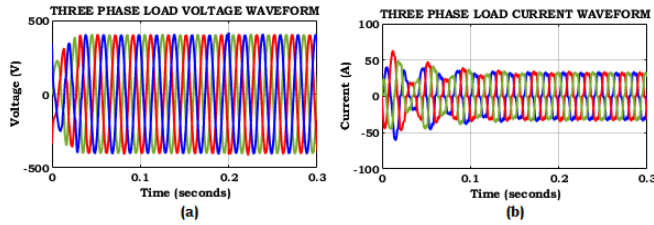


Fig. 15. Three phase Load waveform for case 2.

Fig. 15(a) and (b) represents the three phase load voltage waveform, which shows that the voltage and current vary at first, then steadily stabilized at 415V and 30A. In order to ensure the current delivered to the load is stable and free of sustainable distortion, the UAPF promptly responds to the swell event by compensating for the voltage drop.

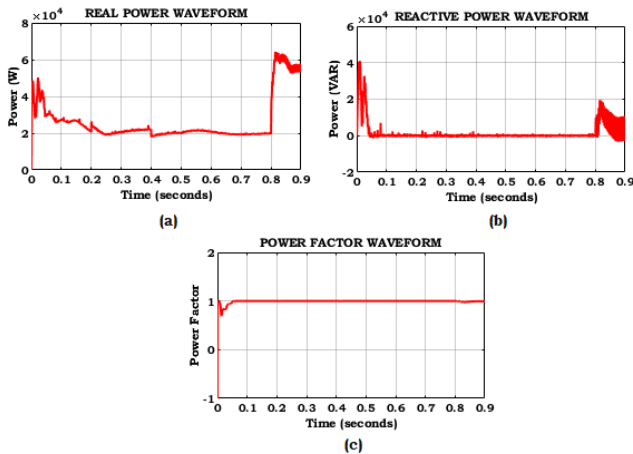


Fig. 16. (a) Real power (b) Reactive power and (c) Power factor waveform.

Fig. 16(a) and (b) depict the real and reactive power waveforms, which show active reactive power management and compensation to handle varying load situations. A compensating device like UAPF actively manages reactive power. Furthermore, the power factor waveform shows that

the system continue to use power efficiently and stays near to 1 during the period of time with slight oscillations as shown in Figure 16(c).

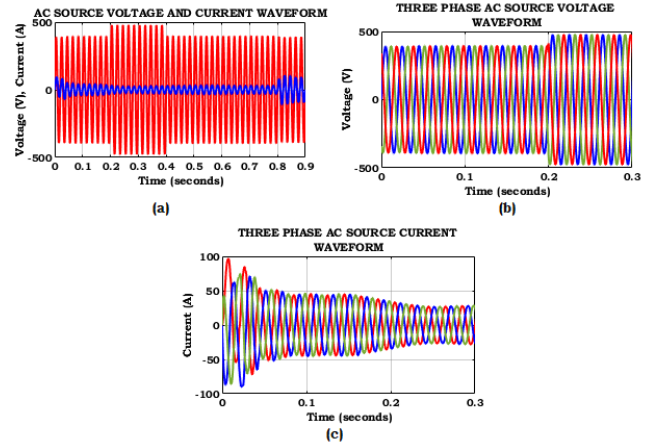


Fig. 17. Three phase AC source waveform (a) Voltage and current (b) voltage and (c) Current waveform.

Fig. 17(a) shows the in phase waveform for the AC source, which illustrates there are the stabilized voltage and current. Figure 17(b) shows the three-phase AC source waveform for the voltage, which provides a stabilized range at 415V. Figure 17(c) shows the current waveform, which indicates that the current oscillates greatly in the beginning and then steadily stabilizes at 45A after 0.25 seconds

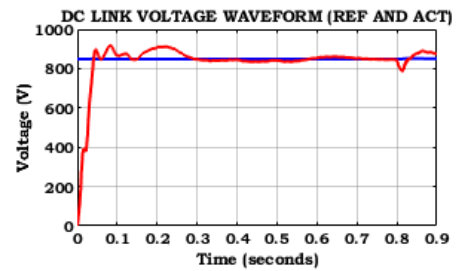


Fig. 18. DC-link voltage waveform.

In Figure 18, the DC-link voltage waveform is depicted, the reference voltage, represented by the blue line, which varies as a result of variations in load circumstances or power demand. Comparably, the red line shows the real voltage waveform seen on the DC link, which mostly follows the reference waveform and reach a constant value of 850V, respectively.

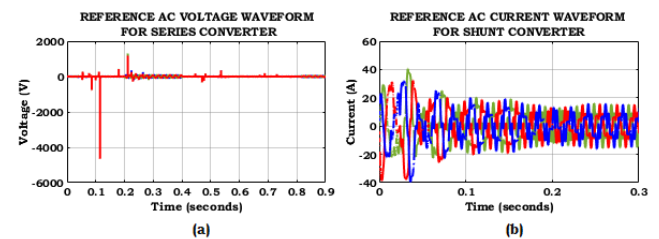


Fig. 19. Reference AC waveform (a) voltage for series converter and (b) Current for shunt converter.

The reference AC voltage and current waveform for the series and shunt converter is shown in Figure 19. The series

converter waveform from Figure 19. (a) shows that the converter's voltage produces the intended power flow. The shunt converter's AC current waveform is shown in Figure 19(b), through the synchronization of these two converters, the UAPF method accomplishes effective and adaptable power flow control.

Figure 20 shows the THD waveform for current attained by the developed work, which is observed that the proposed Cascaded ANN controller attains the THD value of 0.98%, thereby effectively mitigating the PQ disturbances.

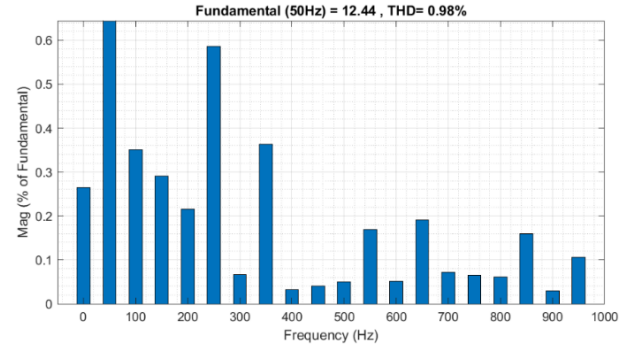


Fig. 20. THD waveform.

Table 2. Comparison of Proposed UAPF (Cascaded Fuzzy controller) with conventional control approach

Sl. No	Features	UPQC (SRF controller) [24]	UPQC (ANN controller)[25]	UAPF (Cascaded Fuzzy controller)
1.	Complexity	High	low	Very low
2.	Dynamic response	low	High	High level
3.	Accuracy	low	Medium	High level
4.	Process of Controlling	Slower	Fast	Very High
5.	% THD	3.56%	2.97%	0.98%

Table 2 shows that the proposed UAPF with cascaded fuzzy control is a much better option than the conventional SRF and ANN-based controller. A cascaded fuzzy controller has the advantage of keeping complexity low without compromising the dynamic response and accuracy, which are very important for the real-time PQ improvement. Most significantly, the proposed method bring down the THD to 0.98%, which is far below the limit set by the IEEE-519 standard, thus proving its capability in harmonics reduction. Such a massive drop in THD level lead to system stabilization, less energy wastage and longer equipment life.

Fig. 21 illustrates voltage gain of the integrated Boost-proposed converter constantly produces higher voltage gain than other converters, which proves its appropriateness for the PV-based systems where stable and high voltage level is required.

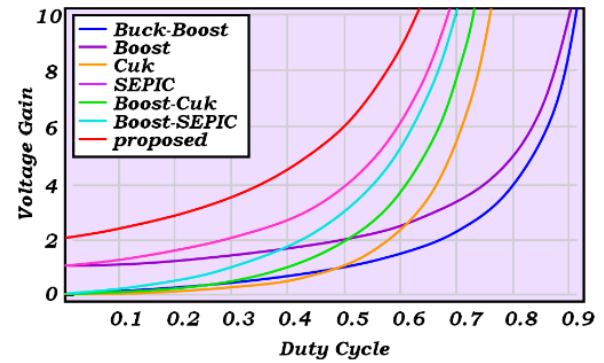


Fig. 21. Comparison of voltage gain.

Table 3. Comparison of traditional converters [20] with the proposed Boost-Luo converter

Converters	Inductors	Capacitors	Switches	Diodes	Input resistance	Voltage gain	Switching loss
Boost	1	1	1	1	$(1-D)^2 R_L$	$\frac{1}{1-D}$	High
Buck-Boost	1	1	1	1	$\frac{(1-D)^2}{D^2} R_L$	$\frac{D}{1-D}$	Low
Cuk	2	1	1	1	$\frac{(1-D)^2}{D^2} R_L$	$-\frac{D}{1-D}$	Low
SEPIC	2	1	1	1	$\frac{(1-D)^2}{D^2} R_L$	$\frac{D}{1-D}$	Low
Proposed Boost-Luo	2	3	1	3	$\frac{(1-D)^2}{D^2} R_L$	$\frac{SD-1}{2D-1}$	Very Low

Table 3 illustrate that the proposed BoostLuo converter has a greater voltage gain than the conventional converters and at the same time switching losses have been reduced. This is a major upgrade for PV systems whose output is low and intermittent which needs to be efficiently boosted and stabilized. The converter's structure lowers the stress of switching devices and enhances efficiency. Thus, the Boost-Luo converter is a more dependable and environmentally friendly option for renewable energy integration.

Fig. 22 depicts the MSE value comparison among three optimization algorithms such as IARO, Artificial Rabbit Optimization (ARO) and Particle Swarm Optimization (PSO). It indicates that IARO mainly obtains lower MSE values than other algorithms at different iterations, thus outperforming both ARO and PSO in terms of convergence rate and error reduction.

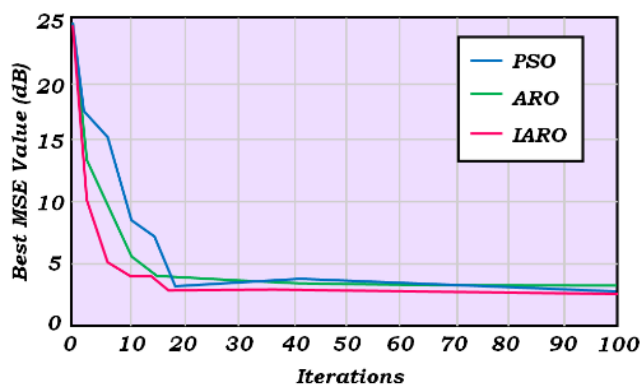


Fig. 22. Comparison of best MSE value.

5. Conclusion

This paper proposes UAPF integrated with the High gain Integrated Boost-Luo converter for PQ enhancement. The UAPF effectively mitigates PQ issues like harmonics, reactive power and load unbalance in linear and non-linear loads. By employing a Cascaded Fuzzy controller, the UAPF achieves superior control accuracy and robustness in managing harmonic current. The UAPF integration with High gain Integrated Boost-Luo converter enhances the output voltage of PV efficiently with high voltage gain ratio and reduced switching stress. Moreover, the utilization of an Improved ARO optimized PI controller, which allowing for precise control and adaptive tuning performance, thereby providing the overall system stability with reduced MSE error. The MATLAB/Simulink is implemented for analyzing the proposed system effectiveness and the comparative analysis outcomes demonstrates that the proposed system attains better dynamic response, reduced THD value of (0.98%), high voltage gain and minimized MSE compared to the traditional approaches. Thus, the proposed system not only addresses current PQ issues effectively but also paves the way for future enhancement in renewable energy integration and load stability.

Acknowledgements

Not applicable.

Author Contributions

K. Natarajan: Conceptualization, Methodology, Writing-Original Draft

Mohammadha Hussaini M, Siddheswar Kar, Krishna Prakash Arunachalam: Data Curation, Methodology, Supervision

Pranita Chavan, S. Baskaran: Project administration, Validation, Writing - Review & Editing

All authors reviewed and approved the final version.

Conflict of Interest

The authors declare no conflict of interest.

References

- [1] P. S. Sanjan, N. Gowtham, M. S. Bhaskar, U. Subramaniam, D. J. Almkhles, S. Padmanaban, and N. G. Yamini, "Enhancement of power quality in domestic loads using harmonic filters", *IEEE Access*, vol. 8, pp. 197730-197744, Oct. 2020, doi: <https://doi.org/10.1109/ACCESS.2020.3034734>
- [2] A. Y. Qasim, F. R. Tahir, and A. N. B. Alsammak, "Utilizing UPQC-Based PAC-SRF techniques to mitigate power quality issues under non-linear and unbalanced loads", *Journal Européen des Systèmes Automatisés*, vol. 56, no. 5, Oct. 2023.
- [3] P. Sujidha, M. Devi, A. Manjula, N. Thillainayagi, and A. Usha, "Novel approach of power quality issues suppression using cascaded h-bridge multilevel inverter based DSTATCOM", *Int. J. Adv. Res. Sci. Commun. Technol.*, 2022.
- [4] K. Hasan, M. M. Othman, S. T. Meraj, M. Ahmadipour, M. H. Lipu, and M. Gitizadeh, "A unified linear self-regulating method for active/reactive sustainable energy management system in fuel-cell connected utility network", *IEEE Access*, vol. 11, pp. 21612-21630, Feb. 2023, doi: <https://doi.org/10.1109/ACCESS.2023.3249483>
- [5] S. J. Alam, and S. R. Arya, "Control of UPQC based on steady state linear Kalman filter for compensation of power quality problems", *Chinese Journal of Electrical Engineering*, vol. 6, no. 2, pp. 52-65, Jun. 2020, <https://doi.org/10.23919/CJEE.2020.000011>
- [6] S. G. Reddy, S. Ganapathy, and M. Manikandan, "Three phase four switch inverter based DVR for power quality improvement with optimized CSA approach", *IEEE Access*, vol. 10, pp. 72263-72278, Jul. 2022, doi: <https://doi.org/10.1109/ACCESS.2022.3188629>
- [7] E. Akbari, and A. Z. G. Seyyedi, "Power quality enhancement of distribution grid using a photovoltaic based hybrid active power filter with three level converter", *Energy Reports*, vol. 9, pp. 5432-5448, Dec. 2023, doi: <https://doi.org/10.1016/j.egyr.2023.04.368>

- [8] S. Chandrakala Devi, B. Singh, and S. Devassy, "Modified generalised integrator based control strategy for solar PV fed UPQC enabling power quality improvement", *IET Generation, Transmission & Distribution*, vol. 14, no. 16, pp. 3127-3138, Aug. 2020, doi: <https://doi.org/10.1049/iet-gtd.2019.1939>
- [9] T. Ravi, and K. Sathish Kumar, "Analysis, monitoring, and mitigation of power quality disturbances in a distributed generation system", *Frontiers in Energy Research*, vol. 10, pp. 989474, Nov. 2022, doi: <https://doi.org/10.3389/fenrg.2022.989474>
- [10] M. Golla, S. Thangavel, S. P. Simon, and N. P. Padhy, "A novel control scheme using UAPF in an integrated PV grid-tied system", *IEEE Transactions on Power Delivery*, vol. 38, no. 1, pp. 133-145, Jun. 2022, doi: <https://doi.org/10.1109/TPWRD.2022.3180681>
- [11] M. Aijaz, I. Hussain, S. A. Lone, and M. Chankaya, "GRLF-LAD control based active power filter operation with QSG-SOGI algorithm for grid voltage harmonics disturbance rejection", *IEEE Access*, vol. 11, pp. 135753-135763, Nov. 2023, doi: <https://doi.org/10.1109/ACCESS.2023.3337551>
- [12] A. M. Bloul, M. Abuhamdah, A. M. Sharaf, H. H. Aly, and J. Gu, "An efficient shunt modulated AC green plug-switched filter compensation scheme for nonlinear loads", *Energies*, vol. 17, no. 10, pp. 2426, May. 2024, doi: <https://doi.org/10.3390/en17102426>
- [13] M. A. Hannan, G. Sebastian, A. Q. Al-Shetwi, P. J. Ker, S. A. Rahman, M. Mansor, K. M. Muttaqi, and M. Uddin, "Particle swarm optimization algorithm based fuzzy controller for solid-state transfer switch toward fast power transfer and power quality mitigation", *IEEE Transactions on Industry Applications*, vol. 59, no. 5, pp. 5570-5579, Jun. 2023, doi: <https://doi.org/10.1109/TIA.2023.3289440>
- [14] T. Ravi, K. S. Kumar, C. Dhanamjayulu, B. Khan, and K. Rajalakshmi, "Analysis and mitigation of PQ disturbances in grid connected system using fuzzy logic based IUPQC", *Scientific Reports*, vol. 13, no. 1, pp. 22425, Dec. 2023, doi: <https://doi.org/10.1038/s41598-023-49042-z>
- [15] S. Parthiban, and V. Madhaiyan, "Experimental validation of solar PV sustained ZSI based unified active power filter for enrichment of power quality", *Automatika*, vol. 62, no. 1, pp. 137-153, Jan. 2021, <https://doi.org/10.1080/00051144.2021.1908013>
- [16] S. S. Dheeban, and N. B. Muthu Selvan, "ANFIS-based power quality improvement by photovoltaic integrated UPQC at distribution system", *IETE Journal of Research*, vol. 69, no. 5, pp. 2353-2371, Jul. 2023, doi: <https://doi.org/10.1080/03772063.2021.1888325>
- [17] B. N. Reddy, F. Alsaif, C. R. Reddy, and S. S. Kumar, "Development of multiple input supply based modified SEPIC DC-DC converter for efficient management of DC microgrid", *Scientific Reports*, vol. 14, no. 1, pp. 11066, May. 2024, doi: <https://doi.org/10.1038/s41598-024-61713-z>
- [18] W. El Aouni, and L. A. Dessaint, "Real-time implementation of input-state linearization and model predictive control for robust voltage regulation of a DC-DC boost converter", *IEEE Access*, vol. 8, pp. 192101-192108, Oct. 2020, doi: <https://doi.org/10.1109/ACCESS.2020.3032327>
- [19] S. Prakash, M. Alkhatib, H. F. Sindi, S. Alghamdi, R. K. Behera, and U. R. Muduli, "Adaptive control for shunt active power filter under stochastic solar photovoltaics behavior", *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 13, no. 3, pp. 3673-3687, 2025, <https://doi.org/10.1109/JESTPE.2025.3525489>
- [20] S. Coelho, V. Monteiro, T. J. Sousa, L. A. Barros, D. Pedrosa, C. Couto, and J. L. Afonso, "A unified power converter for solar PV and energy storage in dc microgrids", *Batteries*, vol. 8, no. 10, pp. 143, 2022, doi: <https://doi.org/10.3390/batteries8100143>
- [21] R. Boopathi, and V. Indragandhi, "Enhancement of power quality in grid-connected systems using a predictive direct power controlled based PV-interfaced with multilevel inverter shunt active power filter", *Scientific Reports*, vol. 15, no. 1, pp. 7967, 2025, <https://doi.org/10.1038/s41598-025-92693-3>
- [22] V. Sheeja, R. Kalpana, U. Subramaniam, and D. J. Almakhlles, "Control of converter for a solar PV-BESS powered telecom load with real, reactive and harmonic power exchange with grid", *IEEE Access*, vol. 11, pp. 141008-141021, 2023, <https://doi.org/10.1109/ACCESS.2023.3340433>
- [23] K. Hemasri, and C. S. Kumar, "Fuzzy controller with shunt active power filter in reducing THD for three phase system", *International Transactions on Electrical Engineering and Computer Science*, vol. 3, no. 2, pp. 101-108, 2024, <https://doi.org/10.62760/iteecs.3.2.2024.93>
- [24] H. Mahar, H. M. Munir, J. B. Soomro, F. Akhtar, R. Hussain, M. F. Elnaggar, S. Kamel, and J. M. Guerrero, "Implementation of ANN controller based UPQC integrated with microgrid", *Mathematics*, vol. 10, no. 12, pp. 1989, Jun. 2022, doi: <https://doi.org/10.3390/math10121989>
- [25] R. Gopalasami, B. Chokkalingam, and S. Muthusamy, "A novel method for hybridization of super lift Luo converter and boost converter for electric vehicle charging applications", *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, vol. 45, no. 3, pp. 8419-8437, Aug. 2023, doi: <https://doi.org/10.1080/15567036.2023.2226104>

Real Time Assessment of Robust Power Control based DFIG-WT: Power Quality Enhancement Delivered to the AC Balanced Load using dSPACE-1103

Fayssal Amrane*[†], Azeddine Chaiba**, Habib Benbouhenni***, Bruno Francois****, Oussama Gherouat*****[†], Hichem Itouchene *****[†]

* LAS Research Laboratory, LEPCI Research Laboratory, Department of Electrotechnic, Faculty of Technology, Ferhat ABBAS Setif-1 University, 19000 Setif, Algeria

** Department of Electrical Engineering, Faculty of Technology, University of Batna-2, Algeria

*** Department of Electrical Engineering, Faculty of Technology, Hassiba Benbouali University of Chlef, Chlef, Algeria

**** Univ. Lille, Arts et Métiers Institute of Technology, Centrale Lille, Junia, ULR 2697 - L2EP, F-59000 Lille, France

***** LEPCI Research Laboratory, Department of Automatic, Faculty of Electrical Engineering, University of Sciences and Technology Houari Boumediene, Algeria

***** Université de Bejaia, Faculté de Technologie, Lab de Techn Ind et de l'Information (LTII), 06000 Bejaia, Algeria

(amrane_fayssal@univ-setif.dz, azeddine.chaiba@univ-batna2.dz, habib0264@gmail.com, bruno.francois@centralelille.fr, oussama.gherouat@usthb.edu.dz, hichem.itouchene@univ-bejaia.dz)

[†]Corresponding Author; Fayssal Amrane, Campus El-Maabouda, Université Sétif-1, route de Bejaia, Setif 19000, Tel: +213 658 26 75 65, amrane_fayssal@univ-setif.dz amranefayssal@gmail.com

Received: 24.07.2025 Accepted: 24.12.2025

Abstract- The increasing demand for reliable and efficient renewable energy systems has intensified the need for advanced control strategies in Variable Speed Wind Energy Conversion Systems (VSWECS), particularly when operating in stand-alone mode. Doubly Fed Induction Generators (DFIGs) require precise and robust power control to maintain stable operation under varying wind and load conditions. Addressing this challenge, this paper presents the hardware implementation of a Vector Power Control (VPC) strategy for DFIGs operating in stand-alone mode within VSWECS. The proposed VPC approach employs robust Integral-Proportional (IP) controllers to regulate the Rotor Side Converter (RSC) through the d-q components of the rotor current (I_{rd}^* and I_{rq}^*) using an AC-DC-AC converter. The control scheme is experimentally implemented on a dSPACE dS1103 platform and evaluated during both under-synchronous and over-synchronous operation (below and above the 1500 rpm synchronous speed). Experimental results demonstrate that the IP-based control significantly improves dynamic performance, ensures high system stability, and achieves effective decoupled power control of the DFIG-driven wind turbine.

The system exhibits accurate reference tracking, fast response, and minimal power error, even under abrupt changes in wind speed and rotor current references.

Keywords Vector power control (VPC), doubly fed induction generator (DFIG), integral-proportional (IP), wind energy conversion system (WECS), dSPACE dS1103

1. Introduction

Wind power is a highly favoured and commonly utilized renewable energy source for generating electricity [1-3]. It is accessible year-round, cost-free, and environmentally friendly, as it does not emit harmful gases during energy generation. Turbines play a vital role in converting wind energy into mechanical energy, and there have been notable advancements in wind turbine technology in recent years [4-9].

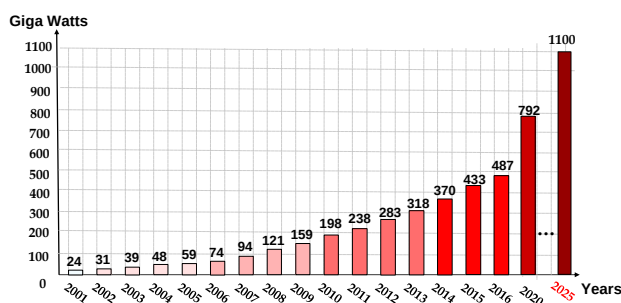


Fig. 1. On-shore cumulative wind power capacity (Giga Watts) from 2001 to 2025.

These advantages include the ability to operate at variable speeds for optimal power capture, decoupled control of active and reactive power, lower converter costs, and reduced overall power losses [10-13]. Figure 1 depicts the global evolution of installed wind power capacity between 2001 and 2020. Over this period, wind energy experienced steady and continuous growth, increasing from just 24 GW in 2001 to more than 1,100 GW in 2020. The figure highlights a gradual rise during the early 2000s, followed by a sharper acceleration after 2010 as wind technology became more cost-effective and widely adopted. In particular, the years after 2015 show significant expansion, with installations reaching 732 GW by 2019 before surpassing the terawatt threshold in 2020. Overall, the figure demonstrates the rapid global shift toward large-scale deployment of wind energy, driven by technological advancements, supportive policies, and increasing demand for clean and sustainable power sources.

The traditional vector power control (VPC) of Doubly Fed Induction Generator (DFIG) based wind turbines has several limitations. First, its performance heavily depends on accurate machine parameters, such as stator and rotor inductances, which can vary with operating conditions, leading to control inaccuracies [14-16]. Second, it relies on precise rotor position measurements, making it sensitive to encoder faults or misalignments [17-18]. Third, the use of proportional-integral (PI) controllers introduces challenges in tuning gains for optimal dynamic response under varying wind speeds [19]. Additionally, the decoupled control of

active and reactive power is often imperfect due to cross-coupling effects, especially during grid disturbances. The method also lacks robustness against grid voltage imbalances and harmonics, which can degrade power quality [20-21].

The Integral-Proportional (IP) controller offers superior performance over traditional PI controllers in DFIG power control due to its enhanced dynamic response and stability [22-23]. Unlike PI controllers, which introduce phase lag and require careful tuning to avoid overshoot, the IP structure provides faster transient response by placing the integral action in the feedback path, reducing oscillations in active and reactive power. This design minimizes steady-state error while improving robustness against parameter variations, such as changes in wind speed or grid disturbances [24-25]. Additionally, IP controllers simplify implementation in stand-alone mode by eliminating the need for decoupling terms, as they inherently handle cross-coupling effects between d- and q-axis currents. In grid-connected operation, IP-based direct power control (DPC) achieves lower harmonic distortion and smoother power tracking compared to PI-based vector control, enhancing power quality [26-27]. The IP controller's adaptability to nonlinearities, such as unbalanced grid voltages, further ensures reliable performance under fault conditions, making it ideal for both isolated and grid-tied DFIG systems [28-30].

In this paper, robust IP controller is proposed instead the traditional PI controller in order to control independently the stator active P_s (W) and reactive powers Q_s (Var) along d-q axes for stand-alone operating mode under RL-balanced load. MPPT strategy is proposed to maintain the maximum power regardless wind speed variation, by keeping the unity power factor close to the unity means the DFIG exchange the active power to the grid.

The main contributions of this paper are illustrated as follow:

- Improved Dynamic Response – The IP controller reduces overshoot and settling time by placing the integral action in the feedback path, enabling faster and smoother power tracking compared to PI controllers.
- Reduced Steady-State Error – The IP structure inherently minimizes power deviations, ensuring more precise regulation of P_s (W) and Q_s (var) under varying operating conditions.
- Elimination of Decoupling Requirements – Unlike PI-based vector control, which needs additional decoupling terms for d-q axis currents, the IP controller naturally mitigates cross-coupling effects, simplifying implementation.
- Simplified Tuning Process – IP controllers require fewer tuning adjustments than PI controllers, as their structure inherently reduces dependency on exact gain matching for optimal performance.
- Lower Harmonic Distortion – When applied in DPC schemes, IP controllers reduce current THD by minimizing

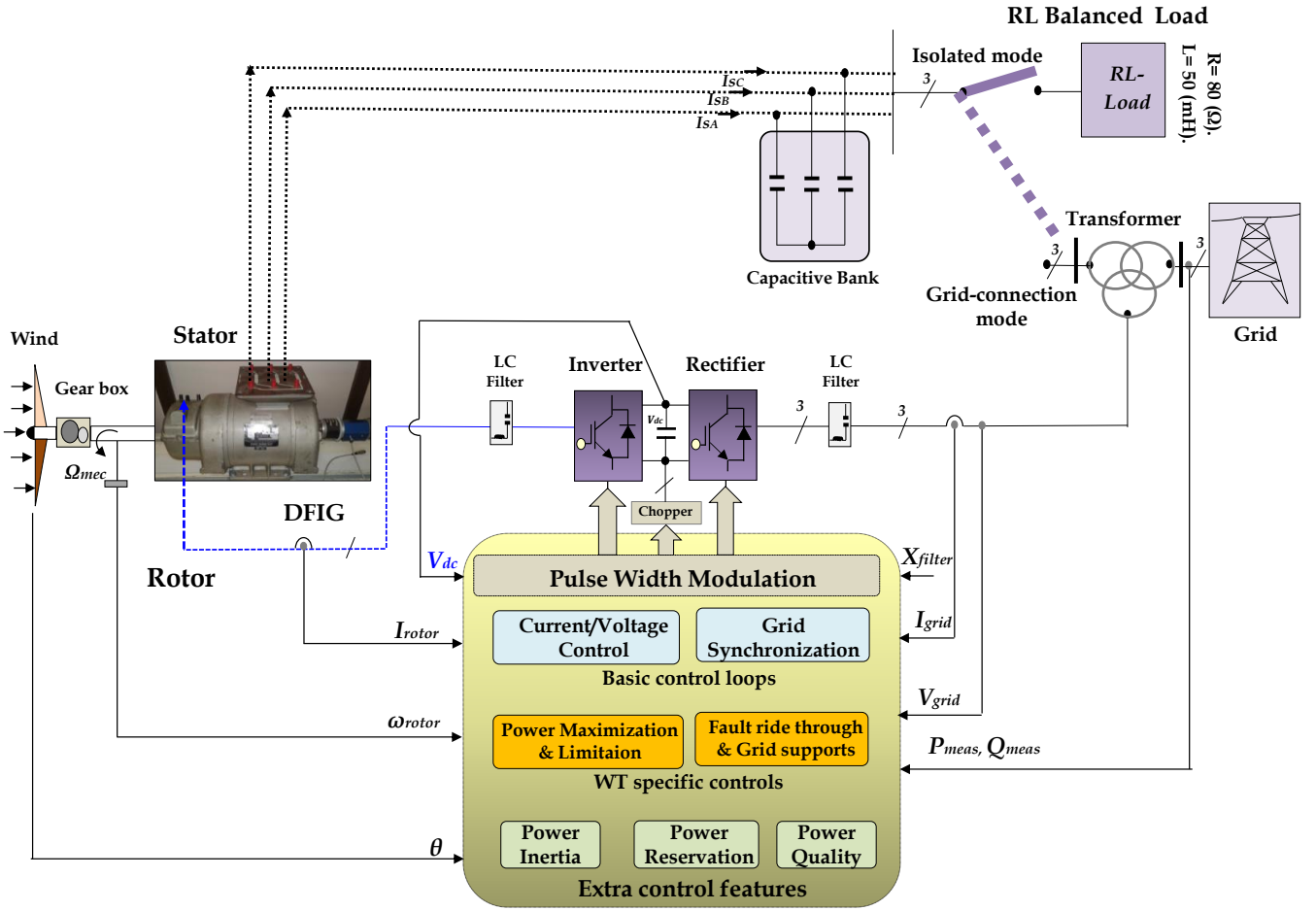


Fig. 2. The power control scheme based on DFIG variable speed Wind turbine for both operating modes: “grid-connection and stand-alone”.

power oscillations, enhancing power quality.

➤ Unified Control for Stand-Alone and Grid-Tied Modes – The IP structure ensures consistent performance in both modes, eliminating the need for control reconfiguration when switching between isolated and grid-connected operations.

This paper is organized as follows; firstly, the modeling of Wind turbine (WT) and DFIG are presented respectively in sections (2 and 3). In Section-4 Vector power control is applied using advanced controllers. In Section 5 power flow characteristics across speed ranges is illustrated and explained. In Section-6, the proposed Integral–Proportional (IP) regulators applied in DFIG-Vector power control is presented. In Section-7, experimental results are shown and discussed. Finally, the reported work is concluded.

Figure 2 presents the DFIG power control scheme for both grid-connection and stand-alone operating modes.

2. Mathematical Model of Wind Turbine (WT)

The input power of a WT can be expressed as mention in Equation (1) [31-36] :

$$P_v = \frac{1}{2} \cdot \rho \cdot S_w \cdot v^3 \quad (1)$$

Where: S_w is the WT blade swept area; ρ is the air density; v is the wind speed. The mechanical power generated by the WT can be expressed as mentioned in Equation (2):

$$P_m = C_p \cdot P_v = \frac{1}{2} \cdot C_p \cdot \rho \cdot S_w \cdot v^3 \quad (2)$$

Where the power coefficient (C_p) represents the WT's power conversion efficiency. C_p is a nonlinear function of the Tip Speed Ratio (TSR or λ) and the blade pitch angle β° (in degrees $^\circ$). λ is defined as the ratio of the turbine blades' tip speed to the wind speed. TSR is given in Equation (3):

$$\lambda = \frac{R \Omega_t}{v} \quad (3)$$

Where: Ω_t is the angular speed of the turbine, and R is the blade radius.

The expression for $C_p(\lambda, \beta)$ can be represented as mentioned in Equation (4): [31-36] :

$$C_p(\lambda, \beta) = (0.5 - 0.0167 \cdot (\beta - 2)) \cdot \sin\left[\frac{\pi(\lambda + 0.1)}{18.5 - 0.3(\beta - 2)}\right] - 0.00184 \cdot (\lambda - 3) \cdot (\beta - 2) \quad (4)$$

In this paper, the sensorless MPPT strategy is applied for variable speed DFIG based on stand-alone mode.

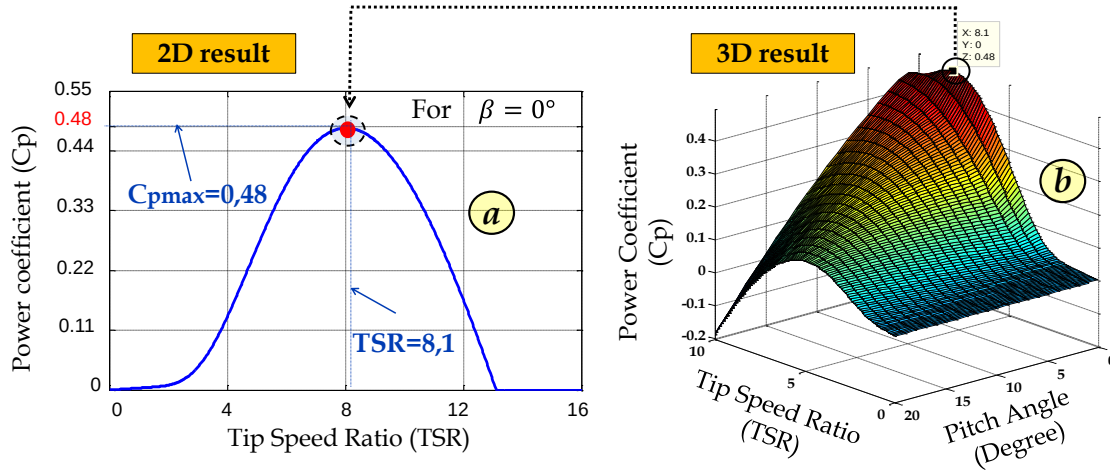


Fig. 3. MPPT simulation results; a: 2D power coefficient versus TSR based on zero pitch angle, and b: 3D power coefficient C_p versus TSR based for different pitch angle β° .

This algorithm calculates the stator power reference as P_s^* by the product of the MPPT's output (the mechanical speed Ω_{mec}) by the electromagnetic torque T_{em}^* , which yields to $P_s^* = \Omega_{mec} \cdot T_{em}^*$. Figure 3a the C_p presents the maximum $C_p=0.48$, is achieved at a pitch angle of zero ($\beta^\circ=0^\circ$), corresponding to the optimal TSR ($\lambda=8.1$). Figure 3b illustrates the three-dimension (3D) characteristic of C_p as a function of the TSR and pitch angles (β°), we can see how the variations of the step angles (β°) influence the C_p result, in this case study, and the relationship in these factors is inversely proportional.

3. Mathematical Model of DFIG

The general electrical state model using Park transformation [31-36]:

Stator and rotor voltages are shown in Equation (5) to Equation (8) :

$$V_{sd} = R_s \cdot I_{sd} + \frac{d}{dt} \Phi_{sd} - \omega_s \cdot \Phi_{sq} \quad (5)$$

$$V_{sq} = R_s \cdot I_{sq} + \frac{d}{dt} \Phi_{sq} + \omega_s \cdot \Phi_{sd} \quad (6)$$

$$V_{rd} = R_r \cdot I_{rd} + \frac{d}{dt} \Phi_{rd} - (\omega_s - \omega_r) \cdot \Phi_{rq} \quad (7)$$

$$V_{rq} = R_r \cdot I_{rq} + \frac{d}{dt} \Phi_{rq} + (\omega_s - \omega_r) \cdot \Phi_{rd} \quad (8)$$

Stator and rotor fluxes are shown in Equation (9) to Equation (12) :

$$\Phi_{sd} = L_s \cdot I_{sd} + L_m \cdot I_{rd} \quad (9)$$

$$\Phi_{sq} = L_s \cdot I_{sq} + L_m \cdot I_{rq} \quad (10)$$

$$\Phi_{rd} = L_r \cdot I_{rd} + L_m \cdot I_{sd} \quad (11)$$

$$\Phi_{rq} = L_r \cdot I_{rq} + L_m \cdot I_{sq} \quad (12)$$

The electromagnetic torque is given in Eq. (13):

$$T_{em} = P \cdot L_m \cdot (I_{rd} \cdot I_{sq} - I_{rq} \cdot I_{sd}) \quad (13)$$

And its associated motion equation are given in Equation (14) to Equation (16)):

$$T_{vis} = f \cdot \Omega_{mec} \quad (14)$$

$$T_{em} - T_r = J \cdot \frac{d}{dt} \Omega_{mec} + T_{vis} \quad (15)$$

$$J = \frac{J_{turbine}}{G^2} + J_g \quad (16)$$

Where; R_s , R_r , L_r , and L_s : are respectively the resistances and the inductances of the stator of the rotor circuit and L_m is the mutual inductance, σ : is the leakage factor $\sigma = 1 - \frac{L_m^2}{L_s \cdot L_r}$.

V_{sd} , V_{sq} , V_{rd} , V_{rq} , I_{sd} , I_{sq} , I_{rd} , I_{rq} , Φ_{sd} , Φ_{sq} , Φ_{rd} and Φ_{rq} : illustrate respectively the components along the d and q axis of the stator and rotor voltages, currents and flux. T_{em} , T_r , and T_{vis} : are the electromagnetic, load, and viscous torques. J_g , $J_{turbine}$ and J : are respectively the generator, turbine and total inertia, Ω_{mec} : is the mechanical speed, and G : is the gain of gearbox. P : is the number of pole pairs, ω_s is the stator pulsation, ω_r : is the rotor pulsation, ω_{slip} : is the slip pulsation and f : is the friction coefficient. Knowing that: $\omega_{slip} = (\omega_s - \omega_r)$.

Figure.4 shows a descriptive diagram of the three-phase stator and rotor windings.

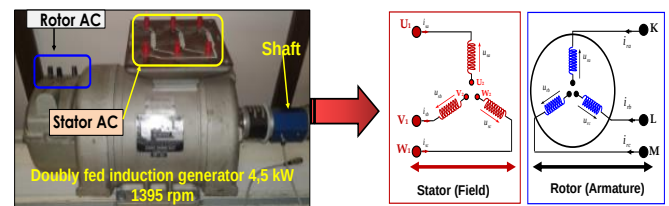


Fig. 4. The DFIG' stator and rotor windings.

4. Vector Power Control Based on Advanced Controller

From Equation (18), it is evident that the torque can be controlled by manipulating the rotor quadrature current component (I_{rq}) of the DFIG. Similarly, the direct rotor current component (I_{rd}) is employed to manage the generated reactive power (Equation (17)):

$$Q_s^* = \frac{V_s^2}{\omega_s \cdot L_s} - V_s \frac{L_m}{L_s} \cdot I_{rd}^* \quad (17)$$

$$I_{rq}^* = \frac{L_s}{P \cdot L_m \cdot \Phi_s} \cdot T_{em}^* \quad (18)$$

$$I_{rd}^* = \frac{\Phi_s}{L_m} - \frac{L_s}{V_s \cdot L_m} \cdot Q_s^* \quad (19)$$

$$I_{rq}^* = \frac{L_s}{V_s \cdot L_m} \cdot P_s^* \quad (20)$$

Figure 5 shows the fundamental mechanical characteristic torque as a function of the speed of the DFIG. We note the different operating quadrants of the DFIM, in our case study we will be exclusively interested in the generator operating mode (negative electromagnetic torque $T_{em} < 0$). The ideal operating zone of the DFIG is the stable zone (or so-called nominal or rated), this zone represents +/- 30% of the rotation speed of the rotor shaft, we can see that the torque/speed characteristic behaves like a linear straight line, beyond this zone the characteristic becomes non-linear.

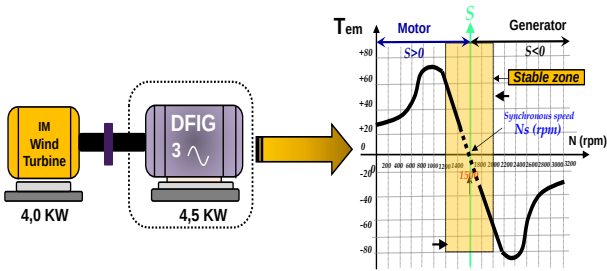


Fig. 5. The DFIG mechanical characteristic torque versus speed of the DFIG.

5. Power Flow Characteristics Across Speed Ranges

Figure 6 clearly demonstrates the relationship between rotor speed and power flow direction. The system exhibits two distinct operational modes [31-36]:

5.1 Sub-synchronous Operation ($n < 1500$ rpm):

The rotor absorbs power from the grid through the back-to-back converter, which corresponds to positive slip conditions.

5.2 Super-synchronous Operation ($n > 1500$ rpm):

The rotor delivers power to the grid via the back-to-back converter, which corresponds to negative slip conditions.

5.3 The synchronous speed ($n = n_s = 1500$ rpm):

This speed zone represents the critical transition point between operational modes. As illustrated in Figure 6, the back-to-back converter enables seamless bidirectional power

transfer across this threshold, effectively managing the transition between sub- and super-synchronous states.

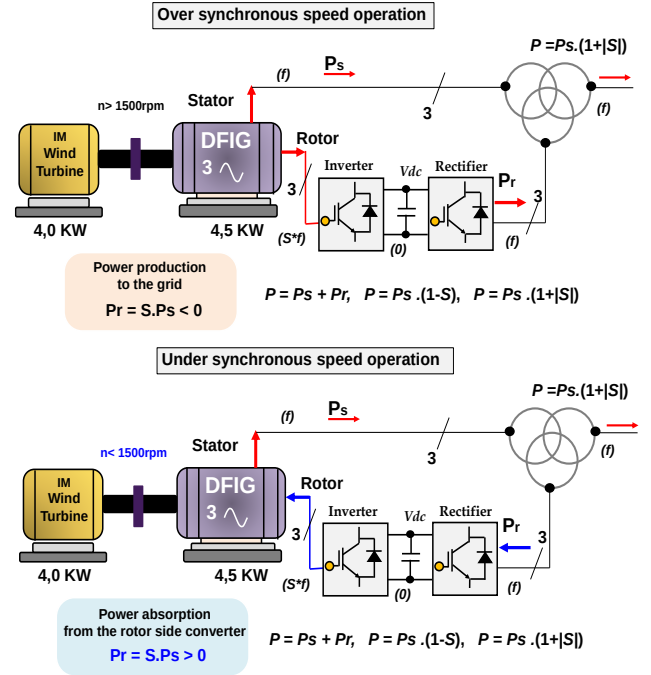


Fig. 6. Rotor power flow when the rotor speed changes (Over synchronous and Under-synchronous operating modes).

Figure 7 represents simulation results of generated power from the DFIG when the rotation speed changes. From this figures, there are three operating zone: starting zone, MPPT (maximum power point tracking) zone and blade orientation zone. The MPPT zone is ideal one, in this case the rotation speed is near the synchronous speed which means the stable zone (linear function: Torque versus Speed, the slip is very small (close to 5%) and the rotor power flow depends on the sign of the slip (+: production the power and -: injection the power).

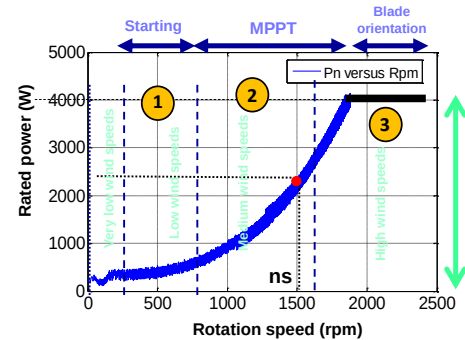


Fig. 7. Power curve versus rotation speed: under three operating zones.

6. The Proposed Integral-Proportional (IP) Regulators Applied in Vector Power Control

For compensation implementation, the open-loop transfer function (OLTF) is formulated with a time constant fixed at 10ms, which ensures satisfactory dynamic response suitable for the slow wind speed variations and large mechanical time constants involved [22].

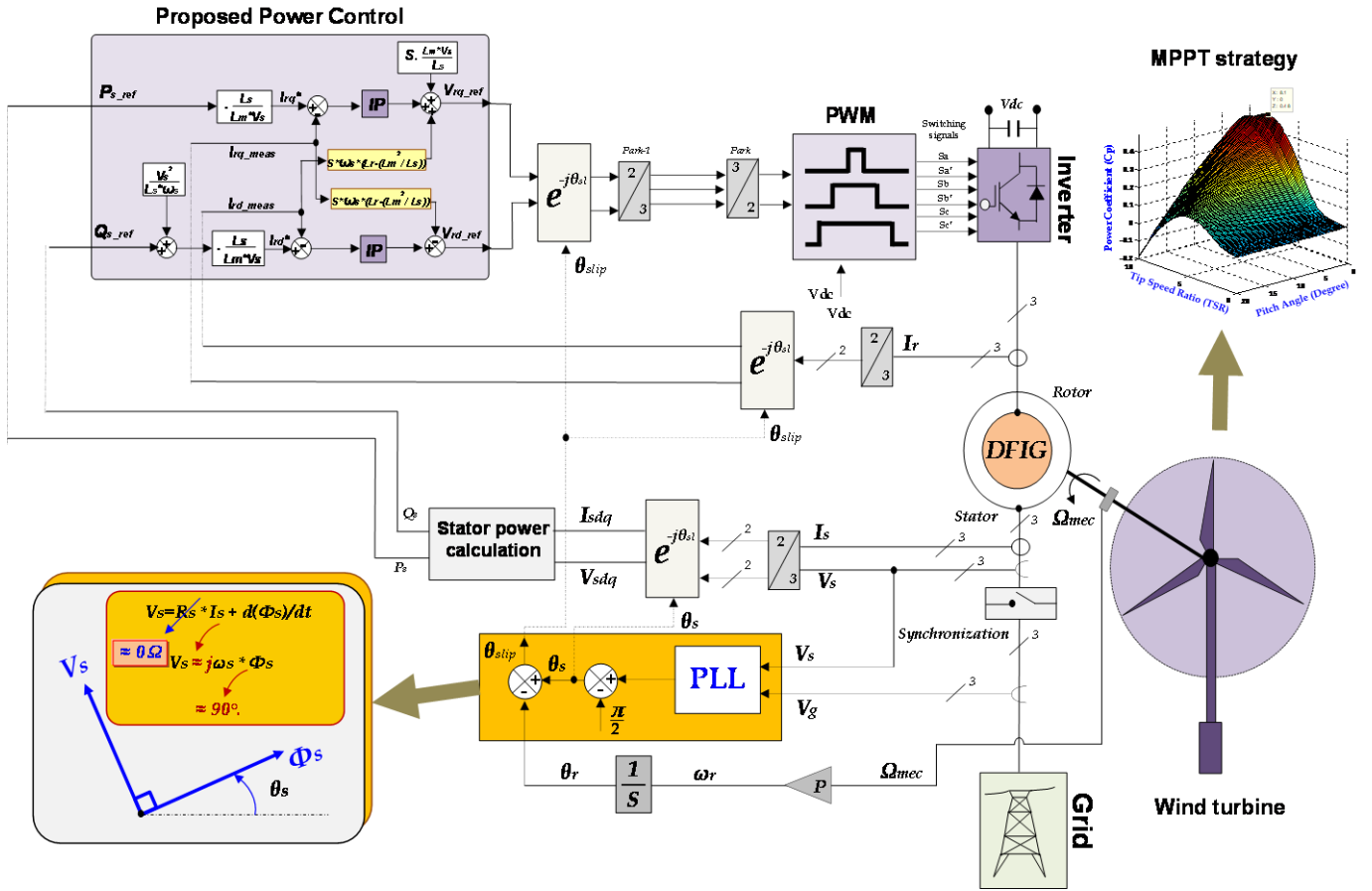


Fig. 8. Block Diagram of a WECS based on DFIG with proposed power control.

The control design process begins by simplifying the system to a single-variable model. The closed-loop transfer function (CLTF) incorporating the PI controller is then derived, where "S" denotes the Laplace variable. Through identification with a standard second-order system transfer function, the controller gains are expressed in terms of the machine parameters. Substituting the expressions for parameters A and B yields the final controller design equations.

The initial control strategy involves reducing the complex system to a manageable single-variable representation. The resulting CLTF with IP control action is formulated as shown below, with "S" representing the complex frequency variable in the Laplace domain (as mentioned in Equation (21)).

$$CLTF = \frac{\text{Output}}{\text{Input}_{ref}} = \frac{K_{ip} \cdot K_{p_{ip}} \cdot A}{S^2 + (K_{p_{ip}} \cdot A + B)S + K_{ip} \cdot K_{p_{ip}} \cdot A}$$

Such as:
$$\begin{cases} A = \frac{L_m \cdot V_s}{L_s \cdot L_r - L_m^2} \\ B = \frac{L_s \cdot R_r}{L_s \cdot L_r - L_m^2} \end{cases} \quad (21)$$

Using the identification process with a 2nd-order transfer function (TF) system [22] as mentioned in Equation (22):

$$CLTF = \frac{V_{rdq}}{I_{rdq}} = \frac{k \cdot \omega_n^2}{S^2 + (2 \cdot \xi \cdot \omega_n) \cdot S + \omega_n^2} \quad (22)$$

The correctors' gains will be calculated as a function of the machine parameters, as shown in Equation (23):

$$\begin{cases} K_{ip} = \frac{\omega_n^2}{K_{p_{ip}} \cdot A} \\ K_{p_{ip}} = \frac{2 \cdot \xi \cdot \omega_n - B}{A} \end{cases} \quad (23)$$

Upon substitution of A and B with their respective expressions, as mentioned in Equation (24):

$$\begin{cases} K_{ip} = \frac{\omega_n^2 \cdot (L_s \cdot L_r - L_m^2)}{K_{p_{ip}} \cdot L_m \cdot V_s} \\ K_{p_{ip}} = \frac{2 \cdot \xi \cdot \omega_n \cdot (L_s \cdot L_r - L_m^2) - L_s \cdot R_r}{L_m \cdot V_s} \end{cases} \quad (24)$$

The damping coefficient ξ governs the system's behavior at its natural frequency, determining whether the response

will be attenuated or exhibit resonance. To achieve the desired performance specification of less than 5% overshoot, a damping ratio exceeding 0.7 is required.

The system's dynamic response varies significantly with different ξ values. For critically damped and over damped conditions ($\xi \geq 1$), both rise time and settling time deteriorate. In the under damped region ($\xi < 1$), the response time increases as damping decreases due to amplified oscillations and extended transient periods.

An optimal compromise between adequate damping and fast response is attained at approximately $\xi = 0.7$. This value maintains the overshoot below the 5% threshold while providing minimal response time. The theoretically optimal damping ratio is $\xi = 1/\sqrt{2} \approx 0.707$, which represents the ideal balance between these competing requirements. During simulation, the natural frequency will be tuned to achieve this optimal performance characteristic

Figure 8 presents a detailed diagram of the proposed power algorithm based on IP regulators, in order to control independently the stator active and reactive powers $P_s(W)$ and $Q_s(Var)$ of the DFIG along the two d-q axes.

7. Experimental Assessment under dSPACE1103

Experimental tests were performed on a 4.5 kW laboratory-scale setup to assess the performance of the pro-

DFIG and the 4 kW wind turbine emulator and experimental conditions are provided in Appendix (Tables 4, 5 and 7 respectively). Figure 9 displays the experimental setup at the L2EP Laboratory (École Centrale de Lille), highlighting the key components and equipment used in this study.

In this configuration (refer to Figure 10), the stator is connected to an RL balanced load through bank capacitors; the RL-Load parameters are illustrated in Table 6. Experimental results are presented for three operational modes: Under-synchronous, synchronous, and Over-synchronous operation. The hardware tests were conducted using a dSPACE1103 card integrated with MATLAB environment and ControlDesk.

This section investigates the DFIG's operational behavior by analyzing sinusoidal rotor current dynamics. Figure 11 demonstrates the measured rotor current response during speed transitions around 1500 rpm (synchronous zone), capturing both sub-synchronous to super-synchronous transitions and vice versa.

The rotor currents ($I_{rabc}(A)$) follow patterns that correlate with wind speed variations. These measurements, along with shaft speed data, were acquired using an oscilloscope through dSPACE1103 and ControlDesk system. Current regulation is achieved through slip angle control

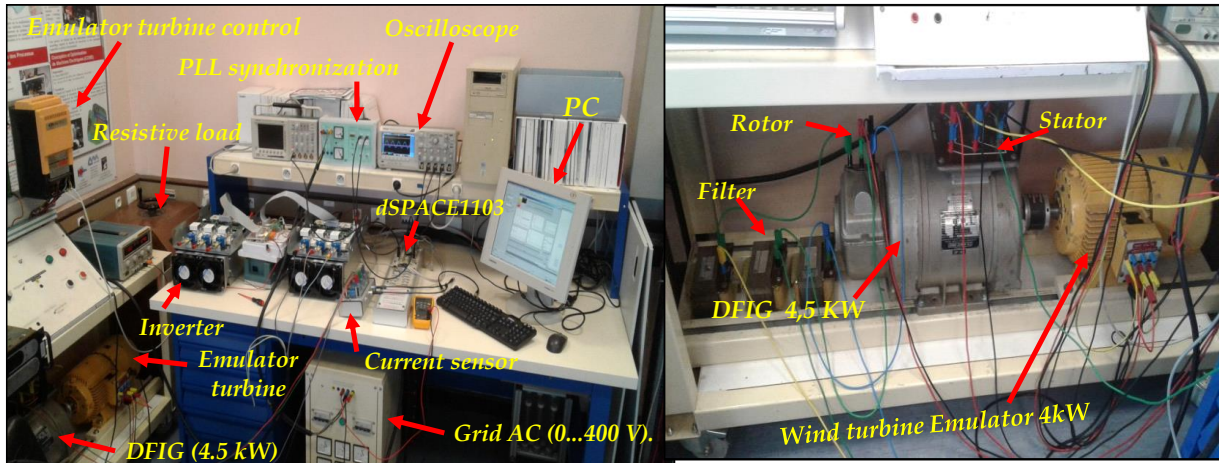


Fig. 9. Hardware test bench based on a 4.5 KW DFIG via dSPACE1103 (L2EP Laboratory, EC-Lille).

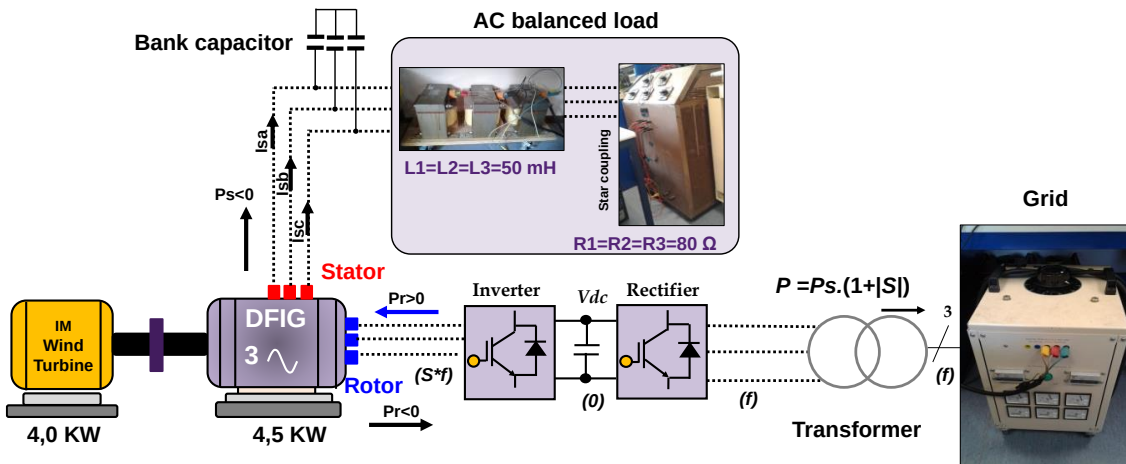


Fig. 10. The proposed experimental DFIG power control scheme.

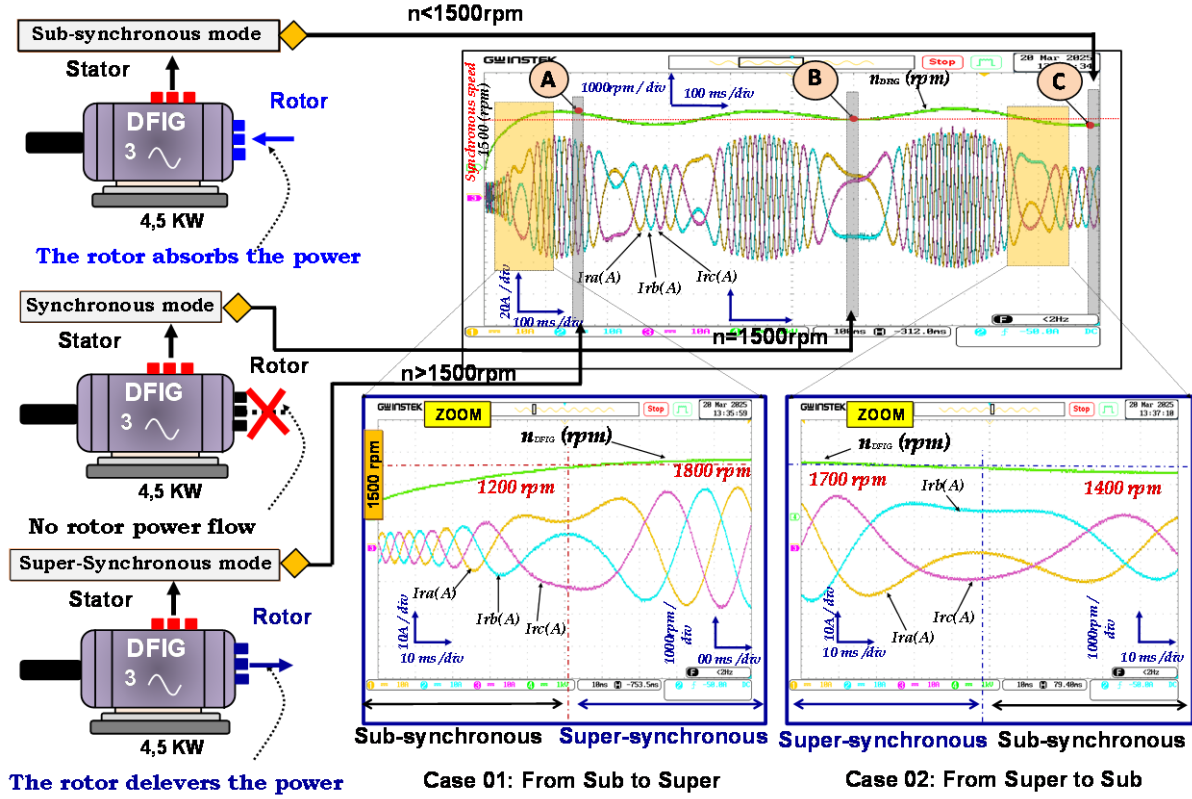


Fig. 11. Experimental results for the various operating modes of the DFIG.

$(\theta_{slip} = \int [\omega_{slip} = (\omega_s - \omega_r)] dt + \theta_0$, where: $\omega_s = 2\pi f$, (stator frequency) and $\omega_r = P \cdot \Omega_{mec}$ (rotor speed). As the rotor speed varies with wind speed (governed by MPPT control), the power flow direction adapts accordingly:

- Sub- to super-synchronous transition: Rotor absorbs grid power.
- Super- to sub-synchronous transition: Rotor injects power into the grid via back-to-back converter.

Table 1 provides a comprehensive summary of DFIG speed values for both operational scenarios.

Table 1. Shaft speed values for DFIG operating modes.

Cases	DFIG operation mode :
Case 01:	Transition from Sub to Super-synchronous speed: $\Rightarrow$ 1200 rpm to 1800 rpm
Case 02:	Transition from Super to sub-synchronous speed: $\Rightarrow$ 1700 rpm to 1400 rpm

According to Figure 11, point "A" corresponds to Super-synchronous operation, meaning that the DFIG injects electrical energy into the grid via B-2-B converters; the amount of energy delivered corresponds exclusively to the value of the slip realized at each instant of operation of the DFIG. In this case study, the slip $S_A = (1500-1750) / 1500 = -0.143$, therefore the rotor power injected into the grid equals $P_r = -0.143 \cdot 4000 = -572W$.

Point "B" corresponds to Synchronous operation, meaning that the DFIG neither injects electrical energy into the grid nor absorbs energy, this is due to the absence of slip ($S_B = 0$), in other words the shaft rotation speed equals the synchronous speed $n = n_s = 1500rpm$, therefore the rotor power equals $P_r = 0 \cdot 4000 = 0W$.

Point "C" corresponds to Sub-synchronous operation, meaning that the DFIG absorbs energy from the grid via the B-2-B converters. The amount of energy absorbed depends exclusively on the slip value achieved at each instant of DFIG operation. In this case study, the slip $S_C = (1500-1400)/1500 = +0.067$, so the rotor power injected into the grid is equal to $P_r = +0.067 \cdot 4000 = +268W$.

Figure 12 illustrates the behavior of the stator and rotor currents under varying d-q axis rotor currents for three generator speeds: 1000 rpm, 1500 rpm, and 1700 rpm. The results demonstrate that the DFIG operates effectively with high performance across all operating regimes—sub-synchronous, synchronous, and super-synchronous. The current trajectories closely follow their references, exhibiting excellent tracking at both low and high speeds, which highlights the superior stability provided by the proposed IP controller.

The direct and quadrature rotor currents, I_{rd} (A) and I_{rq} (A), were varied between 0 and -10 A, with the negative sign indicating generator mode operation. Notably, the stator and rotor currents (Figure 12-(a, b, and c)) maintain a perfectly sinusoidal waveform, confirming the robustness and efficiency of the IP controller. The system exhibits a fast response time, minimal overshoot (nearly negligible), and a low static power error (less than 3%).

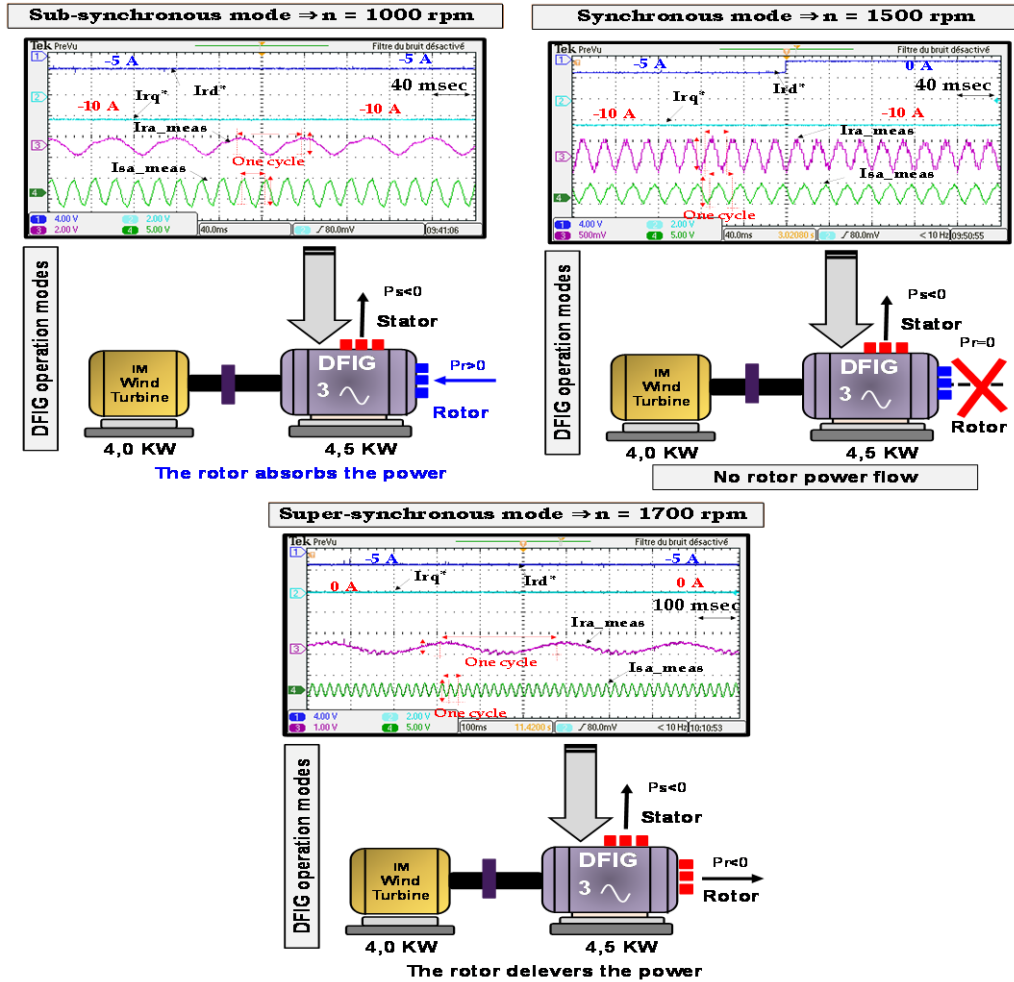


Fig. 12. Experimental analysis of stator and rotor current dynamics across speed regimes (1000, 1500, 1700 rpm) under d-q axis current variation.

Figure 13 presents a comparative study based on three important criteria (THD of the stator current, overshoot and static error in steady state) for the two configurations presented in this work, namely: power control based on a classic PI regulator and power control based on a robust IP regulator.

We clearly notice a remarkable superiority of the proposed IP controller compared to that of the classic regulator; whose energy quality is improved THD $I_s = 1.5\%$ for power control via IP against 3.8% for control via PI, the tracking is almost perfect using the power control based on IP (overshoot equal to 1% against 12% for power control via PI. All these indices clearly show the whatever the wind variation and the RL load change; and finally the static error in the permanent regime is negligible equals to 5% for power control via IP against 12% improvement offered by the proposed power algorithm the nominal values displayed in the nameplates in the Appendix below (Table.4 and 5).

This analysis (refer to Table.2) evaluates the static performance of proposed Integral-Proportional (IP) and conventional Proportional-Integral (PI) controllers in controlling active and reactive power in DFIG-based wind turbines. To further highlight the effectiveness of the proposed DPC-IP strategy, a comparative analysis with

previously reported control methods from the literature is conducted.

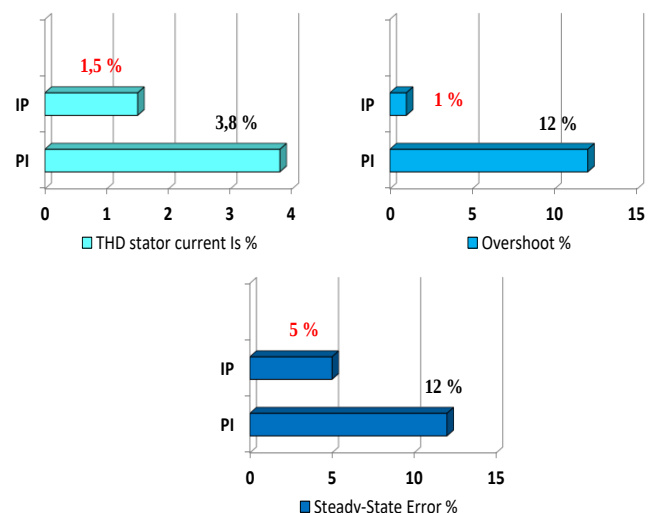


Fig. 13. The DFIG- wind turbine performance metrics for proposed and traditional power control algorithms.

Table 3 summarizes key performance indicators, including overshoot, response time, THD, ripples, and robustness, for different control approaches applied to DFIG-

Table 2. The performance recapitulation of the conventional and proposed algorithm control

Citerions	IP Controller	PI Controller
Steady-State Error	5–8%	8–12%
Total Harmonic Distorsion THD	1.5–2%	5–6%
Robustness	High (compensates parameter variations)	Low (sensitive to parameter drift)
Overshoot	<2%	> 12%
Power error	+/- 80 W_Var≈ 2%	+/- 150 W_Var≈ 3.75 %
Power tracking	Excellent	Good
Dynamic response	Very Fast (12.5* ms)	Fast (167 ms)
Stability	Moderate (nominal conditions)	High (adaptive to disturbances)
Grid compliance	Requires external compensators	Autonomous LVRT capability
Tuning complexity	Moderate (fixed gains)	High (adaptive laws)
Computational Load	Low	Moderate to High
Hardware Cost	Low (simple structure)	Low (simple structure)

Table 3. A comparative analysis of different control strategies applied to DFIG-based wind turbines

Ref	Year	Control Method	Overshoot (%)	Power Rated	THD Is (%)	Response time (ms)	Ripples (%)	Robustness
[37]	2023	TOSMC	Neglected	DFIG (10kW)	1.45	0.65	32.79	High
[38]	2024	FBC	7.41	PMSG (2MW)	1.78	84	16.66	High
[39]	2024	Adaptive FL	11.86	PMSG	0.76	60	80	----
[40]	2022	PD-(1+PI)	Neglected	DFAG (1.5MW)	0.62	Fast (-)	56.66	High
[41]	2025	DPC	99.81	AG (1.5kW)	0.69	0.706	Low	High
[42]	2023	BC-SSMC-MRAS	0	IM (1.5kW)	0.56	370	82	High
[43]	2025	DPC-PDPI	70.31	IG (1.5MW)	0.60	0.31	60	High
[44]	2023	DTC-FOSOCSCMC	1.5	DFIG (1.5 MW)	0.12	Fast (-)	---	High
[45]	2023	FOC-PII	8.95	IM (1.5kW)	1.86	Low (-)	75.16	----
[46]	2023	FOC-FOSTA	7.23	AG (1.5MW)	0.01	0.02075	53.56	---
[47]	2023	DPC-SPI-GA	---	AG (1.5MW)	0.54	Fast (-)	22.95	High
[48]	2023	BC-TOSMC	---	AM (1.5kW)	1.09	---	57.14	High
[49]	2023	ANN-DPC	---	DFIG (1.5kW)	2.22	---	---	High
[50]	2024	DPC-FPI	37.93	DFIG (1.5MW)	0.13	1.7	58.60	---
[51]	2023	DPC-FOSC	85	AG (1.5MW)	0.13	6.58	72.5	---
[52]	2024	DPC-NSTSMC	32.20	DFIG (1.5kW)	0.83	0.0054	10	High
[53]	2024	DFOC-FOSC-FOPI-PSO	67.77	AG (1.5MW)	0.02	5	99.67	High
[54]	2024	DPC-NSTA	65.35	DFIG (1.5MW)	0.18	0.0087	73.54	High
[55]	2025	BC	0	SEIG	0.53	---	---	High
[56]	2024	DPD-DSTSMC	---	DFIG (1.5MW)	0.19	---	83.33	---
[57]	2024	IFOC-PDI	57.79	DFIG (1.5MW)	2.25	8.2	46.24	Medium
[58]	2020	DFC-PI	< 7%	DFIG (3 kW)	---	Meduim	---	High
[59]	2011	VOC-PR3	---	DFIG (2.2 kW)	< 5	Good	---	Good
[60]	2014	PDPC-PI	< 10%	DFIG (20 kW)	5.98	Good	---	Medium
[61]	2025	DFC-SVM PI	≈ 2%	DFIG (3.0 kW)	< 5	Medium	---	High
[62]	2010	FVC PI-R	< 6%	DFIG (2.2 kW)	< 5	Excellent	---	Good
[63]	2025	DVC FOFL	None	DFIG (3.0 kW)	< 4	Excellent	---	High
[64]	2025	VPC-T2-FLC	Neglected	DFIG (4.0 kW)	0.60	Excellent	---	---
[65]	2024	STA-SMC	Neglected	DFIG (1.5 MW)	1.85	5.6873	---	---
Proposed	---	DPC-IP	2	DFIG (4.5kW)	1.5	12.5	15.5	High

based and other wind energy conversion systems. This benchmarking enables a fair evaluation of the proposed method relative to state-of-the-art strategies, thereby clarifying its advantages, limitations, and overall contribution to the field. It is worth noting, however, that for some criteria marked with (–), the corresponding data were not reported in the original references.

8. Conclusion

This paper presents a novel power vector control strategy for DFIG operating in stand-alone mode, successfully implemented and validated through real-time testing. The

proposed approach replaces traditional PI controllers with IP controllers for regulating the rotor current components I_{rd} and I_{rq} , which directly control reactive power (Q_s) and active power (P_s), respectively. Experimental validation was conducted using dSPACE DS1103 hardware and ControlDesk software platform across varying rotor speeds.

The test results successfully demonstrated both sub-synchronous and super-synchronous operational modes, confirming the control strategy's effectiveness under dynamic wind conditions. Experimental validation confirmed the superior performance of the proposed control system,

particularly in response speed, overshoot minimization, and accuracy in current and power regulation.

To advance this research further, the following directions are recommended:

- Power Quality Enhancement: Integrate Shunt Active Power Filter (SAPF) technology to reduce harmonic distortion and improve power quality for load or microgrids integration.
- Grid Integration Extension: Adapt the control scheme for grid-connected operation, incorporating synchronization protocols, grid support features, and fault ride-through capabilities.
- Robustness Assessment: Evaluate system performance under realistic conditions including electrical faults, load variations, and communication delays for comprehensive reliability analysis.
- Comparative Performance Studies: Conduct benchmarking against advanced control methodologies such as H-infinity control, Model Predictive Control (MPC), and Artificial Neural Network (ANN)-based approaches to quantify the proposed method's advantages.

Abbreviations and acronyms

DFIG	Double fed induction generator
WT	Wind Turbine
VSWECS	Variable Speed Wind Energy Conversion Systems
dSPACE	Digital Signal Processing and Control System
RSC	Rotor Side Converter
GSC	Grid Side Converter
SAPF	Shunt Active Power Filter
TSR	Tip Speed Ratio
DPC	Direct Power Control
PI	Proportional Integral
IP	Integral Proportional
MPPT	Maximum Power Point Tracking
OLTF	Open Loop Transfer Function
CLTF	Closed Loop Transfer Function
TF	Transfer Function
VPC	Vector Power Control
PDPC	Predictive Direct Power Control
PWM	Pulse Width Modulation
PLL	Phase-Locked Loop
MPC	Model Predictive Control.
ANN	Artificial Neural Network

Appendix

Table 4. The DFIG parameters

Parameters:	Values:
Rated power:	4.5 kW
Stator resistance:	$R_s = 0.4 \Omega$
Rotor resistance:	$R_r = 0.8 \Omega$
Stator inductance:	$L_s = 0.082 \text{ H}$
Rotor inductance:	$L_r = 0.082 \text{ H}$
Mutual inductance:	$L_m = 0.081 \text{ H}$
Rated Voltage Δ/Y :	$V_s/U_s = 220/380 \text{ V}$
Number of pole pairs:	$P = 2$
Rated speed:	$n = 1395 \text{ rpm}$
Friction coefficient:	$f_{DFIG} = 0.001 \text{ N m/s}$
The moment of inertia:	$J = 0.2 \text{ kg.m}^2$

Table 5. The operational parameters of the emulator turbine (SCIM)

Parameters:	Values:
Rated power:	4.0 kW
Rated voltage Δ/Y :	$V_s/U_s = 220/380 \text{ V}$
$\cos \phi$:	0.82.
Gain:	$G = 3.9$
Rated speed:	$n = 1440 \text{ rpm}$

Table 6. The RL-balanced load parameters

Parameters:	Values:
Resistance:	$R_{LOAD} = 80 \Omega$
Self-inductance:	$L_{LOAD} = 50 \text{ mH}$

Table 7. The simulation and experimental conditions using Matlab/Simulink.

Type:	Fixed-Step.
Ode-4:	Range Kutta Order4
Fixed-step Size (Fundamental sample time):	Simulation study: 1e-5.
Fixed-step Size (Fundamental sample time):	Experimental study: 1e-4
Tasking mode for periodic sample time:	Auto.

Acknowledgements

The authors thank the Algerian Ministry of the Higher Education and Scientific Research MESRS. The authors express their sincere gratitude to the research laboratories teams (L2EP Ecole Centrale de Lille France, LEPCI and LAS Sétif-1 University, Algeria); for providing particular assistance in preparing this article.

Author Contributions

Conceptualization, F. A., and B. F.; methodology, F. A., and A.C.; software, F. A., B. F., and A.C.; validation, F.A., A. C., B. F., and O. G.; formal analysis, F. A., O. G., H. I., and B.F.; investigation, F. A., A. C., B. F., H. B., H.I., and G. O.; resources, F. A., B. F., H. B., G. O., and A. C.; data curation, F. A., A. C., H. B., G. O., and H. I.; writing-original draft preparation, F. A., B. F., A. C., and H. I.; writing-review and editing, F. A., B. F., A. C., I. H., O. G., and H. B. ; visualization, F. A., B. F., A. C., H. I., and O. G.; supervision, B. F.; project administration, F.A., B.F., and A.C.;. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

- [1] B. Debnath, M. S. Shakur, M. T. Siraj, A.B.M. M. Bari, and A. R. M. T. Islam, "Analyzing the factors influencing the wind energy adoption in Bangladesh: A pathway to sustainability for emerging economies". *Energy Strategy Reviews*, vol. 50, pp. 101265, 2023.
<https://doi.org/10.1016/j.esr.2023.101265>
- [2] T.-Z. Ang, M. Salem, M. Kamarol, H. S. Das, M. A. Nazari, and N. Prabakaran, "A comprehensive study of renewable energy sources: Classifications, challenges and suggestions", *Energy Strategy Reviews*, vol.43, pp.100939, 2022.
<https://doi.org/10.1016/j.esr.2022.100939>
- [3] H. Benbouhenni, I. Colak, Z.M.S Elbarbary, and M. I. Shaik, "Reducing power ripple for multi-rotor wind energy systems using FOPDPI controllers", *Sci Rep* 15, pp. 12524, 2025.
<https://doi.org/10.1038/s41598-025-96625-z>
- [4] C. C. W. Chang, T. J. Ding, T. J. Ping, K. C. Chao, and M. A. S. Bhuiyan, "Getting more from the wind: Recent advancements and challenges in generators development for wind turbines", *Sustainable Energy Technologies and Assessments*, vol.53, Part C, pp. 102731, 2022.
<https://doi.org/10.1016/j.seta.2022.102731>
- [5] K. Liu, W. Chen, G. Chen, D. Dai, C. Ai, X. Zhang, and X. Wang, "Application and analysis of hydraulic wind power generation technology", *Energy Strategy Reviews*, vol.48, pp. 101117, 2023.
<https://doi.org/10.1016/j.esr.2023.101117>
- [6] Z.B. Duranay, H. Güldemir, and B. Coşkun, "The role of wind turbine siting in achieving sustainable energy goals", *Processes*, vol.12, pp. 2900, 2024.
<https://doi.org/10.3390/pr12122900>
- [7] F. Amrane, A. Chaiba, and B. François, "Improved adaptive nonlinear control for variable speed wind turbine Fed by direct matrix converter". *Revue Roumaine des Sciences Techniques-Série Électrotechnique et Énergétique*, vol. 68, pp. 58–64, 2023.
<https://doi.org/10.59277/RRST-EE.2023.68.1.10>
- [8] A. Milles, E. Merabet, H. Benbouhenni, N. Debouché, and I. Colak, "Robust control technique for wind turbine system with interval type-2 fuzzy strategy on a dual star induction generator", *Energy Reports*, vol.11, pp. 2715-2736, 2024.
<https://doi.org/10.1016/j.egyr.2024.01.060>
- [9] F. Blaabjerg, M. Chen, and L. Huang, "Power electronics in wind generation systems", *Nature Reviews Electrical Engineering*, vol.1, pp. 234-250, 2024. <https://doi.org/10.1038/s44287-024-00032-x>
- [10] R.I. Bolaños, H. Pinto Vega, L.F. Grisales-Noreña, O.D. Montoya, and J.C. Hernández, "Intelligent active and reactive power management for wind-based distributed generation in microgrids via advanced metaheuristic optimization", *Appl. Syst. Innov.*, vol.8, pp.87, 2025. <https://doi.org/10.3390/asi8040087>
- [11] H. Itouchene, Z. Boudries, and F. Amrane, "Improved power control based variable speed wind-turbine DFIG under hard work conditions: application of sliding mode theory", *Periodica Polytechnica Electrical Engineering and Computer Science*, vol.68, pp. 392–412, 2024.
<https://doi.org/10.3311/PPee.36760>
- [12] H. Itouchene, F. Amrane and Z. Boudries, "Robust control of DFIG wind turbines in sub/super synchronous operation using integral backstepping controller", *Journal of Renewable Energies*, vol.1, p. 23–31, 2024. <https://doi.org/10.54966/jreen.v1i1.1170>
- [13] H. Saboori, H. Pishbahar, S. Dehghan, G. Strbac, N. Amjady, D. Novosel, and V. Terzija, "Reactive power implications of penetrating inverter-based renewable and storage resources in future grids toward energy transition-A review", *Proceedings of the IEEE*, vol.113, pp. 66-104, 2025,
<https://doi.org/10.1109/JPROC.2025.3555509>
- [14] H. Benbouhenni, I. Colak, N. Bizon, and E. Abdelkarim, "Fractional-order neural control of a DFIG supplied by a two-level PWM inverter for dual-rotor wind turbine system", *Measurement and Control*, vol.57, pp. 301-318, 2023.
<https://doi.org/10.1177/00202940231201375>
- [15] Y. Sahri, S. Tamalouzt, F. Hamoudi, S. Lalouni Belaid, M. Bajaj, M. M. Alharthi, M. S. Alzaidi, and S. S.M. Ghoneim, "New intelligent direct power control of DFIG-based wind conversion system by using machine learning under variations of all operating and compensation modes", *Energy Reports*, vol.7, pp: 6394-6412, 2021.
<https://doi.org/10.1016/j.egyr.2021.09.075>
- [16] M. N. Aboozar, T. Behrouz, and S. Farnaz, "Power control of a grid-connected doubly fed induction generator using H_∞ control and Kalman filter", *International Transactions on Electrical Energy Systems*, vol.19, pp. 3771752, 2022.
<https://doi.org/10.1155/2022/3771752>
- [17] Y. Cao, C. Shi, X. Li, M. Li, and J. Bian, "Unbalanced position recognition of rotor systems based on long and short-term memory neural networks", *Machines*, 12, pp.865, 2024.
<https://doi.org/10.3390/machines12120865>

- [18] V. Abramenko, I. Petrov, and J. Pyrhönen, "Variable reluctance resolver with a modular stator: main design aspects", *IEEE Transactions on Industry Applications*, vol.61, pp.6236- 6247, 2025.
<https://doi.org/10.1109/TIA.2025.3546911>
- [19] H. Alrajhi, Y. Al-Harbi, A. Al-Zahrani, S. A. Raza, A. Daraz, and M. Al-Kaabi, "Comprehensive analysis of PI tuning techniques for VSC applications", *J. Umm Al-Qura Univ. Eng.Archit*, 2025.
<https://doi.org/10.1007/s43995-025-00139-8>
- [20] M. Khan, W. Wu, and L. Li, "Grid-forming control for inverter-based resources in power systems: A review on its operation, system stability, and prospective", *IET Renew. Power Gener*, vol.18, pp.887–907, 2024.
<https://doi.org/10.1049/rpg2.12991>
- [21] M. Li, Y. Wang, W. Hu, S. Shu, P. Yu, Z. Zhang, and F. Blaabjerg, "Unified modeling and analysis of dynamic power coupling for grid-forming converters", *IEEE Transactions on Power Electronics*, vol.37, pp.2321-2337, 2022.
<https://doi.org/10.1109/TPEL.2021.3107329>
- [22] F. Amrane, B. Francois, and A. Chaiba, "Experimental investigation of efficient and simple wind-turbine based on DFIG-direct power control using LCL-Filter for stand-alone mode", *ISA Transactions*, vol. 125, pp. 631–664, 2022.
<https://doi.org/10.1016/j.isatra.2021.07.008>
- [23] H. Benbouhenni, I. Colak, M.Yessef, Z.M.S. Elbarbary, and N. Bizon, "Feedback action and genetic algorithm-based proportional-integral controller to improve the performance of the direct power control of a variable-speed contra-rotating wind turbine generation system", *Energy Reports*, vol.13, pp. 2153-2173, 2025.
<https://doi.org/10.1016/j.egyr.2025.01.064>
- [24] R. Inomoto, A. J. Sguarezi Filho, J. R. Monteiro, and E. C. Marques da Costa, "Genetic algorithm based tuning of sliding mode controllers for a boost converter of PV system using internet of things environment", *Results in Control and Optimization*, vol.14, pp.100389, 2024.
<https://doi.org/10.1016/j.rico.2024.100389>
- [25] M.Z. Mohd Tumari, M.A. Ahmad, M.H Suid, and M.R Hao, "An improved marine predators algorithm-tuned fractional-order PID controller for automatic voltage regulator system", *Fractal Fract.*, vol.7, pp.561, 2023.
<https://doi.org/10.3390/fractalfract7070561>
- [26] A. M. Mossa, H. Echeikh, A.A.Z. Diab, and N.V Quynh, "Effective direct power control for a sensorless doubly fed induction generator with a losses minimization criterion", *Electronics*, vol.9, pp.1269, 2020.
<https://doi.org/10.3390/electronics9081269>
- [27] M. Hamidat, A. M. Massoud and K. Kouzi, "Nonlinear control of brushless dual-fed induction generator with a flywheel energy storage system for improved system performance", *IEEE Access*, vol. 13, pp. 52036-52050, 2025.
<https://doi.org/10.1109/access.2025.3552703>
- [28] M. Soomro, Z.A Memon, M.H Baloch, N.H Mirjat, L. Kumar, Q.T Tran, and G. Zizzo, "Performance improvement of grid-integrated doubly fed induction generator under asymmetrical and symmetrical faults", *Energies*, vol.16, pp. 3350, 2023.
<https://doi.org/10.3390/en16083350>
- [29] A. Loulijat, H. Chojaa, M. El marghichi, N. Ettalabi, A. Hilali, A. Mouradi, A.Y Abdelaziz, Z.M.S Elbarbary, and M.A Mossa, "Enhancement of LVRT ability of DFIG wind turbine by an improved protection scheme with a modified advanced nonlinear control loop", *Processes*, vol.11, pp 1417, 2023.
<https://doi.org/10.3390/pr11051417>
- [30] A. Dida, F. Merahi, and S. Mekhilef, "New grid synchronization and power control scheme of doubly-fed induction generator based wind turbine system using fuzzy logic control", *Computers & Electrical Engineering*, vol.84, pp.106647, 2020.
<https://doi.org/10.1016/j.compeleceng.2020.106647>
- [31] H. Itouchene, F. Amrane, O. Gherouat, Z. Boudries, S. Mekhilef, P. Thonthong, and N. Bizon, "Design and implementation of a grey wolf optimization-based higher-order sliding mode controller for a DFIG-based wind turbine using dSPACE 1104", *Energy Reports*, 14(4), pp.4324-4352, 2025.
<https://doi.org/10.1016/j.egyr.2025.11.040>
- [32] H. Itouchene, F. Amrane, Z. Boudries, et al. "Enhancing the performance of grid-connected DFIG systems using prescribed convergence law", *Sci Rep* 15, 28550, 2025.
<https://doi.org/10.1038/s41598-025-13847-x>
- [33] H. Itouchene, F. Amrane, and Z. Boudries, "A robust maximum power point tracking control strategy for doubly-fed induction generator wind turbines using advanced sliding mode control under variable wind conditions", *Scientia Iranica*, In Press, 2025
<https://doi.org/10.24200/sci.2025.64527.8992>
- [34] F. Amrane, O. Gherouat, H. Itouchene, K. B. O. Medani, A. Chaiba, H. Benbouhenni, and N. Bizon, "Novel adaptive power control based 3L-VSI for

- variable-speed wind turbine: HIL-Experimental investigation", *Energy Reports*, 14(4), pp.4654-4687, 2025. <https://doi.org/10.1016/j.egy.2025.11.059>
- [35] F. Amrane, O. Gherouat, B. Francois, H. Itouchene, K. B. O. Medani, A. Chaiba and Y. Belkhier, "Robust PSO-Optimized Power Control for Stand-alone Variable-Speed DFIG Wind based High Stability and Power Quality Enhancement: Hardware Investigation based dSPACE1103", *International Journal of Energy Research*, vol.2025, ID 2004125, 29 pages, 2025. <https://doi.org/10.1155/er/2004125>
- [36] F. Amrane, B. Francois and A. Chaiba, "Hardware Implementation study of Variable Speed Wind-Turbine-DFIG in stand-alone mode", 22nd European Conference on Power Electronics and Applications, EPE 2020 ECCE Europe, Sept 7-11, 2020, Lyon-France. <https://doi.org/10.23919/epe20ecceurope43536.2020.9215946>
- [37] S. Kadi, H. Benbouhenni, E. Abdelkarim, K. Imarazene, El M. Berkouk, "Implementation of third-order sliding mode for power control and maximum power point tracking in DFIG-based wind energy systems", *Energy Reports*, Vol: 10 , pp. 3561-3579, 2023
<https://doi.org/10.1016/j.egy.2023.09.187>
- [38] A. Sakouchi, A. Djahbar, E. Bounadja, H. Benbouhenni, A. Iqbal, A. Moualdia, A. Kechida, "Enhanced control of grid-connected multi-machine wind power generation", *Energy Reports*, vol. 12, pp. 4208-4231, 2024. <https://doi.org/10.1016/j.egy.2024.09.077>
- [39] K. N. Khallouf, Z. Laid, H. Benbouhenni, N. Debdouche, Z.M.S. Elbarbary. "Adaptive fuzzy logic control for microgrid-connected hybrid photovoltaic/wind generation systems", *Energy Reports*, vol. 12, pp. 4741-4756, 2024. <https://doi.org/10.1016/j.egy.2024.10.042>
- [40] H. Benbouhenni, E. Bounadja, H. Gasmi, N. Bizon, I. Colak, "A new PD-(1+PI) direct power controller for the variable-speed multi-rotor wind power system driven doubly-fed asynchronous generator", *Energy Reports*, vol. 8, pp. 15584-15594, 2022. <https://doi.org/10.1016/j.egy.2022.11.136>
- [41] H. Benbouhenni, N. Bizon, I. Colak, Z. M. S. Elbarbary, S. F. Al-Gahtani, "Controlling the energies of the single-rotor large wind turbine system using a new controller", *Scientific Reports*, vol. 15, 2025. <https://doi.org/10.1038/s41598-025-87832-9>
- [42] D. Zellouma , Y. Bekakra , H. Benbouhenni, "Robust synergetic-sliding mode-based-backstepping control of induction motor with MRAS technique", *Energy Reports*, vol. 10, pp. 3665-3680, 2023. <https://doi.org/10.1016/j.egy.2023.10.035>
- [43] H. Benbouhenni M. Yesséf, NicuBizon, S. Kadi, A. Alhejji, B. Bossoufi, "HIL test verification of PDPI control of induction generator-based multi-rotor wind turbine systems", *Energy Science & Engineering*, pp. 140-159, 2025. <https://doi.org/10.1002/ese3.1976>
- [44] A. Nadhim J. Almakki, A. Mazalov, H. Benbouhenni, N. Bizon, "Comparison of two fractional-order high-order SMC techniques for DFIG-based wind turbines: Theory and Simulation Results", *ECTI Transactions on Electrical Engineering, Electronics, and Communications*, vol. 21, no. 2, 2023. <https://doi.org/10.37936/ecti-eec.2023212.249817>
- [45] D. Zellouma, Y. Bekakra, H. Benbouhenni, "Field-oriented control based on parallel proportional-integral controllers of induction motor drive", *Energy Reports*, vol. 9, pp. 4846-4860, 2023. <https://doi.org/10.1016/j.egy.2023.04.008>
- [46] H. Gasmi, H. Benbouhenni, S. Mendaci, I. Colak, "A new scheme of the fractional-order super twisting algorithm for asynchronous generator-based wind turbine", *Energy Reports*, vol. 9, pp. 6311-6327, 2023. <https://doi.org/10.1016/j.egy.2023.05.267>
- [47] H. Benbouhenni, H. Gasmi , I. Colak, N. Bizon, P. Thounthong, "Synergetic-PI controller based on genetic algorithm for DPC-PWM strategy of a multi-rotor wind power system", *Scientific Reports*, vol. 13, 2024. <https://doi.org/10.1038/s41598-023-40870-7>
- [48] D. Zellouma, H. Benbouhenni, Y. Bekakra, "Backstepping control based on a third-order sliding mode controller to regulate the torque and flux of asynchronous motor drive", *Periodica Polytechnica Electrical Engineering and Computer Science*, vol. 67, no.1, pp. 10-20, 2023. <https://doi.org/10.3311/PPEe.20333>
- [49] H. Chojaa, A. Derouich, O. Zamzoum, S. Mahfoud, M. Taoussi and H. Albalawi, "Novel DPC approach for DFIG-based variable speed wind power systems using Dspace", *IEEE Power & Energy Society Section*, vol. 11, pp. 9493- 9509, 2023. <https://doi.org/10.1109/ACCESS.2023.3237511>
- [50] M. Yesséf; H. Benbouhenni, M. Taoussi; A. Lagrioui; I. Colak and B. Bossoufi, "Experimental validation of feedback PI controllers for multi-rotor wind energy conversion systems", *IEEE Access*, vol. 12, pp. 7071-7088, 2024. <https://doi.org/10.1109/ACCESS.2024.3351355>
- [51] H. Benbouhenni, M. I. Mosaad, I. Colak, N. Bizon, H. Gasmi, M. Aljohani, and E. Abdelkarim, "Fractional-order synergetic control of the asynchronous generator-based variable-speed multi-rotor wind

- power systems”, IEEE Access, vol. 11, pp. 133490-133508, 2023.
<https://doi.org/10.1109/ACCESS.2023.3335902>
- [52] M. Yessef; H. Benbouhenni; M. Taoussi; A. Lagrioui; I. Colak and S. Mobayen, “Real-time validation of intelligent super-twisting sliding mode control for variable-speed DFIG using dSPACE 1104 board”, IEEE Access, vol. 12, pp. 31892-31915, 2024.
<https://doi.org/10.1109/ACCESS.2024.3367828>
- [53] H. Benbouhenni, H. Gasmi, M. Oproescu, N. Bizon, P. Thounthong and I. Colak, “Application of fractional-order synergetic-proportional integral controller based on PSO algorithm to improve the output power of the wind turbine power system”, Scientific Reports, vol. 14, 2024.
<https://doi.org/10.1038/s41598-024-51156-x>
- [54] M. Yessef, M. Taoussi, H. Benbouhenni, A. Lagrioui, I. Colak, H. Ameziane, B. Majout and B. Bossoufi, “Two different controllers-based DPC of the doubly-fed induction generator with real-time implementation on dSPACE 1104 controller board”, Measurement and Control, vol. 57, no.8, pp. 1123–1145 2024.
<https://doi.org/10.1177/00202940241236288>
- [55] H. Zekraoui, T. Ouchbel, M. L. El Hafyani, M. El Fahssi, B. Majout, B. Bossoufi, P. Skruch, A. Zhilenkov, and S. Mobayen, “Experimental implementation of design of an asynchronous machine-based wind emulator using Backstepping control”, Scientific Reports, vol. 15, 2025.
<https://doi.org/10.1038/s41598-025-94042-w>
- [56] H. Benbouhenni, M. Yessef, I. Colak, N. Bizon, H. Kotb, K. M. Abo RasandA. EL-rashidi, “Dynamic performance of rotor-side nonlinear control technique for doubly-fed multi-rotor wind energy based on improved super-twisting algorithms under variable wind speed”, Scientific Reports, vol. 14, 2024.
<https://doi.org/10.1038/s41598-024-55271-7>
- [57] H. Gasmi, H. Benbouhenni, I. Colak, T. Tafticht, N. Bizon. “Using the proportional dual integral strategy to improve the characteristics of the indirect field-oriented control of DFIG-based wind turbine systems”, e-Prime-Advances in Electrical Engineering, Electronics and Energy, vol. 9, 2024.
<https://doi.org/10.1016/j.prime.2024.100749>
- [58] M. Rostami, S. M. Madani, & S. Ademi, “Sensorless closed-loop voltage and frequency control of stand-alone DFIGs introducing direct flux-vector control”. IEEE Trans. Ind. Electron. 67, 6078–6088, 2020.
<https://doi.org/10.1109/TIE.2019.2955421>
- [59] V.-T. Phan, & H.-H. Lee, “Stationary frame control scheme for a stand-alone doubly fed induction generator system with effective harmonic voltages rejection”. IET Electr. Power Appl. 5, 697–707, 2011.
<https://doi.org/10.1049/iet-epa.2010.0280>
- [60] Y. Zhang, J. Hu, & J. Zhu, “Three-vectors-based predictive direct power control of the doubly fed induction generator for wind energy applications”. IEEE Trans. Power Electron. 29, 3485–3500 (2014).
<https://doi.org/10.1109/TPEL.2013.2282405>
- [61] M. S. Chabani, M. T. Benchouia, A. Golea, A. Y. Abdealziz, & M. A. Mossa, “A new sensor-less voltage and frequency control of stand-alone DFIG based dead-beat direct-rotor flux control-experimental validation”. ISA Trans. 158, 715–734, 2025.
<https://doi.org/10.1016/j.isatra.2024.12.039>
- [62] F. Bouchafaa, D. Beriber, & M. S. Boucherit, “Modeling and control of a grid connected PV generation system”. In 18th Mediterranean Conference on Control and Automation, MED’10 315–320, 2010.
<https://doi.org/10.1109/MED.2010.5547687>
- [63] F. Boucetta, M. Alturki, A. Albaker, et al. "Robust direct voltage control of stand-alone DFIG wind systems using a fractional-order fuzzy logic approach". Sci Rep 15, 28762, 2025.
<https://doi.org/10.1038/s41598-025-11910-1>
- [64] F. Amrane, H. Itouchene, "Enhanced Fuzzy-Power Control for WECS based on Variable wind speed-driven DFIG using SVM strategy under sub- and super-synchronous operating modes", Periodica Polytechnica Electrical Engineering and Computer Science, 2025.
<https://doi.org/10.3311/PPee.39807>
- [65] H. Itouchene, F. Amrane, Z. Boudries, et al. "design of a robust controller using Lyapunov function for DFIG wind turbines," International Conference on Advances in Electrical and Communication Technologies (ICAECOT), Setif, Algeria, pp. 1-5, 2024.
<https://doi.org/10.1109/ICAECOT62402.2024.10829237>

A Hybrid JAYA and Teaching-Learning Based Optimization Algorithm for Single- and Multi-Objective Optimal Power Flow

Oğuz Taşdemir*[†], Salih Ermiş*[‡]

*Kırşehir Ahi Evran University, Faculty of Engineering and Architecture, Department of Electrical and Electronics Engineering, Kırşehir, Turkey, 40100.

(oguz.tasdemir@ahievran.edu.tr, sermis@ahievran.edu.tr)

[†]Oğuz Tasdemir; Kırşehir Ahi Evran University, Kırşehir, Turkey, Tel: +90 386 280 54 22,

Fax: +90 386 280 38 00, oguz.tasdemir@ahievran.edu.tr

Received: 05.03.2026 Accepted: 23.04.2026

Abstract- This study presents a novel multi-objective optimization framework for the Optimal Power Flow (OPF) problem in an IEEE 30-bus system, aiming to simultaneously minimize generation costs, active power losses, and voltage deviations. Given the highly nonlinear and heavily constrained nature of OPF, conventional optimization techniques often fall short. To overcome these computational challenges, we propose a parameter-less hybrid metaheuristic approach that integrates Teaching-Learning-Based Optimization (TLBO) with the JAYA algorithm. This hybridization strategically synergizes TLBO's global exploration capabilities with JAYA's rapid, convergence-driven exploitation. By employing Pareto optimization and rigorously evaluating the outcomes using quantitative performance indicators (Spacing, Maximum Spread, and Hypervolume), a well-balanced and statistically robust set of optimal solutions is derived. Furthermore, the practical robustness of the framework is explicitly validated under a severe smart-grid stress scenario featuring high Electric Vehicle (EV) charging penetration. The comparative results reveal that the proposed hybrid TLBO-JAYA algorithm significantly enhances solution quality, convergence reliability, and overall system robustness compared to Particle Swarm Optimization (PSO) and standalone baselines. While the hybrid approach incurs a computational-time penalty due to its sequential phases, this research ultimately establishes the method as a highly effective tool for complex, multi-objective power system operational problems.

Keywords: Multi-objective optimization, optimal power flow problem, teaching-learning-based optimization (TLBO) algorithm, JAYA algorithm, pareto optimal technique.

1. Introduction

Optimal power flow (OPF) has been a subject of research since the early 1960s [1]. Ensuring the reliable, efficient, and economical operation of power systems is

one of the most significant engineering challenges faced by increasingly complex electrical grids. In this context, the OPF problem provides a framework for optimizing certain objectives under various constraints to maintain the balance between power generation and consumption

in power systems [2, 3]. These objectives include cost minimization, reduction of active power losses, and improvement of voltage profiles. Striking a balance among these objectives represents a significant challenge, particularly in multi-objective optimization studies [4]. Consequently, energy companies must adopt an effective OPF method to establish secure, economical, and efficient production systems [3].

The OPF problem is an optimization problem that is both nonlinear and non-convex [5]. While traditional methods such as Newton-Raphson or gradient-based approaches have been employed, they struggle with the non-convex and multi-modal characteristics of modern power systems [6, 7], often converging to local optima or requiring precise initial estimates [8]. Furthermore, the transition from traditional power networks to modern smart grids has fundamentally transformed the OPF problem. Today's smart grids are cyber-physical systems characterized by the widespread integration of Distributed Energy Resources (DERs), which introduce high volatility and uncertainty into daily operations. The dynamic nature of smart grids demands communication-aware operation and real-time deployment capabilities from modern Energy Management Systems (EMS). Traditional OPF solvers, and even highly parameterized metaheuristic algorithms, struggle to adapt autonomously to these rapid grid fluctuations. Therefore, there is an urgent need for robust, parameter-free computational methods that can ensure optimized power delivery without requiring continuous manual tuning.

To address these limitations, various metaheuristic algorithms (e.g., PSO, DE, TLBO) and hybrid approaches (e.g., HMJDE, ESNST, CDMTMO) have been extensively applied to OPF problems to achieve a better balance between economic and technical objectives [9-18]. While the existing literature presents a broad array of optimization techniques, it is crucial to distinguish between incremental hybridizations and genuinely new methodological contributions to the OPF problem. Many recent studies focus on incremental hybridization—such as simply cascading two standard algorithms. Although these approaches marginally improve convergence speed, they often increase algorithmic complexity and introduce new user-defined tuning parameters, making them difficult to scale for real-world grid operators.

Conversely, genuinely new OPF contributions address the fundamental challenges of modern power systems through innovative, autonomous architectures. The proposed TLBO-JAYA hybrid algorithm directly addresses this smart-grid requirement by providing a highly reliable, autonomous optimization engine capable of handling complex, non-linear grid conditions. Rather than just combining two random metaheuristics, it structurally integrates two fundamentally parameter-free

algorithms. The TLBO algorithm mimics the teacher-student interactions in an educational environment, operating through teacher and learner phases to ensure fast optimization [19]. Similarly, the JAYA algorithm converges solely towards the best solution in the current search space while moving away from the worst, maintaining a simple structure with minimal parameter requirements [20]. The complete absence of parameter tuning in both algorithms makes their integration a highly successful and autonomous alternative for complex OPF problems.

In power systems, the simultaneous optimization of multiple objective functions leads to a multi-objective OPF problem [21]. Pareto optimization is widely used in these problems to establish a balance between different conflicting objectives, offering decision-makers a broader range of choices instead of a single optimal solution [3]. In this work, the TLBO, JAYA, and Hybrid TLBO-JAYA algorithms are used to solve the OPF problem for the IEEE 30-bus power system, targeting voltage deviation, active power loss, and generation cost.

The key contributions of this study are summarized as follows:

- 1- A novel TLBO-JAYA hybrid metaheuristic algorithm is introduced, structurally integrating two parameter-free algorithms. This novel integration achieves an optimal balance in the search process by combining the powerful global exploration capability of TLBO with the fast and straightforward exploitation power of JAYA.

- 2- By implementing the hybrid TLBO-JAYA algorithm on the IEEE 30-bus test system, a thorough multi-objective OPF framework is established to simultaneously minimize fuel costs, active power losses, and voltage deviations. Additionally, the algorithm's real-world applicability is verified through a heavy-loading smart grid scenario simulating extreme EV charging penetration (Case 7).

- 3- Comparative analyses with standalone TLBO and JAYA, strongly supported by rigorous quantitative Pareto metrics (Spacing, Maximum Spread, and Hypervolume), mathematically demonstrate that the hybrid approach achieves superior convergence reliability and an expansive Pareto-optimal front, albeit with an acceptable computational-time penalty.

Together, these contributions clearly articulate the necessity, originality, and broader applicability of the proposed hybrid approach beyond mere controller superiority. This investigation organizes the subsequent sections as follows: The OPF problem is delineated in Section 2. In Section 3, the optimization algorithms employed are introduced. Detailed descriptions of the

case studies and simulation results are provided in Section 4. The study's conclusions are ultimately presented in Section 5.

1.1. Formulation of Optimal Power

The primary objective of the Optimal Power Flow (OPF) problem is to identify the most efficient operating state of a power system. This involves minimizing specific objective functions—namely, generation cost, power loss, and voltage deviation—subject to a set of equality and inequality constraints. The generalized mathematical formulation of the OPF problem is expressed in Eqs. (1-3).

$$\text{Minimize: } f(x, u) \quad (1)$$

$$\text{Subject to: } g(x, u) \quad (2)$$

$$h(x, u) \leq 0 \quad (3)$$

where the equality constraints govern the nodal power balance, and the inequality constraints ensure that all system variables remain strictly within their operational limits. The concise formulation above summarizes the OPF structure while allowing focus on the study's novel optimization approach rather than standard mathematical definitions.

A. Variables of State

In power systems, state variables are values that provide information about the current state of the system and need to be optimized within specific limits. The state variables are defined as x and are given in Eq. (4).

$$x = [P_{G_1}, V_{L_1} \dots V_{L_{NL}}, Q_{G_1} \dots Q_{G_{NG}}, S_{l_1} \dots S_{l_{nl}}] \quad (4)$$

Here, P_{G_1} is defined as the active power of the selected slack bus, Q_G represents the reactive power of the generators, V_L denotes the voltage values of the load buses, and S_l is the loading of the transmission line.

B. Variables of Control

In power systems, control variables are decision variables adjusted to optimize the system according to specific objectives (e.g., cost minimization, loss minimization). The control variables are defined as u^T and are given in Eq. (5).

$$u^T = [P_{G_2} \dots P_{G_{NG}}, V_{G_1} \dots V_{G_{NG}}, Q_{C1} \dots Q_{C_{NC}}, T_1 \dots T_{NT}] \quad (5)$$

Here, transformer tap settings are defined as T , and parallel reactive power compensators are defined as Q_C . In order to ensure the safe and efficient operation of the system, certain limits are taken into consideration when handling the OPF problem. These limitations fall within the categories of inequality and equality limitations. They establish the parameters that the control and state variables must stay inside when solving the problem.

1) Constraints on Equality

In OPF issues, equality limits are crucial to maintaining the physical and operational balance of the system. At every bus in the power system, these limitations guarantee the balance between power generation, consumption, and losses. The Active Power and Reactive Power constraints are the two primary equality constraints in OPF problems. These can be found in Eqs. (6-7).

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{N_B} V_j [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)] = 0 \quad (6)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{N_B} V_j [G_{ij} \sin(\delta_i - \delta_j) + B_{ij} \cos(\delta_i - \delta_j)] = 0 \quad (7)$$

Here, P_{Gi} refers to the active power generated by the generators at the i -th bus, while P_{Di} represents the active power demand at the i -th bus. Similarly, Q_{Gi} indicates the reactive power generated by the generators at the i -th bus, and Q_{Di} refers to the reactive power demand at the i -th bus. G_{ij} and B_{ij} denote the real and imaginary components of the transmission line connecting the i -th and j -th buses, respectively. V_i and V_j are the voltages of the i -th and j -th buses, respectively, and N_B is the number of buses. δ_i and δ_j represent the voltage phase angles of the i -th and j -th buses.

2) Inequality Constraints

In OPF formulations, inequality constraints are imperative for confining state and control variables within their predefined limits, thereby guaranteeing secure system operation. The primary inequality constraints addressed encompass the following:

Eqs. (8-9) specify the permissible active and reactive power generation limits.

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max}, \quad 1 \leq i \leq N_G \quad (8)$$

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}, \quad 1 \leq i \leq N_G \quad (9)$$

Here, P_{Gi}^{min} and P_{Gi}^{max} are the minimum and maximum active power of the generator, respectively. Similarly, Q_{Gi}^{min} and Q_{Gi}^{max} are the minimum and maximum reactive power of the generator, respectively. N_G represents the number of generators.

The voltage limits of generators are presented in Eq. (10).

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max}, \quad 1 \leq i \leq N_G \quad (10)$$

Here, V_{Gi}^{min} and V_{Gi}^{max} are the minimum and maximum voltage values of generator i -th, respectively.

The limits of shunt compensators are defined in Eq. (11).

$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max}, \quad 1 \leq i \leq N_C \quad (11)$$

Here, the minimum and maximum values of the shunt compensator are Q_{Ci}^{min} and Q_{Ci}^{max} , respectively. N_C is the shunt compensator number.

The transformer tap limits are provided in Eq. (12).

$$T_i^{min} \leq T_i \leq T_i^{max}, \quad 1 \leq i \leq N_T \quad (12)$$

Here, T_i^{min} and T_i^{max} are the minimum and maximum tap values of transformer i -th, respectively. N_T is the tap number of the transformer.

The voltage limits of load buses are defined in Eq. (13).

$$V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max}, \quad 1 \leq i \leq N_L \quad (13)$$

Here, V_{Li}^{min} and V_{Li}^{max} are the minimum and maximum voltage values of the load bus i -th, respectively. N_L is the loadbus number.

The apparent power limits are provided in Eq. (14).

$$S_{li} \leq S_{li}^{max}, \quad 1 \leq i \leq N_l \quad (14)$$

Here, S_{li} , i -th apparent power load flow, S_{li}^{max} are the maximum apparent power load flow values.

In power system operations, a strict voltage tolerance band of 0.95–1.05 p.u. is mandated for load buses to protect end-user equipment. However, for generator buses, the upper voltage limit is intentionally extended to 1.1 p.u. to actively compensate for the inevitable voltage drops along lengthy transmission lines.

C. Objective Functions

Three primary goal functions have been established to address the OPF problem in power systems: lowering active power losses, limiting fuel usage, and lowering voltage variations.

1) Basic Fuel Cost Reduction

The objective in solving this problem is to minimize the fuel cost of each generation unit while meeting the required electricity demand. Accordingly, the total generation cost of the system is formulated as shown in Eq. (15).

$$F_{Cost} = \sum_{i=1}^{N_G} f_i(P_{Gi}) \quad (15)$$

Here, F_{Cost} represents the total fuel cost, $f_i(P_{Gi})$ is the fuel cost function of the i -th generator, which depends on its power output (P_i), and N_G denotes the number of generators in the system.

Typically, the fuel cost function is expressed as shown in Eq. (16).

$$f_i(P_i) = a_i + b_i P_{Gi} + c_i P_{Gi}^2 \quad (16)$$

In this function, the coefficients a_i , b_i and c_i are specific to each generator and vary depending on the

generator's fuel type and efficiency. Table 1 provides the generator coefficients for the IEEE 30-bus power system.

Table 1. Generator cost coefficients (IEEE 30 bus) [22]

Cost coefficients	Bus No.					
	1	2	5	8	11	13
a	0	0	0	0	0	0
b	2	1.75	1	3.25	3	3
c	0.00375	0.0175	0.0625	0.00834	0.025	0.025

Eq. 16 represents the quadratic fuel cost function of thermal generating units, which captures the nonlinear relationship between generation output and total fuel cost. The quadratic form is widely used in OPF formulations because it realistically models the incremental fuel consumption characteristics of practical generators. The cost coefficients (a, b, c) correspond to each generator's fuel cost parameters, obtained from the standard IEEE 30-bus test system data as reported in [22]. These coefficients were adopted to ensure consistency and comparability with benchmark OPF studies in the literature.

2) Active Power Loss Minimization

Active Power Loss Minimization is an optimization problem aimed at enhancing energy efficiency in a power system by minimizing active power losses in transmission lines and transformers. Active power loss is calculated considering the transmission resistance and voltage values between each line (i, j) in the system. It is expressed as shown in Eq. (17).

$$P_{loss} = \sum_{i=1}^{N_B} \sum_{j \neq i}^{N_B} G_{ij} [V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j)] \quad (17)$$

Here, P_{loss} represents the total active power loss, N_B denotes the total number of buses in the system, and G_{ij} is the conductance coefficient of the transmission line between buses i and j . V_i and V_j are the voltage magnitudes at buses i and j , respectively, while δ_i and δ_j are the voltage phase angles at buses i and j . Additionally, $\cos(\delta_i - \delta_j)$ represents the cosine of the voltage phase angle difference between the two buses.

3) Voltage Deviation Minimization

Voltage Deviation Minimization is an optimization technique used to ensure that the voltage levels at the nodes in a power system are close to a specified reference voltage value, typically 1 p.u (per unit). This problem aims to improve the system's stability and voltage profiles. The voltage deviation minimization equation is given in Eq. (18).

$$VD = \sum_{i=1}^{N_B} |V_i - 1| \quad (18)$$

Here, VD represents the voltage deviation, N_B is the total number of buses in the system, and V_i denotes the voltage magnitude at the i -th bus.

Three multi-objective functions have been defined to solve the OPF problem:

- Minimization of fuel cost and active power loss ($F_{Cost} + P_{Loss}$)
- Minimization of fuel cost and voltage deviation ($F_{Cost} + VD$)
- Minimization of fuel cost, active power loss, and voltage deviation ($F_{Cost} + P_{Loss} + VD$)

For all cases, the single and multi-objective functions for the OPF problem in the power system are presented in Table 2.

Table 2. Working conditions in test systems

Cases	Objective functions	Test system
Case 1	Basic F_{cost} minimization	IEEE 30
Case 2	P_{loss} minimization	
Case 3	VD minimization	
Case 4	F_{cost} and P_{loss} minimization	
Case 5	F_{cost} and VD minimization	
Case 6	F_{cost} , P_{loss} , and VD minimization	
Case 7	EV Charging Penetration	

D. Pareto-Optimal Solution

Within the context of multi-objective optimization, non-dominated solutions are formally recognized as Pareto-optimal. Such solutions become essential when inherent conflicts between objectives preclude simultaneous absolute optimization. The resulting Pareto front illustrates the optimal balance, thereby equipping the decision-maker with a diverse array of compromised solutions.

For a solution to be Pareto-optimal, it must satisfy the following conditions:

1. Dominance Criterion: A solution is considered Pareto-optimal as long as it is not dominated by any other solution. For instance, as defined in Eq. (19), a solution X_1 dominates another solution X_2 if it performs equally well or better in all objective functions and is strictly better in at least one objective function [8, 9].

$$\begin{aligned} \forall i \in \{1, 2, \dots, n\}, F_i(X_1) &\leq F_i(X_2) \\ \exists j \in \{1, 2, \dots, n\}, F_j(X_1) &< F_j(X_2) \end{aligned} \quad (19)$$

2. Non-Dominated Solution: If a solution is not dominated by any other solution, it is considered a non-dominated solution and is included in the Pareto front. The membership function μ^k for each non-dominated solution k is defined in Eq. (20) [23].

$$\mu^k = \frac{\sum_{i=1}^N \mu_i^k}{\sum_{k=1}^M \sum_{i=1}^N \mu_i^k} \quad (20)$$

Formed by the aggregation of all possible non-dominated solutions, the Pareto front manifests as a

continuous boundary in the objective space. Consequently, any movement along this front signifies a direct compromise, or trade-off, between the conflicting objectives inherent in the problem. Any solution on this front represents a state where improving one objective function is impossible without compromising another [24, 25].

Among Pareto-optimal solutions, a decision-maker may need to select a solution by prioritizing a specific objective. This resolution is designated as the Best Compromise Solution (BCS). The user or operator's preferences define designated weighting factors that select the BCS from the Pareto front [26].

In the multi-objective OPF framework, the proposed hybrid TLBO-JAYA algorithm employs an external archive to store the non-dominated Pareto-optimal solutions discovered during the iterative process. To prevent the archive from exceeding its predefined maximum capacity and to ensure a uniformly distributed Pareto front, the Crowding Distance mechanism is utilized. The crowding distance metric calculates the density of solutions surrounding a particular candidate in the objective space. When the number of non-dominated solutions exceeds the archive limit, solutions situated in densely populated regions (i.e., those with the lowest crowding distance values) are systematically removed. Conversely, boundary solutions (representing the absolute minimums of individual objectives) are assigned an infinite crowding distance and are strictly preserved. This mechanism ensures that the final Pareto front maintains excellent diversity and spread, avoiding premature convergence to a limited sub-region.

While the Pareto front provides a diverse set of optimal trade-off solutions, system operators typically require a single deterministic operating point for deployment. To extract the Best Compromise Solution (BCS) reported in the multi-objective case studies (Tables 5, 9, 10, and 11), a fuzzy set theory-based approach is applied, utilizing the membership function (μ^k) previously defined in Eq. 20. The exact rule for extracting the BCS involves calculating the aggregate membership value for each non-dominated solution. In this study, a strictly neutral evaluation approach was adopted; therefore, equal weighting factors were assigned to all competing objective functions (e.g., $\omega_1 = \omega_2 = \omega_3 = 1/3$ for Case 6). Ultimately, the solution that yields the maximum aggregate membership value $\max(\mu^k)$ is mathematically selected as the BCS, representing the most balanced equilibrium among fuel cost, active power loss, and voltage deviation without biasing any specific objective.

E. Multi-Objective Performance Indicators

To rigorously evaluate the quality, distribution, and convergence of the obtained Pareto fronts, multi-objective performance indicators are calculated. Relying solely on visual evaluation is insufficient for a comprehensive

assessment. Therefore, three standard quantitative metrics are employed in this study: Spacing (SP), Maximum Spread (MS), and Hypervolume (HV).

1) Spacing (SP)

This metric evaluates the uniformity of the spread of the non-dominated solutions along the Pareto front. A smaller SP value indicates that the solutions are evenly distributed. It is calculated as:

$$SP = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (\bar{d} - d_i)^2} \quad (21)$$

where n is the number of non-dominated solutions, d_i is the minimum distance between the i -th solution and its nearest neighbor, and $\bar{d}$ is the mean value of all d_i .

2) Maximum Spread (MS)

This indicator measures the extent of the Pareto front. A larger MS value demonstrates that the algorithm is capable of exploring a broader region of the objective space. For an MS objective problem, it is defined as:

$$MS = \sqrt{\sum_{k=1}^M (\text{MAX}_{i=1} F_i^k - \text{MIN}_{i=1} F_i^k)^2} \quad (22)$$

where F_i^k is the k -th objective function value of the i -th solution.

3) Hypervolume (HV)

HV evaluates both the convergence and diversity of the Pareto front by calculating the volume of the objective space dominated by the obtained solution set, bounded by a predefined reference point. A higher HV value indicates superior overall performance.

2. Optimization Algorithms

2.1. Teaching-Learning-Based Optimization

The Teaching-Learning-Based Optimization (TLBO) algorithm is a metaheuristic paradigm that simulates the dynamic knowledge acquisition process between a teacher and students. The computational framework of TLBO is systematically divided into two sequential phases: teaching and learning. The instructional phase encompasses the educator sharing knowledge with the learners and facilitating their growth journey. The learning phase, conversely, emulates interactions among students, facilitating knowledge exchange and enhancing their learning levels. The TLBO algorithm conceptualizes the population as a class, with the best-performing individual among the students representing the teacher. During the initialization phase, a random population is created, and the individual exhibiting the highest objective function value is designated as the teacher. During the instructional phase, the educator seeks to impact others, elevating their understanding to align more closely with the educator's expertise. During the learning phase,

individuals engage with each other, sharing insights and enhancing their understanding. This interaction aims to improve the effectiveness of the algorithm's solutions. [27, 28].

- **Teaching Phase:** This phase denotes the process by which pupils enhance their knowledge by acquiring information from the teacher. At this stage, the educator seeks to enhance the class's average performance to match their own level. The disparity between the teacher's knowledge level and the class's average level is determined using Eq. (23).

$$F_{mean}^k = gx(X_{best}^k - T_F M^k) \quad \text{where } M^k = \frac{1}{N} \sum_{i=1}^N X_i^k \quad j = 1, 2, \dots, D \quad (23)$$

Here, g is a random number between 0 and 1, T_F is a heuristic step that can be either 1 or 2, M^k represents the class's average result, X_{best}^k is the result of the best student, and F_{mean}^k is the difference between the teacher's result and the class's average result.

$$X_i^{k+1} = X_i^k + F_{mean}^k \quad (24)$$

In Eq. (24), X_i^{k+1} represents the updated value of X_i^k . All X_i^{k+1} values are stored and passed as input to the learning phase.

- **Learning Phase:** The knowledge of any student improves through interactions with other students, and the students' knowledge levels are updated according to Eqs. (25-26).

$$X_i^{k+1} = X_i^k + m \times (X_i^k - X_n^k), \text{ if } f(X_i^k) < f(X_n^k) \quad n \neq i \quad (25)$$

$$X_i^{k+1} = X_i^k + m \times (X_i^k - X_n^k), \text{ if } f(X_i^k) > f(X_n^k) \quad n \neq i \quad (26)$$

Here, m is a random number between 0 and 1, and X_n^k represents the n -th randomly selected student.

In solving multi-objective functions, the Pareto-optimal solution set is updated at each iteration of the algorithm. These solutions, which are non-dominated with respect to one another, are gathered on the Pareto front. The algorithm terminates when the maximum number of iterations is reached or when the solutions achieve sufficient accuracy. At this point, the Pareto-optimal solution set is obtained. If the stopping criterion has not yet been met, the teaching and learning phases are repeated, and the algorithm continues. Figure 1 presents the flowchart of the TLBO approach.

2.2. Jaya Algorithm

Rao (2016) created the population-based, stochastic metaheuristic JAYA algorithm, which is intended to tackle both constrained and unconstrained continuous optimization problems [29]. The Sanskrit term "JAYA," which means

“victory,” is the source of the algorithm's name, which reflects the idea of finding the optimal solution and succeeding. In order to solve the problem more successfully, the JAYA algorithm's main objective is to increase the propensity to approach the optimal answer while avoiding the worst one.

Metaheuristic algorithms typically depend on common parameters such as population size and the number of iterations, as well as their own unique parameters [30]. However, unlike other metaheuristic algorithms, the JAYA algorithm relies solely on fundamental parameters and does not require additional specific parameters. This parameter independence makes the algorithm more adaptable to various optimization problems. Additionally, during the position update phase, the JAYA algorithm enhances the tendency to move toward the best solution while avoiding the worst solution, minimizing the risk of getting trapped in local minima or maxima. These features make the JAYA algorithm more successful compared to other metaheuristic methods. In the JAYA algorithm, Eq. (27) is defined for the purpose of maximizing or minimizing the objective function [29].

$$X_{i,j,t}^{new} = X_{i,j,t} + r_{1,i,t}(X_{i,best,t} - |X_{i,j,t}|) - r_{2,i,t}(X_{i,worst,t} - |X_{i,j,t}|),$$

$$i = 1, 2, \dots, n; j = 1, 2, \dots, n \quad (27)$$

In the equation provided above, $X_{i,j,t}^{new}$ represents the updated value of the variable, while $r_{1,i,t}$ and $r_{2,i,t}$ are two random numbers in the range [0, 1] for the i -th variable during the t -th iteration. If $X_{i,j,t}^{new}$ represents a better value, it replaces $X_{i,j,t}$. This step is applied to all candidate solutions. Throughout the process, the best solution values are preserved and used as input for the next iteration. In multi-objective OPF problems, the best solutions for different objectives are gathered on the Pareto front. The JAYA algorithm selects non-dominated solutions from those obtained in each generation and updates the Pareto front. Figure 2 shows a flow diagram of the JAYA algorithm.

2.3. Tlbo-Jaya Hybrid Algorithm

The Hybrid TLBO-JAYA Algorithm is designed to achieve superior optimization performance by combining the strengths of two popular metaheuristic optimization methods: The TLBO and the JAYA algorithm. This algorithm integrates the distinct approaches of these two methods:

1. *TLBO Approach*: Focuses on improving the solution quality through two phases: the teaching phase, where the best solution (teacher) guides the population toward better solutions, and the learning phase, where individuals (students) enhance their knowledge through mutual

interactions. TLBO's parameter-free nature makes it robust and versatile.

2. *JAYA Approach*: The algorithm's convergence capability is enhanced by directing the search trajectory toward the optimal solution and actively steering away from the most inferior candidate. JAYA's simplicity, with no algorithm-specific parameters, ensures adaptability and avoids the risk of local optima.

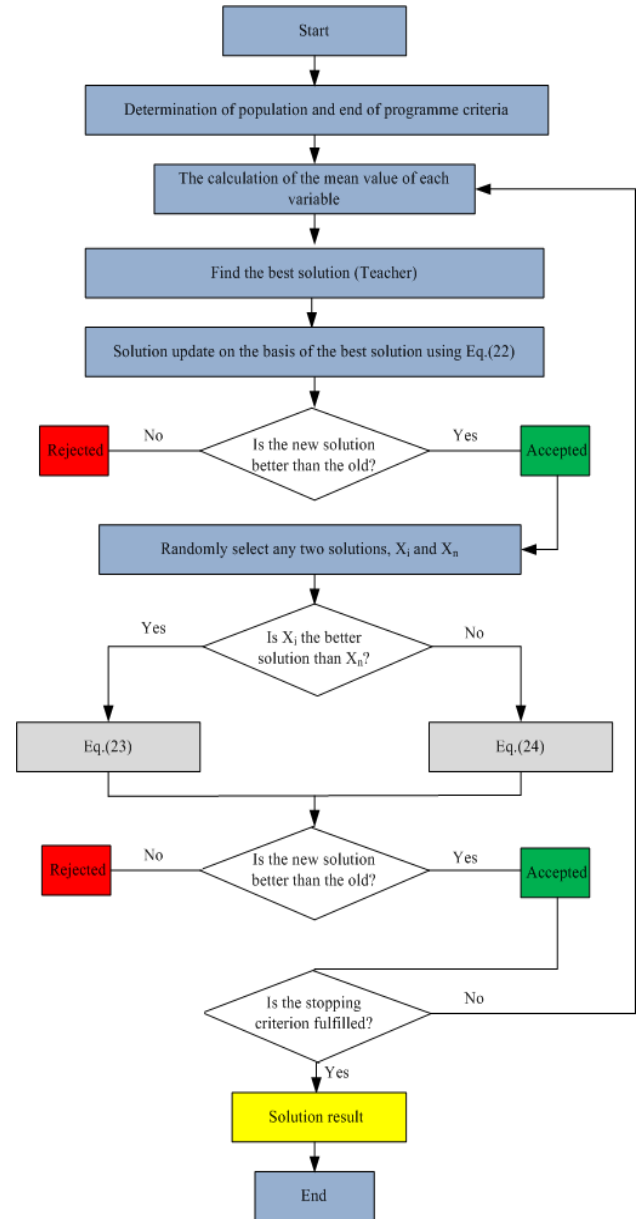


Fig. 1. Flow chart for TLBO algorithm.

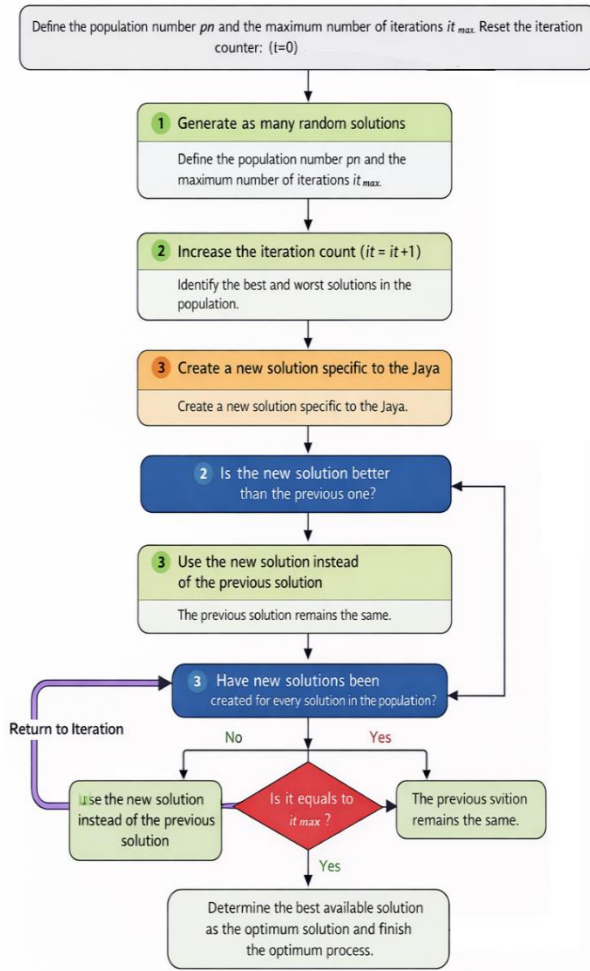


Fig. 2. Flow chart for JAYA algorithm [31].

The hybrid algorithm combines these complementary strengths, enabling the exploration of the solution space using TLBO's teaching-learning dynamics and refining solutions through JAYA's best-worst positioning strategy. This synergy aims to provide more balanced, efficient, and accurate solutions for complex optimization problems like OPF. Figure 3 shows a flow diagram of the Hybrid TLBO-JAYA algorithm.

Steps of the Proposed Hybrid TLBO-JAYA Algorithm.

1. **Initialization**; First, we randomly create a starting population based on the control and state variables of the OPF issue. The initial population depicts each candidate solution as a vector.

2. **Evaluation of Objective Functions and Constraints**; Each candidate solution is evaluated according to the defined objective functions of the multi-objective OPF problem.

3. **Teaching Phase – TLBO**; In this phase, the best individual in the population is identified as the teacher. The

teacher is the solution with the best objective function value compared to others. Each individual is improved by leveraging the teacher's solutions (Eq. 24). Updated solutions replace the previous ones if they achieve better objective function values.

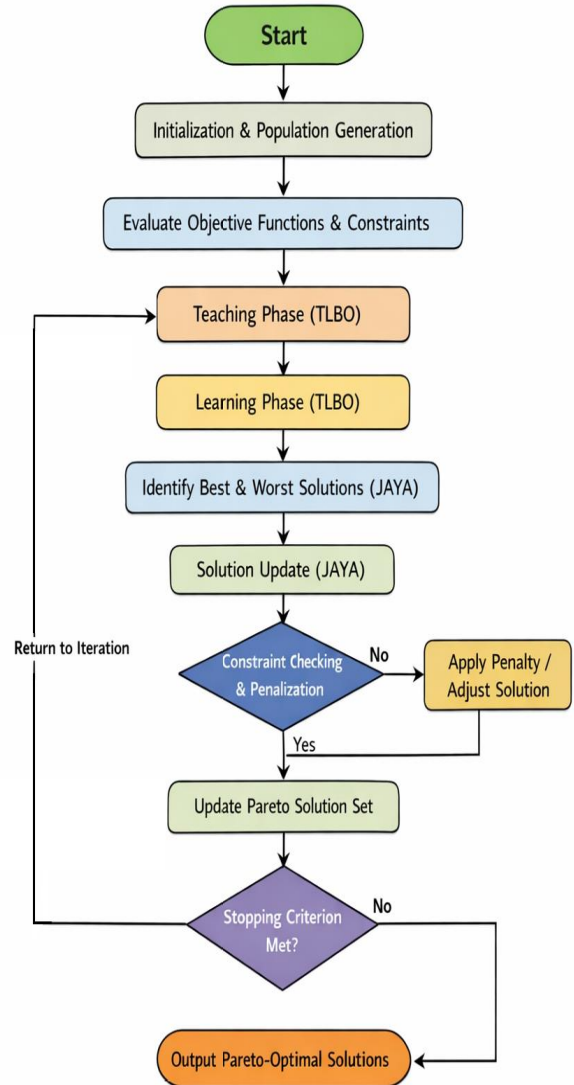


Fig. 3. Flow chart for Hybrid TLBO-JAYA algorithm.

4. **Learning Phase – TLBO**; During the learning phase, each candidate solution is compared with another randomly selected candidate solution for improvement. If one solution has a better objective function value, the other is updated according to Eq. 25. This phase contributes to improving all solutions in the population. Updated solutions replace previous ones if they yield better results.

5. **Identifying the Best and Worst Solutions – JAYA**; Following the TLBO phases, the identification of the best and worst solutions within the population is conducted through the JAYA algorithm. The best solution stands out

because it performs better than others in achieving goals, making it a reference point for improving other options. Throughout the enhancement process, we disregard the least effective solution.

6. *Solution Update – JAYA*; Each candidate solution is updated according to the JAYA algorithm's rule, moving closer to the best solution and farther from the worst solution (Eq. 27).

7. *Constraint Checking and Penalization*; Updated solutions are checked for any violations of the OPF problem constraints, such as voltage limits or generator boundaries. If constraints are violated, penalty functions are applied, or the solutions are adjusted to conform to valid limits.

8. *Pareto Solution Set Update*; Every generation revises the Pareto-optimal solutions because the OPF issue involves multi-objective optimization. The hybrid TLBO-JAYA algorithm finds the best solutions that balance goals like cost and power loss. These solutions are called non-dominated and form the Pareto-optimal solution set.

9. *Stopping Criterion*; The execution of the algorithm concludes either upon reaching the predefined maximum number of iterations or upon attaining the specified convergence tolerance. If these termination criteria remain unsatisfied, the iterative process is systematically repeated to further refine the candidate solutions.

10. *Output of Results*; The Pareto-optimal set generated by the proposed hybrid TLBO-JAYA algorithm yields the definitive solutions for the multi-objective OPF problem. These non-dominated solutions concurrently optimize critical performance metrics, such as generation cost and active power loss, thereby establishing a rigorous balance among competing system objectives. Ultimately, this framework empowers system operators to identify the best compromise solution tailored to specific operational requirements.

The unique integration strategy of the TLBO-JAYA hybrid algorithm is based on a sequential update mechanism that leverages the complementary strengths of both parameter-independent algorithms. In each iteration, the TLBO phases (Teacher and Learner Phases) are executed first. With its two-stage structure, TLBO excels at diversifying the population and avoiding local minima (exploration). Immediately after the TLBO update, the JAYA phase is applied to the new population. By updating only the best and worst solutions, the JAYA algorithm provides a strong, parameter-independent attraction (exploitation) towards the optimum during this phase. This sequential combination is superior to other TLBO hybrids (e.g., TLBO-PSO [32], which require speed/inertia parameters) because it provides an effective trade-off while maintaining the key advantage of parameter independence:

TLBO expands the search space, while JAYA refines the best candidate solutions quickly and reliably.

A primary advantage of the proposed hybrid TLBO-JAYA algorithm is its complete independence from algorithm-specific tuning parameters. Traditional metaheuristics require rigorous tuning of inertia weights, cognitive factors, or mutation rates, making their performance highly sensitive to parameter variations. In contrast, both TLBO and JAYA are inherently parameter-free. Consequently, the proposed hybrid approach exhibits zero parameter sensitivity regarding algorithmic control mechanisms.

Regarding computational complexity, the hybrid algorithm executes the TLBO Teacher, TLBO Learner, and JAYA phases sequentially within each iteration. For a population size N , problem dimension D (number of control variables), and maximum iterations T_{max} , the asymptotic time complexity evaluates the objective function $3 \times N$ times per iteration. Thus, the overall computational complexity is bounded by $O(N \times D \times T_{max})$. While this sequential execution introduces a marginal increase in runtime per iteration compared to standalone methods, this operational cost is fundamentally offset by the superior convergence reliability and the elimination of the pre-tuning phase.

2.4. Constraint Handling and Penalty Formulation

To ensure that the proposed hybrid TLBO-JAYA algorithm consistently converges to feasible solutions, a rigorous constraint handling mechanism is integrated into the optimization process. The constraints in the OPF problem are divided into control variables and state variables, which are handled using distinct strategies.

For the control variables (such as generator active powers, generator voltages, transformer taps, and shunt compensators), a boundary repair strategy is strictly applied during the position update phases of both TLBO and JAYA. If any control variable x_i exceeds its predefined upper limit (x_i^{max}) or falls below its lower limit (x_i^{min}), it is forcefully pulled back to the violated boundary. This repair rule is mathematically expressed as:

$$x_i = \begin{cases} x_i^{max}, & \text{if } x_i > x_i^{max} \\ x_i^{min}, & \text{if } x_i < x_i^{min} \\ x_i, & \text{otherwise} \end{cases} \quad (28)$$

On the other hand, for the state variables (such as load bus voltages, generator reactive power outputs, and transmission line loadings), a static quadratic penalty function is employed. Since state variables are obtained as a result of the load flow process (via Newton-Raphson), their violations cannot be directly repaired. Instead, violations are heavily penalized by adding penalty terms to

the original objective function (F_{obj}). The augmented objective function (F_{aug}) is formulated as follows:

$$F_{aug} = F_{obj} + \lambda_V \sum_{i=1}^{NL} (V_{Li} - V_{Li}^{lim})^2 + \lambda_Q \sum_{i=1}^{NG} (Q_{Gi} - Q_{Gi}^{lim})^2 + \lambda_S \sum_{i=1}^{NL} (S_{Li} - S_{Li}^{lim})^2 \quad (29)$$

where λ_V , λ_Q and λ_S are the large penalty factors (typically set to 10^4 or 10^6 in this study) assigned to the load bus voltages, generator reactive powers, and line apparent powers, respectively. The limit value parameter (x^{lim}) for any state variable is defined as the actual variable value if it operates within limits, or the violated boundary value if a limit is exceeded, formulated identically to the repair strategy rule mentioned above. This exact penalty formulation ensures that any infeasible candidate solution is naturally eliminated during the selection mechanism of the hybrid algorithm.

3. Simulations and Results

To address the constrained single- and multi-objective OPF problems, the standard TLBO, the original JAYA, and the proposed hybrid TLBO-JAYA metaheuristic algorithms were employed. All computational simulations were coded in MATLAB R2022b and executed on a 64-bit personal computer equipped with an Intel Core i7-2620 CPU (2.70 GHz) and 8 GB of RAM. To guarantee a fair and reproducible comparative analysis, identical control parameters were assigned across all evaluated methods: a population size (N) of 30 and a maximum iteration count (T_{max}) of 100. Furthermore, to ensure robust statistical evaluation, each algorithm was subjected to 30 independent trial runs. The performance validation of the proposed and existing techniques was conducted on the standard IEEE 30-bus test system (depicted in the single-line diagram of Figure 4). To comprehensively evaluate the performance of the proposed hybrid framework, seven distinct optimization scenarios are investigated, as outlined in Table 2. Cases 1–3 focus on single-objective optimizations (fuel cost, active power loss, and voltage deviation). Cases 4–6 address multi-objective OPF problems using Pareto optimization. Finally, Case 7 introduces a modern smart-grid stress scenario focusing on heavy Electric Vehicle (EV) charging penetration to test the algorithm's robustness under severe load conditions.

3.1. IEEE 30 Bus System

The IEEE 30-bus power system was used to evaluate the suggested TLBO, JAYA, and hybrid TLBO-JAYA algorithms for solving single/multi-objective OPF problems. Within this system:

- The total number of transmission lines is 41.
- There are 6 generators, 24 load buses, 4 transformers, and 9 shunt VAR compensators.

- The active and reactive power requirements at the load buses are 283.4 MW and 126.2 MVar, respectively.

- Each shunt VAR compensator possesses a capacity of 5 MVar, with transformer tap setting limitations established between 0.9 and 1.1.

- The voltage limitations for all load buses are expected to be 0.95–1.05 per unit [25].

To assess the efficacy of the TLBO, JAYA, and hybrid TLBO-JAYA algorithms in addressing OPF problems inside the IEEE 30-bus power system, various scenarios featuring distinct objective functions were examined as outlined.

1) Single-Objective OPF Solutions

For the IEEE 30-bus power system, the study tackled three different single-objective OPF problems: minimizing voltage variance, lowering active power losses, and minimizing fuel costs. For the single-objective OPF problem solutions, Table 3 displays the statistical measures (Best, Worst, Mean, and Standard Deviation) and algorithm computation durations obtained from the 30 independent runs. The findings showed that the suggested hybrid TLBO-JAYA algorithm performed well, as seen by the best objective function value and the least standard deviation value. As confirmed in Table 3, the consistently lower Standard Deviation (St. Dev.) values achieved by the hybrid algorithm (e.g., Case 1 St. Dev.: 0.0233) compared to TLBO (St. Dev.: 0.5781) and JAYA (St. Dev.: 0.2187) serve as the empirical guarantee of its superior stability and reliable convergence across multiple runs, a critical feature for non-linear OPF problems.

However, as accurately reflected in Table 3, this enhanced stability and solution quality come at a computational-time penalty. The runtime of the hybrid TLBO-JAYA algorithm is slower than both standalone TLBO and JAYA. This trade-off is an expected outcome of the iterative coordination and sequential execution of the two distinct updating phases. Ultimately, the algorithm sacrifices computational speed to guarantee a more robust and reliable convergence.

Furthermore, to address the uncertainties of cross-literature comparisons, a rigorous same-platform benchmarking was conducted. a standard particle swarm optimization (pso) algorithm was implemented and executed under the exact same computational environment, population size, and iteration limits for the single-objective OPF scenarios (Cases 1-3). As clearly detailed in the updated Table 3, while PSO exhibits the fastest execution times, the proposed hybrid TLBO-JAYA consistently outperforms this standard baseline in terms of optimal solution quality (Best) and convergence stability (e.g., Standard Deviation of 0.8488 for PSO vs. 0.0233 for

TLBO-JAYA in Case 1). This specific benchmarking mathematically validates the superior robustness of the hybrid framework without the bias of differing hardware or constraint definitions.

This reliability, when compared to the high speed of the Interior Point Method (IPM) [33], demonstrates the trade-off between solution quality and speed in non-convex problems like OPF. While methods such as IPM are fast, their ability to find the global optimum is limited, as they are often trapped in local optima in the complex non-convex search space. Moreover, the proposed hybrid framework remains scalable for larger systems such as IEEE-57 and IEEE-118 bus test networks. By incorporating parallel computation, adaptive population sizing, and efficient initialization strategies, the method can be

effectively applied to higher-dimensional OPF problems without a proportional increase in computation time. This scalability discussion strengthens the practical applicability of the proposed hybrid method in real-world power system optimization contexts.

The bus voltage values graph is shown in Figures 5(a), (b), and (c) in accordance with single-objective functions. The voltage magnitude profiles plotted in Figure 4 demonstrate that all bus voltages were successfully maintained strictly within their respective operational constraints. Specifically, it is clearly observed that the generator bus voltages remained within the 0.95–1.1 p.u. limits, while the load bus voltages strictly adhered to the narrower 0.95–1.05 p.u. allowable range, ensuring high system security [14].

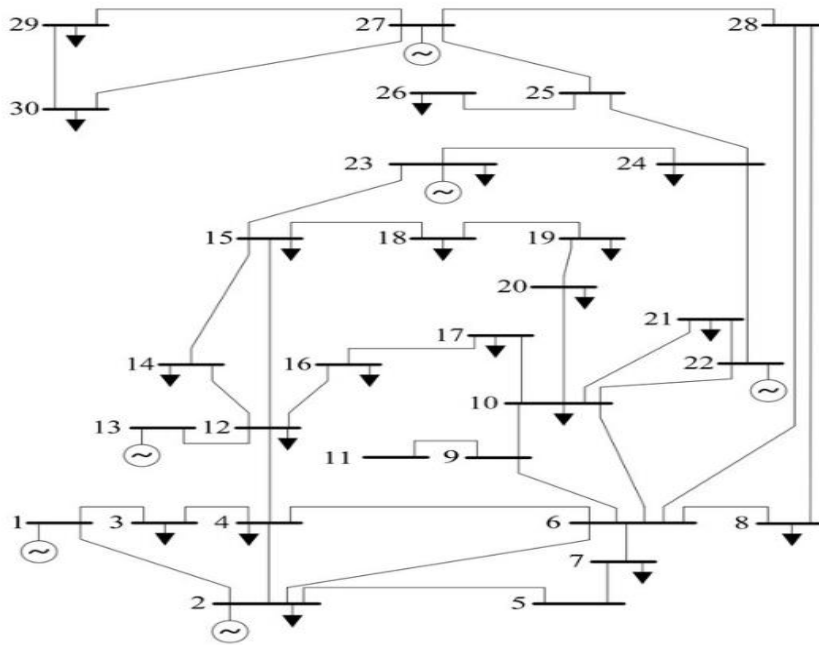


Fig. 4. Schematic representation of the standard IEEE 30-bus test network.

Table 3. Statistical minimization results for objectives in single-objective cases 1–3 (IEEE 30-bus system)

	CASE 1 [Best-Worst-Mean (\$/h)]				CASE 2 [Best-Worst- Mean (MW)]				CASE 3 [Best-Worst- Mean (p.u)]			
	TLBO	JAYA	PSO	TLBO-JAYA	TLBO	JAYA	PSO	TLBO - JAYA	TLBO	JAYA	PSO	TLBO-JAYA
Best	800.576	800.699	800.570	800.523	0.031	0.031	0.032	0.031	0.091	0.101	0.108	0.088
Worst	802.954	801.641	803.736	800.611	0.034	0.035	0.035	0.032	0.113	0.155	0.215	0.104
Mean	801.173	800.946	801.233	800.550	0.032	0.033	0.034	0.031	0.100	0.120	0.133	0.093
St. Dev.	0.578	0.219	0.849	0.023	0.001	0.001	0.008	0.000	0.005	0.014	0.025	0.004
Time (Sec)	32.952	17.193	14.482	55.453	39.085	18.467	17.053	53.703	36.197	18.125	15.505	43.641

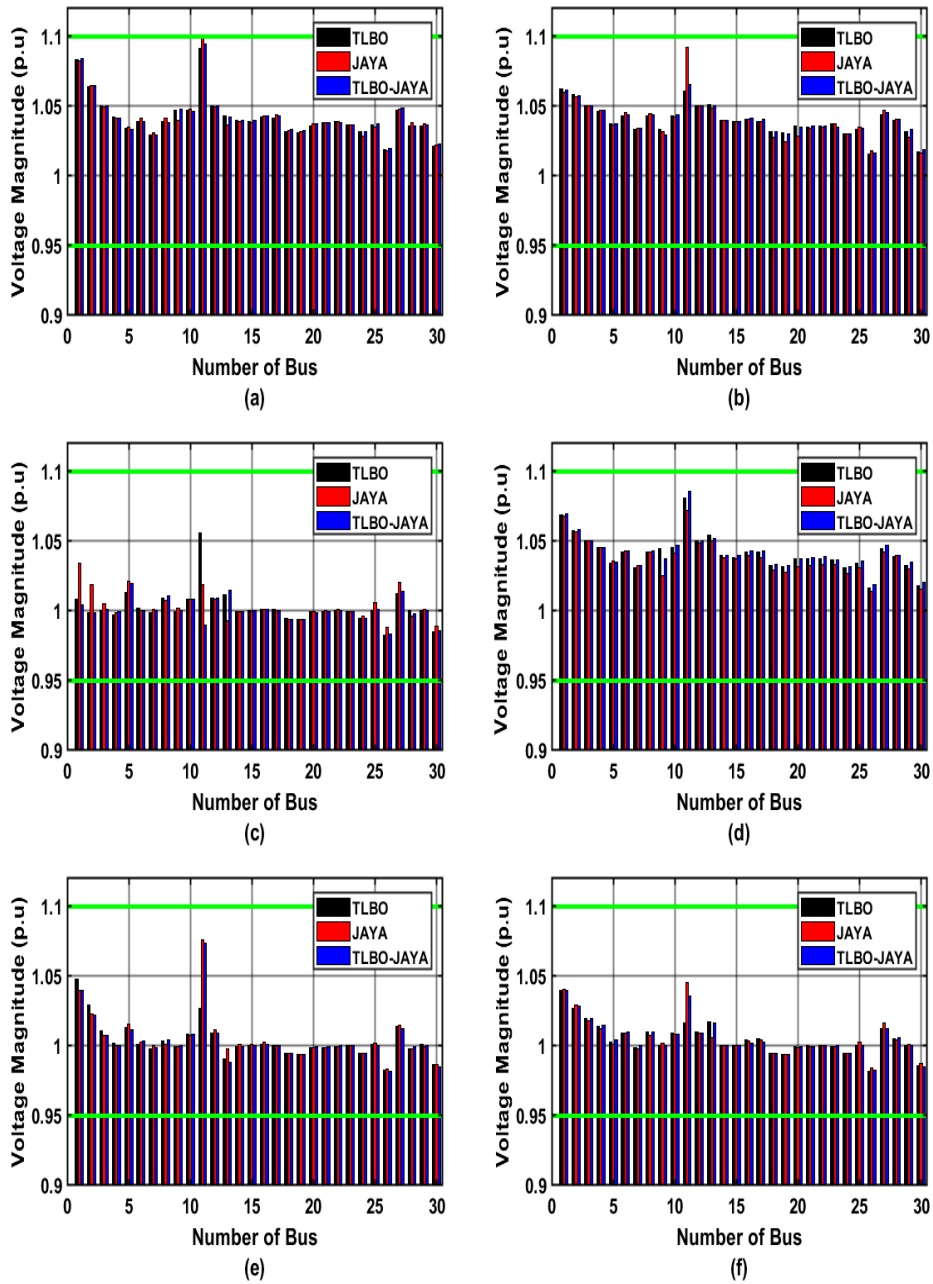


Fig. 5. IEEE 30-bus system buses voltage values: (a) Case 1, (b) Case 2, (c) Case 3, (d) Case 4, (e) Case 5, (f) Case 6.

Case 1: Basic fuel cost minimization

In this case, the performance of the proposed algorithms in minimizing total cost values was targeted. According to the analysis results presented in Table 4, for Case 1, the hybrid TLBO-JAYA algorithm achieved a better result than the other two algorithms, with the lowest F_{cost} value of 800.523 \$/h. This demonstrates the hybrid algorithm's greater effectiveness in cost optimization. The F_{cost} values for the TLBO and JAYA algorithms were observed to be 800.5754 \$/h and 800.6989 \$/h,

respectively. The JAYA algorithm has a slightly higher cost compared to TLBO. However, the difference is quite small, indicating that both algorithms have similar performance in cost optimization. Figure 6-a shows that the graph of the objective function shows the better performance of the TLBO-JAYA algorithm in terms of convergence. Table 6 juxtaposes the proposed algorithm with existing algorithms in the literature on total fuel cost, demonstrating its efficacy.

Table 4. Optimal power flow test results for control and state variables for single-objective cases 1–3.

	Limits		CASE 1			CASE 2			CASE 3		
	Min	Max	TLBO	JAYA	TLBO-JAYA	TLBO	JAYA	TLBO-JAYA	TLBO	JAYA	TLBO-JAYA
P_{g1} (MW)	50	250	177.56	176.858	177.200	51.539	51.530	51.503	139.393	200.72	96.338
P_{g2} (MW)	20	80	48.495	48.595	48.771	79.976	80.000	79.999	56.597	46.288	58.449
P_{g5} (MW)	15	50	21.505	21.114	21.379	50.000	50.000	50.000	34.158	15.000	40.962
P_{g8} (MW)	10	35	20.736	22.042	21.230	35.000	35.000	35.000	14.392	10.000	32.346
P_{g11} (MW)	10	30	12.133	11.848	11.860	30.000	30.000	30.000	29.901	11.139	30.000
P_{g13} (MW)	12	40	12.038	12.001	12.001	39.994	40.000	40.000	16.844	12.690	30.686
V_{g1} (p.u)	0.95	1.1	1.083	1.082	1.084	1.062	1.060	1.061	1.009	1.034	1.005
V_{g2} (p.u)	0.95	1.1	1.064	1.065	1.065	1.058	1.057	1.057	0.998	1.019	0.999
V_{g5} (p.u)	0.95	1.1	1.034	1.035	1.033	1.038	1.037	1.038	1.013	1.021	1.020
V_{g8} (p.u)	0.95	1.1	1.039	1.041	1.038	1.043	1.045	1.044	1.009	1.008	1.011
V_{g11} (p.u)	0.95	1.1	1.092	1.100	1.094	1.061	1.092	1.066	1.056	1.019	0.990
V_{g13} (p.u)	0.95	1.1	1.043	1.036	1.042	1.051	1.049	1.050	1.012	0.993	1.015
Obj. Func.			800.576	800.699	800.523	3.108	3.130	3.101	0.091	0.101	0.088
F_{cost} (\$/h)			800.575	800.699	800.523	967.611	967.734	967.662	832.012	812.029	877.328
P_{loss} (MW)			9.068	9.058	9.040	3.108	3.130	3.101	7.885	12.436	5.380
V_D (pu)			0.906	0.907	0.918	0.878	0.861	0.882	0.091	0.101	0.088

Case 2: Power loss minimization

In Case 2, the objective function is defined as minimizing power loss. According to the analysis results for Case 2 presented in Table 4, the total power losses are observed as follows: TLBO with 3.1078 MW, JAYA with 3.1302 MW, and Hybrid TLBO-JAYA with 3.1013 MW. In this case, the hybrid algorithm achieved the lowest total power loss, demonstrating that the hybrid algorithm is the most successful among the three in minimizing power losses. In Figure 6-b, the convergence graph for active power loss indicates that the proposed algorithm shows the best performance. Table 7 compares the total power loss results with other studies in the literature, highlighting the superiority of the proposed approach.

Case 3: Voltage deviation minimization

Reducing voltage deviation (VD) values is the goal in Case 3. Based on the study results for Case 3 shown in Table 4, the suggested TLBO-JAYA algorithm was the most effective approach for minimizing voltage deviation, achieving the lowest voltage deviation value of 0.0879 p.u, VD values of 0.0911 p.u and 0.1013 p.u were found by the TLBO and JAYA algorithms, respectively. The suggested algorithm once more exhibits the optimum convergence performance in Figure 6-c. The performance of the suggested algorithm is contrasted with that of other algorithms in Table 8, demonstrating its benefits.

1) Multi-Objective OPF Solutions

Three distinct objective functions—fuel cost-active power loss minimization, fuel cost-voltage deviation minimization, and fuel cost-active power loss-voltage deviation minimization—were put forth for multi-objective

OPF solutions. According to the multi-objective functions, the bus voltage values are shown in Figures 5(d), (e), and (f). The plots show that the bus voltage values stay within the 0.95–1.1 p.u range, guaranteeing that the limitations are met.

Case 4: Fuel cost and active power losses minimization

In Case 4, the multi-objective OPF problem was evaluated for fuel cost (F_{cost}) and power loss (P_{loss}). In Table 5 for Case 4, it is observed that the TLBO algorithm has an F_{cost} value of 860.3091 \$/h and a P_{loss} value of 4.5463 MW; the JAYA algorithm has an F_{cost} value of 858.9427 \$/h and a P_{loss} value of 4.6363 MW; and the hybrid TLBO-JAYA algorithm has an F_{cost} value of 856.0601 \$/h and a P_{loss} value of 4.5158 MW. The hybrid TLBO-JAYA algorithm stands out as the most successful algorithm in simultaneously minimizing cost and power loss. The performance improvement over the standalone methods is not merely in marginal cost reduction, but in the enhanced stability and convergence trajectory. The sequential application of TLBO's comprehensive exploration followed by JAYA's rapid, targeted exploitation ensures that the resulting Pareto fronts (Figures 7a, 7b) are not only closer to the true optimal front (better convergence) but are also generated with higher statistical confidence across multiple runs (superior robustness). In the graph in Figure 7-a, the Pareto optimalities between the multi-objective functions, cost and power loss, are shown comparatively for the three different algorithms (TLBO, JAYA, TLBO-JAYA). The TLBO-JAYA algorithm exhibits optimal performance on the Pareto front regarding both minimal cost and reduced power loss. This suggests that the TLBO-JAYA algorithm yields superior answers relative to the other two algorithms.

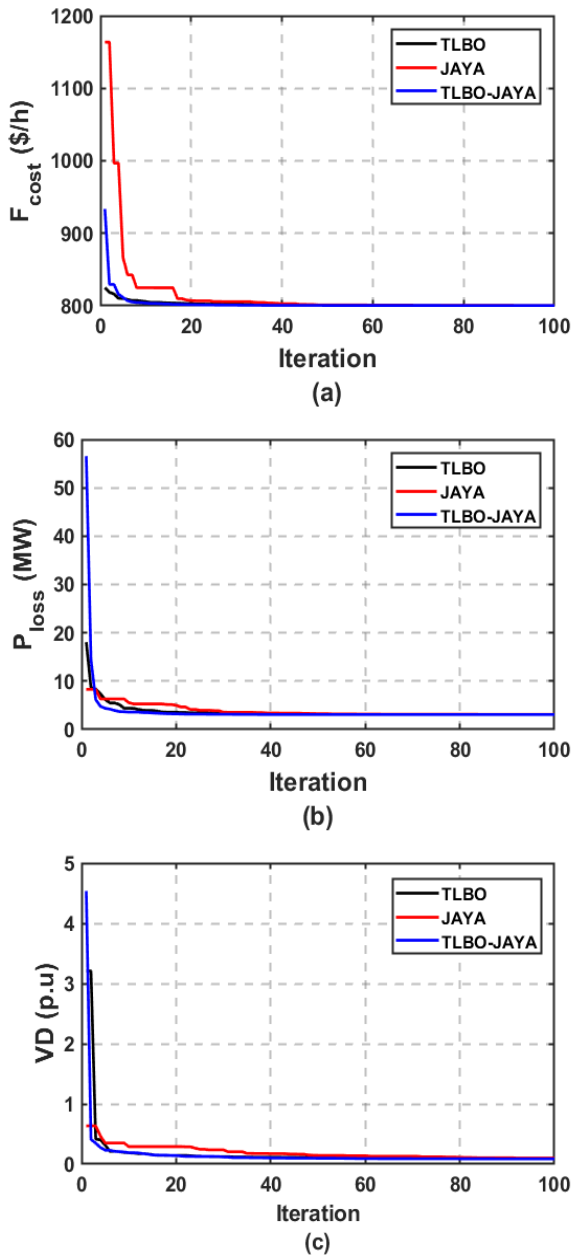


Fig. 6. Convergence characteristics of the objective functions for the standard IEEE 30-bus test system: (a) Case 1, (b) Case 2, and (c) Case 3.

Case 5: Fuel cost and voltage deviation minimization

In this case, the objective is the multi-objective function of fuel cost (F_{cost}) and voltage deviation (VD). Table 5 presents the analysis results for Case 5 for the three algorithms. According to these values, the proposed hybrid TLBO-JAYA algorithm demonstrates the best performance compared to the TLBO and JAYA algorithms, with an F_{cost} value of 803.6796 \$/h and a VD value of 0.0957 p.u. Figure 7-b represents the Pareto-optimal solutions between F_{cost} and VD . These solutions are the best trade-off points

achieved without worsening one parameter while improving the other. The points are distributed along the Pareto curve in the graph. The hybrid TLBO-JAYA solutions generally provide the lowest combinations of F_{cost} and VD . Specifically, in the F_{cost} range of 800 \$/h to 815 \$/h and for low VD values, the most effective solutions are observed. This demonstrates that the hybrid algorithm offers superior performance in simultaneously minimizing F_{cost} and VD compared to the other algorithms. Table 10 highlights the efficiency of the proposed algorithm for multi-objective functions of cost and voltage deviation in comparison with other studies in the literature.

Case 6: Cost, losses, and voltage deviation minimization

In Case 6, the OPF problem was solved for the multi-objective function of F_{cost} , P_{loss} , and VD . Table 5 presents the analysis results for Case 6. According to these results, the proposed TLBO-JAYA algorithm achieved the best values for minimizing P_{loss} (4.7273 MW) and VD (0.1375 p.u.), but it performed poorly in terms of cost minimization, with an F_{cost} value of 864.0922 \$/h compared to TLBO's best F_{cost} value of 862.0042 \$/h. In conclusion, if minimizing power loss and voltage deviation is the priority, the hybrid algorithm is the better choice. However, if cost minimization is more critical, the TLBO algorithm may be a more suitable option. This specific scenario clearly demonstrates that while the hybrid algorithm excels at finding well-balanced compromise solutions and improving overall robustness, it does not uniformly dominate the standalone algorithms across every single evaluation metric in highly complex multi-objective spaces. Figure 7-c displays the Pareto optimization results for the multi-objective functions F_{cost} , P_{loss} , and VD in a three-dimensional representation. The graph shows that as F_{cost} increases, P_{loss} and VD tend to decrease. At lower costs, voltage deviation and power loss increase, while at higher costs, voltage deviation and power loss decrease. This indicates a trade-off where minimizing cost requires compromises in power loss and voltage deviation. Such a Pareto graph provides decision-makers with insights into the relationships between each objective function, offering a perspective on which parameters must be sacrificed to focus on a specific target. Table 11 presents the analysis results of the proposed algorithms compared to other algorithms in the literature.

All comparative results presented in Tables 6–11 were sourced from literature based on the standard IEEE 30-Bus Test System, ensuring a consistent baseline system for evaluation. Due to inherent differences in metaheuristic implementations across various studies (such as specific iteration limits, power system constraints/load modeling, and distinct fitness functions), direct comparisons should focus on the quality metrics: the best reported objective function value (accuracy) and the overall relative ranking

of the proposed method. Our primary claim is the superior accuracy and statistical robustness demonstrated by the hybrid TLBO–JAYA approach under equivalent test conditions.

When we compare the single-objective and multi-objective results, the advantages of the hybrid TLBO–JAYA become more evident. For example, in Case 1 (only

F_{cost} minimization), the hybrid algorithm offers the lowest cost (800.523 \$/h) and the best robustness (SS: 0.023). When we move on to Case 4 (multi-objective $F_{cost} + P_{loss}$), the algorithm performs best in simultaneously optimizing F_{cost} and P_{loss} as 856.060 \$/h and 4.516\$ MW, respectively.

Table 5. Optimal power flow test results for control and state variables for multi-objective cases 4-6

	CASE 4			CASE 5			CASE 6			CASE 7		
	TLBO	JAYA	TLBO-JAYA	TLBO	JAYA	TLBO-JAYA	TLBO	JAYA	TLBO-JAYA	TLBO	JAYA	TLBO-JAYA
$P_{g1}(\text{MW})$	102.57 8	104.13 7	101.99 4	177.09 2	178.34 6	176.46 5	102.01 2	100.79 1	98.185	190.52 5	191.84 7	189.96 4
$P_{g2}(\text{MW})$	55.758	56.523	55.320	48.936	48.642	48.425	55.928	56.063	57.925	51.944	49.043	51.467
$P_{g5}(\text{MW})$	38.067	37.728	38.270	23.181	21.718	21.589	38.814	39.135	38.770	22.240	22.454	22.465
$P_{g8}(\text{MW})$	35.000	34.992	34.999	19.285	20.610	22.525	35.000	35.000	34.953	26.920	26.789	28.652
$P_{g11}(\text{MW})$	30.000	29.999	29.994	12.718	12.122	12.244	30.000	30.000	30.000	15.910	18.144	14.802
$P_{g13}(\text{MW})$	26.544	24.658	27.339	12.000	12.000	12.000	26.465	27.173	28.294	13.574	13.108	13.691
$V_{g1}(\text{p.u.})$	1.069	1.068	1.069	1.048	1.040	1.040	1.040	1.041	1.040	1.086	1.087	1.085
$V_{g2}(\text{p.u.})$	1.058	1.057	1.059	1.029	1.023	1.022	1.027	1.029	1.028	1.066	1.064	1.066
$V_{g5}(\text{p.u.})$	1.034	1.035	1.035	1.013	1.015	1.011	1.003	1.002	1.004	1.030	1.011	1.035
$V_{g8}(\text{p.u.})$	1.042	1.042	1.043	1.003	1.001	1.004	1.010	1.008	1.010	1.033	1.027	1.037
$V_{g11}(\text{p.u.})$	1.081	1.072	1.086	1.027	1.076	1.074	1.016	1.046	1.036	1.100	0.995	1.070
$V_{g13}(\text{p.u.})$	1.055	1.050	1.052	0.991	0.998	0.988	1.018	1.006	1.017	1.050	1.043	1.045
Obj. Func.	1040.9 9	1041.5 6	1040.8 2	813.94	814.40	813.30	1068.9 5	1069.7 3	1068.3 2	901.37	902.93	901.29
$F_{cost}(\$/\text{h})$	860.30 9	858.94 3	856.06 0	803.72 3	803.86 1	803.68 0	862.00 4	866.50 5	864.09 2	901.36 8	902.92 7	901.29 2
$P_{loss}(\text{MW})$	4.546	4.636	4.516	9.813	10.038	9.848	4.819	4.762	4.727	10.563	10.835	10.492
$V_D(\text{pu})$	0.903	0.829	0.918	0.103	0.105	0.096	0.142	0.141	0.138	0.829	0.474	0.804

Table 6. Comparative evaluation of Case 1's OPF possibilities.

Algorithm	Fcost (\$/h)	Ploss (MW)	VD (p.u.)
TLBO-JAYA	800.523	9.040	0.918
TLBO	800.575	9.068	0.906
JAYA	800.699	9.058	0.907
WTLBO [10]	800.570	9.008	0.856
PSO [34]	800.591	9.223	0.853
ABC [35]	800.660	9.033	0.921
MFO [36]	800.686	9.149	0.758
GA [37]	800.767	8.988	0.823
GOA [37]	800.781	8.988	0.691

MDE [36]	800.840	8.837	0.776
GWO [38]	800.931	9.056	0.724
GO [39]	800.973	9.015	0.887
CEO [40]	800.977	9.060	1.170
WOA [41]	801.754	8.936	0.420
PSO [42]	802.190	10.083	0.123
ALO [41]	802.218	9.413	0.464
FPA [36]	802.798	9.541	0.368
I-NSGA-II [43]	803.129	9.609	0.121

Table 7. Comparative evaluation of Case 2's OPF possibilities

Algorithm	F _{cost} (\$/h)	P _{loss} (MW)	VD (p.u)
TLBO-JAYA	967.662	3.101	0.882
TLBO	967.611	3.108	0.878
JAYA	967.734	3.130	0.861
ABC [35]	967.681	3.108	0.901
WTLBO [10]	967.600	3.109	0.895
MFO [36]	967.679	3.111	0.916
GA [37]	967.534	3.134	0.874
MDE [36]	967.654	3.162	0.768
ALCPSO [44]	967.768	3.170	0.809
EGA [42]	967.860	3.201	0.122
GOA [37]	963.099	3.314	0.768
BHBO [45]	932.818	3.504	0.799
FPA [36]	967.114	3.566	0.389
PSO [42]	956.450	3.629	0.129

Table 8. Comparative evaluation of Case 3's OPF possibilities

Algorithm	F _{cost} (\$/h)	P _{loss} (MW)	VD (p.u)
TLBO-JAYA	877.328	5.380	0.088
TLBO	832.012	7.885	0.091
JAYA	812.029	12.436	0.101
WTLBO [10]	891.100	4.991	0.093
BBO [46]	805.758	10.180	0.095
EGA [42]	898.817	6.092	0.104
MSA [36]	803.313	9.721	0.108
PSO [42]	837.060	8.821	0.111
AGA [47]	805.810	10.610	0.121
BHBO [45]	804.598	9.578	0.126

Table 9. Comparative evaluation of Case 4's OPF possibilities

Algorithm	Fcost (\$/h)	Ploss (MW)	VD (p.u)
TLBO-JAYA	856.060	4.516	0.918
TLBO	860.309	4.546	0.903
JAYA	858.943	4.636	0.829
FPA [36]	855.271	4.798	1.014
MGOA [37]	858.454	4.444	0.826
MFO [36]	858.581	4.577	0.899
PSO [37]	858.664	4.572	0.923
WTLBO [10]	858.880	4.772	0.903
MSA [36]	859.192	4.540	0.929
GA [37]	859.535	4.565	0.869
MPSO [36]	859.584	4.541	0.947
CEO [40]	860.076	4.483	1.170
GOA [37]	861.832	4.665	0.714
MDE [36]	868.714	4.389	0.878

Table 10. Comparative evaluation of Case 5's OPF possibilities

Algorithm	F _{cost} (\$/h)	P _{loss} (MW)	VD (p.u)
TLBO-JAYA	803.680	9.848	0.096
TLBO	803.723	9.813	0.103
JAYA	803.861	10.038	0.105
FDBSFS [41]	802.920	9.430	0.113
WTLBO [10]	803.410	9.735	0.106
GOA [37]	803.449	9.775	0.171
PSO [37]	803.623	9.935	0.111
FPA [36]	803.664	9.925	0.137
GA [37]	803.916	9.662	0.126
MPSO [36]	803.979	9.924	0.120
AHA [41]	804.578	9.744	0.126
CEO [40]	804.673	10.068	0.110
BBO [46]	804.998	9.950	0.102
ALO [41]	805.177	9.139	0.155
DE [48]	805.262	10.441	0.136
WOA [41]	806.099	9.072	0.140

Table 11. Comparative evaluation of Case 6's OPF possibilities

Algorithm	F _{cost} (\$/h)	P _{loss} (MW)	VD (p.u)
TLBO-JAYA	864.092	4.727	0.138
TLBO	862.004	4.819	0.142
JAYA	866.505	4.762	0.141
MOPSO [49]	827.820	6.593	0.159
B-MMOFPA [50]	843.180	5.789	0.175
ALO [41]	862.351	4.846	0.184
WOA [41]	863.888	5.059	0.217

In terms of computational time, Case 4 generally takes longer than Case 1 because its multi-objective structure requires a more complex Pareto solution search. However, the hybrid TLBO-JAYA consistently outperforms standalone TLBO and JAYA in both scenarios, proving that the overall structure of the algorithm adapts to both single and multi-objective challenges and offers superior performance.

The quantitative assessment of the Pareto fronts, detailed in Table 12, robustly substantiates the visual superiority of the proposed hybrid approach. As observed, the TLBO-JAYA algorithm consistently achieves the lowest Spacing (SP) values across all multi-objective cases (Cases 4–6). This confirms that the integrated crowding distance mechanism effectively maintains a highly uniform and well-distributed set of non-dominated solutions. Furthermore, while all algorithms successfully reach the maximum spread limits (MS), the hybrid TLBO-JAYA

algorithm consistently records the highest Hypervolume (HV) values. This higher HV mathematically proves that the sequential hybridization of TLBO's exploration and JAYA's exploitation phases prevents premature convergence, allowing the algorithm to capture a strictly superior and more comprehensive Pareto-optimal front compared to the standalone methods.

Table 12. Quantitative evaluation of the Pareto fronts for multi-objective cases

Case	Algorithm	SP	MS	HV
Case 4	TLBO	0.071	1.4142	0.9058
	JAYA	0.0636	1.4142	0.9082
	TLBO-JAYA	0.0497	1.4142	0.9108
Case 5	TLBO	0.0404	1.4142	0.8824
	JAYA	0.0755	1.4142	0.847
	TLBO-JAYA	0.0349	1.4142	0.9112
Case 6	TLBO	0.0747	1.7321	0.8028
	JAYA	0.0664	1.7321	0.8131
	TLBO-JAYA	0.0526	1.7321	0.8181

• Ablation Study and Component Contributions

To explicitly demonstrate the contribution of each individual mechanism within the proposed framework, an ablation study is inherently embedded in our experimental design. By evaluating the standalone TLBO and standalone JAYA algorithms under the exact same platform and operational constraints as the hybrid framework, the precise contribution of each component is isolated. The results across all cases clearly show that when the JAYA phase is ablated (i.e., using only TLBO), the algorithm exhibits strong global exploration but suffers from slower convergence and higher standard deviations.

Conversely, when the TLBO phases are ablated (i.e., using only JAYA), the algorithm demonstrates rapid exploitation but frequently stagnates in local optima, failing to capture an expansive Pareto front (as seen in the lower Hypervolume metrics). The hybrid TLBO-JAYA algorithm mathematically synergizes these components: the TLBO teacher/learner phases provide the necessary broad exploration to avoid local traps, while the subsequent JAYA phase guarantees rapid and precise exploitation. This structural ablation confirms that neither constituent algorithm can achieve the robustness of the hybrid independently.

Case 7: Smart grid scenario with EV charging penetration

To explicitly address the operational challenges of modern smart grids and validate the robustness of the proposed framework under severe stress, a heavy loading

scenario (Case 7) was designed. The widespread adoption of Electric Vehicles (EVs) introduces sudden and uncoordinated heavy power demands on the grid, particularly during evening charging peaks. In this scenario, to simulate extreme EV charging penetration, the active power demand (P_d) at heavily loaded buses (Buses 7, 10, 15, and 21) was intentionally increased by 50%.

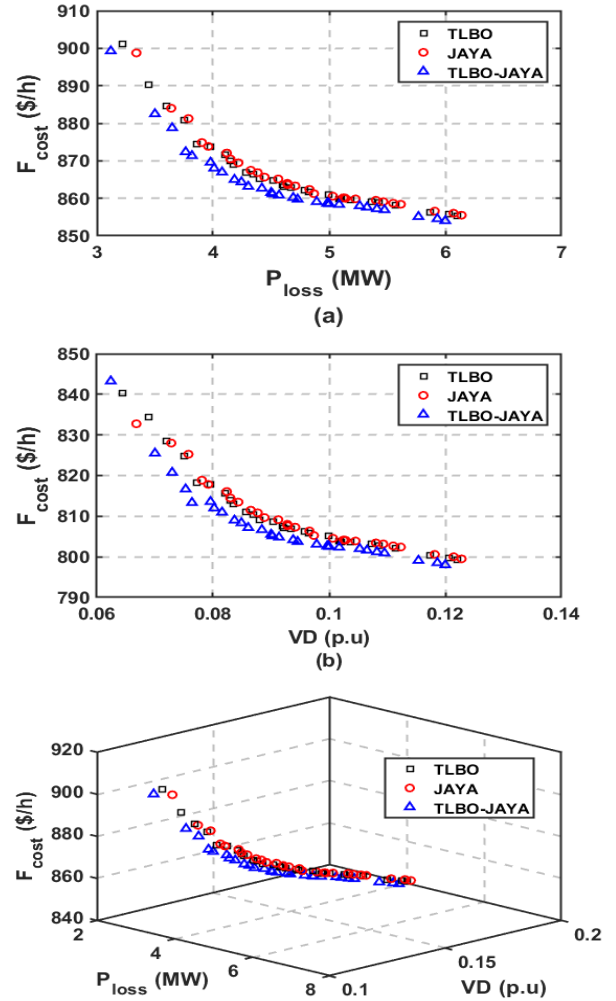


Fig. 7. Pareto optimization results in the multi-objective OPF solution: (a) Case 4, (b) Case 5, (c) Case 6.

As presented in the Case 7 results (Table 5), the extreme loading naturally drives the overall generation fuel cost up to approximately 901 \$/h, compared to the base 800 \$/h observed in Case 1. Despite this severe grid stress and narrowed feasible search space, the proposed hybrid TLBO-JAYA algorithm successfully prevented system collapse and maintained all bus voltages strictly within their secure operational limits. Furthermore, it achieved the lowest global generation cost of 901.292 \$/h, outperforming standalone TLBO (901.368 \$/h) and JAYA (902.927 \$/h). This specialized scenario proves that the

proposed parameter-free hybrid algorithm possesses the robust computational adaptability required for real-time Energy Management Systems (EMS) in modern smart grids facing highly volatile load conditions.

4. Conclusion

This research investigates the application of TLBO, JAYA, and a Hybrid TLBO-JAYA algorithm to the multi-objective Optimal Power Flow (OPF) problem using the IEEE 30-bus test system. While all evaluated methods—including the standard PSO baseline—successfully optimized key operational metrics including fuel cost, power loss, and voltage deviation the Hybrid TLBO-JAYA algorithm yielded markedly superior outcomes. It generally improved solution quality and the robustness of the Pareto-optimal front, providing decision-makers with a highly balanced and diverse set of trade-off solutions. The superior Hypervolume and Spacing metrics mathematically validated that the hybrid framework effectively prevents premature convergence, ensuring a highly uniform and comprehensive distribution of non-dominated solutions. It should be explicitly noted that these improvements entail a computational-time penalty, and the hybrid framework does not uniformly yield the absolute best value for every individual metric in all multi-objective cases (e.g., fuel cost in Case 6). Nevertheless, the significantly enhanced stability and findings establish the hybrid algorithm as a highly effective and robust tool for securing economic and efficient power system operations, highlighting the broader potential of hybridized metaheuristic approaches. Given the explicit demands of modern smart grid environments—which require rapid and reliable decision-making to accommodate the complex integration of Distributed Energy Resources (DERs)—the parameter-free and highly stable nature of the proposed hybrid TLBO-JAYA algorithm offers a substantial computational advantage for real-time deployment. Crucially, the successful execution of the heavy EV charging scenario (Case 7) demonstrated that the hybrid algorithm can prevent system collapse and find the global optimum even under severe smart-grid stress conditions. Future research must focus on validating the scalability of the proposed framework on larger-scale networks and incorporating probabilistic OPF formulations to actively account for renewable generation uncertainties, and the highly stochastic nature of dynamic loads inherent in smart grid energy systems.

Acknowledgements

The authors would like to thank the managers and the members of the “International Journal of Smart Grid” for their valuable remarks and suggestions.

Author Contributions

Oğuz Taşdemir contributed to the research, methodology, software development, drafting of the first

version, writing, reviewing, and editing, as well as the formal analysis and references. Salih Ermiş contributed to the methodology, research, formal analysis, software development, and drafting of the first version. All authors have read and approved the published version of the article.

Conflict of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

- [1] J. K. Skolfield and A. R. Escobedo, "Operations research in optimal power flow: A guide to recent and emerging methodologies and applications," *European Journal of Operational Research*, vol. 300, no. 2, pp. 387-404, 2022.
- [2] E. Naderi, M. Pourakbari-Kasmaei, and H. Abdi, "An efficient particle swarm optimization algorithm to solve optimal power flow problem integrated with FACTS devices," *Applied Soft Computing*, vol. 80, pp. 243-262, 2019.
- [3] T. Niknam, M. Narimani, J. Aghaei, and R. Azizipناه-Abarghoee, "Improved particle swarm optimisation for multi-objective optimal power flow considering the cost, loss, emission and voltage stability index," *IET generation, transmission & distribution*, vol. 6, no. 6, pp. 515-527, 2012.
- [4] G. Chen, J. Qian, Z. Zhang, and S. Li, "Application of modified pigeon-inspired optimization algorithm and constraint-objective sorting rule on multi-objective optimal power flow problem," *Applied Soft Computing*, vol. 92, p. 106321, 2020.
- [5] B. Zhao, C. Guo, and Y. Cao, "Improved particle swarm optimization algorithm for OPF problems," in *IEEE PES Power Systems Conference and Exposition*, 2004., 2004: IEEE, pp. 233-238.
- [6] H. Gao, J. Liu, L. Wang, and Y. Liu, "Cutting planes based relaxed optimal power flow in active distribution systems," *Electric Power Systems Research*, vol. 143, pp. 272-280, 2017.
- [7] J. A. Momoh, S. Guo, E. Ogbuobiri, and R. Adapa, "The quadratic interior point method solving power system optimization problems," *IEEE Transactions on Power Systems*, vol. 9, no. 3, pp. 1327-1336, 1994.
- [8] T. Niknam, M. rasoul Narimani, M. Jabbari, and A. R. Malekpour, "A modified shuffle frog leaping algorithm for multi-objective optimal power flow," *Energy*, vol. 36, no. 11, pp. 6420-6432, 2011.
- [9] E. Naderi, M. Pourakbari-Kasmaei, F. V. Cerna, and M. Lehtonen, "A novel hybrid self-adaptive heuristic

- algorithm to handle single-and multi-objective optimal power flow problems," *International Journal of Electrical Power & Energy Systems*, vol. 125, p. 106492, 2021.
- [10] S. Ermiş, "Multi-objective optimal power flow using a modified weighted teaching-learning based optimization algorithm," *Electric Power Components and Systems*, vol. 51, no. 20, pp. 2536-2556, 2023.
- [11] A. M. Shaheen, R. A. El-Sehiemy, M. M. Alharthi, S. S. Ghoneim, and A. R. Ginidi, "Multi-objective jellyfish search optimizer for efficient power system operation based on multi-dimensional OPF framework," *Energy*, vol. 237, p. 121478, 2021.
- [12] M. Kaur and N. Narang, "Optimal power flow solution using space transformational invasive weed optimization algorithm," *Iranian journal of science and Technology, transactions of electrical engineering*, vol. 47, no. 3, pp. 939-965, 2023.
- [13] V. Bathina, R. Devarapalli, and F. P. García Márquez, "Hybrid approach with combining cuckoo-search and grey-wolf optimizer for solving optimal power flow problems," *Journal of Electrical Engineering & Technology*, vol. 18, no. 3, pp. 1637-1653, 2023.
- [14] V. Yamaçlı, H. İşiker, Z. Yetgin, and K. Abaci, "Solving optimal power flow control problem using honey formation optimization algorithm," *IEEE Access*, 2024.
- [15] S. Gupta et al., "Optimal power flow solution using novel optimization technique: A case study," *Expert Systems with Applications*, p. 128163, 2025.
- [16] A. M. Shaheen, R. A. El-Sehiemy, H. M. Hasanien, and A. Ginidi, "An enhanced optimizer of social network search for multi-dimension optimal power flow in electrical power grids," *International Journal of Electrical Power & Energy Systems*, vol. 155, p. 109572, 2024.
- [17] J. Zhu, X. Yu, F. Wang, and Y. Mao, "Multi-objective optimal power flow problem using constrained dynamic multitasking multi-objective optimization algorithm," *Swarm and Evolutionary Computation*, vol. 93, p. 101850, 2025.
- [18] B. K. Dora, S. Bhat, S. Halder, and I. Srivastava, "Multi-objective optimal power flow problem using Nelder–Mead based Prairie Dog optimization algorithm," *Soft Computing*, vol. 28, no. 21, pp. 12835-12868, 2024.
- [19] R. V. Rao, V. J. Savsani, and D. P. Vakharia, "Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems," *Computer-aided design*, vol. 43, no. 3, pp. 303-315, 2011.
- [20] R. V. Rao and A. Saroj, "A self-adaptive multi-population based Jaya algorithm for engineering optimization," *Swarm and Evolutionary computation*, vol. 37, pp. 1-26, 2017.
- [21] M. Basu, "Multi-objective optimal power flow with FACTS devices," *Energy Conversion and Management*, vol. 52, no. 2, pp. 903-910, 2011.
- [22] T. H. B. Huy, D. Kim, and D. N. Vo, "Multiobjective optimal power flow using multiobjective search group algorithm," *IEEE Access*, vol. 10, pp. 77837-77856, 2022.
- [23] M. Al-Kaabi, V. Dumbrava, and M. Eremia, "Single and multi-objective optimal power flow based on hunger games search with pareto concept optimization," *Energies*, vol. 15, no. 22, p. 8328, 2022.
- [24] H. T. Kahraman, M. Akbel, and S. Duman, "Optimization of optimal power flow problem using multi-objective manta ray foraging optimizer," *Applied Soft Computing*, vol. 116, p. 108334, 2022.
- [25] E. E. Elattar, A. M. Shaheen, A. M. Elsayed, and R. A. El-Sehiemy, "Optimal power flow with emerged technologies of voltage source converter stations in meshed power systems," *IEEE Access*, vol. 8, pp. 166963-166979, 2020.
- [26] M. Ahmadipour et al., "A high-performance democratic political algorithm for solving multi-objective optimal power flow problem," *Expert Systems with Applications*, vol. 239, p. 122367, 2024.
- [27] R. V. Rao and V. Patel, "An improved teaching-learning-based optimization algorithm for solving unconstrained optimization problems," *Scientia Iranica*, vol. 20, no. 3, pp. 710-720, 2013.
- [28] R. V. Rao, V. Savsani, and J. Balic, "Teaching–learning-based optimization algorithm for unconstrained and constrained real-parameter optimization problems," *Engineering Optimization*, vol. 44, no. 12, pp. 1447-1462, 2012.
- [29] R. Rao, "Jaya: A simple and new optimization algorithm for solving constrained and unconstrained optimization problems," *International Journal of Industrial Engineering Computations*, vol. 7, no. 1, pp. 19-34, 2016.
- [30] R. V. Rao and A. Saroj, "Constrained economic optimization of shell-and-tube heat exchangers using elitist-Jaya algorithm," *Energy*, vol. 128, pp. 785-800, 2017.

- [31] E. Irmak, M. Yeşilbudak, and O. Taşdemir, "Enhanced PV Power Prediction Considering PM10 Parameter by Hybrid JAYA-ANN Model," *Electric Power Components and Systems*, vol. 52, no. 11, pp. 1998-2007, 2024.
- [32] T. Cheng, M. Chen, P. J. Fleming, Z. Yang, and S. Gan, "An effective PSO-TLBO algorithm for multi-objective optimization," in *2016 IEEE Congress on Evolutionary Computation (CEC)*, 2016: IEEE, pp. 3977-3982.
- [33] H. Zein, A. S. Kurniasetiwati, and C. K. Wachjoe, "Fuel cost optimization of the power system by involving all operating limits based on the developed interior point algorithm," *International Transactions on Electrical Energy Systems*, vol. 30, no. 5, p. e12337, 2020.
- [34] M. Kaur and N. Narang, "An integrated optimization technique for optimal power flow solution," *Soft Computing*, vol. 24, pp. 10865-10882, 2020.
- [35] M. R. Adaryani and A. Karami, "Artificial bee colony algorithm for solving multi-objective optimal power flow problem," *International Journal of Electrical Power & Energy Systems*, vol. 53, pp. 219-230, 2013.
- [36] A.-A. A. Mohamed, Y. S. Mohamed, A. A. El-Gaafary, and A. M. Hemeida, "Optimal power flow using moth swarm algorithm," *Electric Power Systems Research*, vol. 142, pp. 190-206, 2017.
- [37] M. A. Taher, S. Kamel, F. Jurado, and M. Ebeed, "Modified grasshopper optimization framework for optimal power flow solution," *Electrical Engineering*, vol. 101, pp. 121-148, 2019.
- [38] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Advances in engineering software*, vol. 69, pp. 46-61, 2014.
- [39] A. Alhejji, M. E. Hussein, S. Kamel, and S. Alyami, "Optimal power flow solution with an embedded center-node unified power flow controller using an adaptive grasshopper optimization algorithm," *IEEE Access*, vol. 8, pp. 119020-119037, 2020.
- [40] T. M. Dao, T. H. B. Huy, D.-P. N. Do, and D. Ngoc Vo, "A chaotic equilibrium optimization for temperature-dependent optimal power flow," *Smart Science*, vol. 11, no. 2, pp. 380-394, 2023.
- [41] M. Ebeed et al., "A modified artificial hummingbird algorithm for solving optimal power flow problem in power systems," *Energy Reports*, vol. 11, pp. 982-1005, 2024.
- [42] M. S. Kumari and S. Maheswarapu, "Enhanced genetic algorithm based computation technique for multi-objective optimal power flow solution," *International Journal of Electrical Power & Energy Systems*, vol. 32, no. 6, pp. 736-742, 2010.
- [43] J. Zhang, S. Wang, Q. Tang, Y. Zhou, and T. Zeng, "An improved NSGA-III integrating adaptive elimination strategy to solution of many-objective optimal power flow problems," *Energy*, vol. 172, pp. 945-957, 2019.
- [44] R. P. Singh, V. Mukherjee, and S. Ghoshal, "Particle swarm optimization with an aging leader and challengers algorithm for the solution of optimal power flow problem," *Applied Soft Computing*, vol. 40, pp. 161-177, 2016.
- [45] H. Boucekara, "Optimal power flow using black-hole-based optimization approach," *Applied Soft Computing*, vol. 24, pp. 879-888, 2014.
- [46] A. Bhattacharya and P. Chattopadhyay, "Application of biogeography-based optimisation to solve different optimal power flow problems," *IET generation, transmission & distribution*, vol. 5, no. 1, pp. 70-80, 2011.
- [47] A.-F. Attia, Y. A. Al-Turki, and A. M. Abusorrah, "Optimal power flow using adapted genetic algorithm with adjusting population size," *Electric Power Components and Systems*, vol. 40, no. 11, pp. 1285-1299, 2012.
- [48] A. Abou El Ela, M. Abido, and S. Spea, "Optimal power flow using differential evolution algorithm," *Electric Power Systems Research*, vol. 80, no. 7, pp. 878-885, 2010.
- [49] J. Zhang, Q. Tang, P. Li, D. Deng, and Y. Chen, "A modified MOEA/D approach to the solution of multi-objective optimal power flow problem," *Applied Soft Computing*, vol. 47, pp. 494-514, 2016.
- [50] E. Barocio, J. Regalado, E. Cuevas, F. Uribe, P. Zúñiga, and P. J. R. Torres, "Modified bio-inspired optimisation algorithm with a centroid decision making approach for solving a multi-objective optimal power flow problem," *IET Generation, Transmission & Distribution*, vol. 11, no. 4, pp. 1012-1022, 2017.

CTDE Multi-Agent Deep Q-Network for Grid-Interactive Energy Management of a Saharan Microgrid

Redouane Mihramane ^{*†}, Sidi Salah Ech-Charqaouy ^{*}, Abdelkader Boulezhar ^{*},
Nizar Ech-Charqaouy ^{*}, Amjad Ech-Charqaouy ^{*}

^{*}Department of Physical Sciences, Faculty of Sciences Ain Chock (FSAC), Hassan II University of Casablanca, Casablanca, Morocco

(redmihramane@gmail.com, echcharqaouy@gmail.com, boulezhar@yahoo.fr, nizarechcharqaouy@gmail.com, echcharqaouyamjad@gmail.com)

[†]Corresponding Author: Redouane Mihramane, Department of Physical Sciences, Faculty of Sciences Ain Chock (FSAC), Hassan II University of Casablanca, Casablanca, Morocco. E-mail: redmihramane@gmail.com Tel.: +212 661910758

Received: 25.07.2025 Accepted: 23.04.2026

Abstract- We propose a grid-interactive, decentralized multi-agent Deep Q-Network (MA-DQN) with Centralized Training, Decentralized Execution for energy management in a Saharan hybrid microgrid (Boujdour, Morocco). Independent agents supervise PV, wind, diesel and batteries; a low-overhead PCC coordinator enforces import/export exclusivity, zero-crossing deadband and dwell time. A multi-objective reward balances cost, CO₂ and grid exchange, with penalties on $\pm 10\%$ voltage and SOC violations. On a 24-h case (demand 991.1 kWh), the learned policy delivers renewables-first dispatch (PV 56.4%, diesel 34.4%, grid 9.2%), battery throughput ± 7.6 kWh, and 272.5 kg CO₂ (~ 275 g/kWh). Versus a PSO baseline, cost falls 1250 $\rightarrow$ 1120 MAD (-10.4%), CO₂ 318.9 $\rightarrow$ 272.5 kg (-14.6%), and inference latency 12.8 $\rightarrow$ 2.1 s (-83.6%). Sensitivity on the CO₂ weight β yields tunable cost-carbon trade-offs (β 0.1 $\rightarrow$ 2.0: 310 $\rightarrow$ 240 kg CO₂ at +15.5% cost). Stress tests (PV depression/outage, +20% evening peak) maintain supply and power-quality; ablation confirms reduced PCC chattering versus single-agent DQN.

Keywords: Microgrid energy management, reinforcement learning, multi-agent DQN, CTDE, demand response

1. Introduction

The global energy transition is reshaping power systems under the twin imperatives of cutting greenhouse-gas emissions while preserving reliability and affordability in data-scarce, operationally volatile contexts [1], [2]. Hybrid renewable architectures - especially PV-wind portfolios complemented by storage and dispatchable backup - have expanded rapidly; yet intermittency, forecasting uncertainty, and network constraints still complicate real-time balancing and long-term planning [3], [4], [5].

1.1. PV and Carbon Background

Rapid cost declines and deployment have made PV a central lever for decarbonization, but its net climate benefit ultimately depends on system-level operation that curtails spillage, limits diesel dependence, and avoids unnecessary imports from carbon-intensive grids, [2], [5], [6]. Recent assessments stress that renewable build-out must be coupled

with operational strategies that internalize CO₂ impacts and policy priorities, rather than assuming carbon neutrality by construction [7], [8].

1.2. Saharan Microgrid Context

In Saharan regions such as Boujdour (southern Morocco), extreme irradiance, reliable nocturnal wind, harsh thermal conditions, and limited grid robustness create a compelling yet challenging setting for hybrid microgrids [9]-[11]. Typical distribution feeders are long, radial low-voltage (LV) lines with non-negligible impedance and sparse instrumentation; operational feasibility therefore hinges on coordinated use of PV, wind, batteries, a diesel genset, and a bidirectional point of common coupling (PCC) to the main grid, while respecting $\pm 10\%$ LV voltage envelopes and battery state-of-charge (SOC) safety constraints [12]-[15]. These characteristics motivate supervisory controllers that are both network-aware and policy-tunable (cost, carbon, autonomy).

1.3. Limits of Conventional Supervisory Control

Deterministic scheduling (e.g., day-ahead mixed-integer linear programming, MILP), rule-based heuristics, and meta-heuristics such as particle swarm optimization/genetic algorithms (PSO/GA) have produced valuable baselines; however, they are brittle under regime shifts (seasonality, demand surges, partial outages) and costly to re-solve in real time. They also struggle to embed discrete field actuation and practical PCC rules - import/export exclusivity, zero-crossing deadband, and dwell-time to prevent chattering - while enforcing voltage feasibility along LV feeders at runtime [6], [16]. This motivates learning-based controllers that generalize across operating conditions, ingest local and broadcast signals, and encode grid-feasible actions within the policy.

1.4. From RL to DRL in Microgrids

Reinforcement learning (RL) optimizes sequential decisions through interaction with an environment and has shown promise for distributed energy management in islanded and grid-connected settings [17]-[22]. Deep RL (DRL) scales RL to high-dimensional, nonlinear dynamics typical of hybrid microgrids with uncertain exogenous inputs and network constraints. Within DRL, the Deep Q-Network (DQN) is particularly suited to discrete actuation - diesel on/off, battery charge/hold/discharge, and tiered import/export at the PCC, offering stable training and edge-friendly inference; continuous-action methods (DDPG/SAC/PPO) remain complementary for fine set-point refinement and are considered as future extensions [23]-[27].

1.5. State of the Art and Interaction with the Main Grid

A growing literature tackles centralized energy management with network limits and cost signals, as well as single- and multi-agent DRL for distributed coordination [17], [18], [20], [26]-[28], alongside broader reviews of hybrid renewable systems and operational challenges [3]-[5]. Yet comparatively fewer studies incorporate explicit PCC rules (exclusivity deadband, dwell-time) together with voltage-aware penalties on long LV feeders, while quantifying cost-carbon-autonomy trade-offs under Saharan conditions and benchmarking against strong offline baselines [27]-[29].

1.6. Research Gap

There remains a need for a decentralized, grid-interactive, and voltage-aware DRL controller that: (i) coordinates heterogeneous sources under centralized training and decentralized execution (CTDE); (ii) enforces realistic PCC policies and action feasibility with discrete field commands; (iii) treats carbon as a policy parameter rather than a fixed price; and (iv) reports seasonally robust performance with transparent benchmarks and sensitivity to policy weights [6]-[8], [27], [29].

1.7. Objective

To design and validate such a controller on a realistic Boujdour digital twin (31-node LV feeder, Morocco) with summer/winter scenarios and explicit main-grid interaction.

1.8. Contributions

This work delivers: (i) a CTDE multi-agent DQN with independent learners for PV, wind, diesel, and batteries, plus a lightweight PCC coordination policy enforcing import/export exclusivity, zero-crossing deadband, and dwell-time (discrete actuation well-matched to field hardware) [17]-[20]; (ii) a network-feasible reward that jointly optimizes monetary cost, CO₂, and grid exchange while penalizing voltage ($\pm 10\%$) and SOC violations, aligning with LV practice and battery safety [11]-[15]; (iii) a seasonal digital-twin benchmark of a Saharan hybrid microgrid with explicit main-grid interaction, yielding a renewables-first learned dispatch and, versus a PSO baseline, cost -10.4% , CO₂ -14.6% , and inference latency -83.6% , all without voltage/SOC violations, in line with statistical parametric simulation studies grounded in real-world data [30]; (iv) a policy-weight sensitivity that treats the carbon term as a policy knob, mapping cost-carbon trade-offs across β sweeps [6]-[8]; (v) a robustness evaluation under unseen stressors (PV depression, partial PV outage, $+20\%$ evening peak) and an ablation showing that the multi-agent design reduces PCC chattering and smooths grid interaction relative to a single-agent DQN; (vi) a deployment pathway arguing the edge-friendliness of discrete DQN and outlining continuous-action DRL (DDPG/SAC/PPO) as a future refinement for set-point smoothing without changing the supervisory logic.

2. Related Works

Research on microgrid energy management systems (EMS) has evolved from deterministic scheduling and rule-based control toward data-driven and learning-based supervision capable of handling uncertainty, multi-objective trade-offs, and grid-microgrid interactions [2], [6], [16], [31]. In renewable-dominated and weakly interconnected settings - typical of Saharan sites - this evolution is driven by intermittent resources, long low-voltage feeders, and stringent power-quality constraints [3], [4], [7], [8], [10].

2.1. Deterministic, Heuristic, and Metaheuristic EMS

Conventional EMS formulations cast scheduling as mathematical programming - e.g., LP, MILP, NLP, or DP - aimed at minimizing operating cost under explicit constraints and prespecified forecast scenarios [3], [4]. While such models afford optimality guarantees when forecasts and plant models are dependable, their performance degrades under regime shifts and model-plant mismatch, conditions that are commonplace in desert microgrids with pronounced diurnal and seasonal variability [2], [7], [8]. Heuristic controllers (rule-based and expert systems) improved practicality by codifying operator know-how (e.g., diesel-priority rules, SOC thresholds), yet their fixed rules lack the adaptivity required for hour-to-hour fluctuations and contingencies [4], [11], [17]. Metaheuristics (PSO, GA, ACO) broaden the search to tackle nonlinear, high-dimensional, multi-objective formulations in planning and quasi-static scheduling [19], [32]. They remain valuable baselines, but latency and convergence sensitivities limit their suitability for real-time dispatch when operating conditions evolve faster than optimization loops can track reliably [23], [33]. Recent surveys on hybrid-renewable optimization echo this divide - strong offline optimization

versus weaker online adaptivity - thereby motivating learning-based supervisory control [2], [4], [6]. In parallel, DC-microgrid architectures have demonstrated cost-effective pathways to bolster supply resilience in grid-connected communities [34].

2.2. Reinforcement Learning and Deep RL for Microgrid Control

Reinforcement Learning (RL) learns sequential decision policies by interacting with the environment and receiving scalar rewards, removing the need for fully specified models and enabling adaptation to stochastic conditions [17], [18], [20], [28], [29]. Early Q-learning studies demonstrated fuel savings and improved storage utilization in hybrid microgrids under variable renewables and loads [9], with further applications to demand flexibility and residential contexts [19], [35].

Deep RL (DRL) scales RL to high-dimensional states via neural function approximation, stabilizing training and improving generalization under uncertainty [13], [36]. The Deep Q-Network (DQN) - with experience replay and target networks - has been widely adopted for discrete supervisory actions (diesel on/off, battery charge/hold/discharge modes, tiered PCC exchanges), aligning well with common EMS actuation granularity [23], [37], [38]. Continuous-action methods (DDPG, SAC, PPO) target fine set-point control and have reported gains in renewable penetration and CO₂ reduction in suitable settings, but often at increased implementation and tuning complexity [27], [28]. Hybrid approaches (e.g., DRL with fuzzy logic) also appear in rapidly varying systems to mitigate nonlinearity and measurement noise [9].

For weakly interconnected Saharan microgrids - characterized by costly diesel logistics, unstable grid back-up, and harsh ambient conditions - DRL enables cost- and carbon-aware dispatch while enforcing feasibility via SOC envelopes and voltage limits [11], [24]. Recent contributions in grid-edge control and voltage regulation using dueling and double-Q variants further underline the relevance of value-based DRL when network constraints matter [24], [25], [37].

2.3. Multi-Agent DRL and Grid-Interactive, Voltage-Aware EMS

As microgrids scale in heterogeneity (PV, wind, diesel, multiple batteries, controllable PCC), multi-agent formulations become natural. Centralized-training, decentralized-execution (CTDE) designs combine global learning signals with independent learners per resource to reduce the joint action complexity while retaining implementable local policies [27], [29], [36]. Within this paradigm, coordination at the PCC - import/export exclusivity, anti-chattering deadbands with dwell time, and tariff-aware exchange - can be encoded either through shared constraints or a lightweight coordinator policy without sacrificing decentralization at execution time [11]-[13], [24].

Voltage-aware DRL is particularly pertinent in long LV radial feeders where impedance-driven drops can breach $\pm 10\%$ limits during high PV export or abrupt load ramps. Recent grid-interactive DRL work addresses these issues with

value-based methods (dueling DDQN) and network-informed rewards/penalties that internalize nodal voltages and branch flows during policy learning [24], [37]. Beyond performance, robustness and security are receiving growing attention in EMS design across Industry-5.0 cyber-physical contexts, reinforcing the case for interpretable, network-feasible control logic [6], [22].

2.4. Positioning of the Present Research

Against this backdrop, the present study advances the state of the art along four axes:

CTDE multi-agent DQN with independent learners (PV, wind, diesel, batteries) and PCC-aware coordination that enforces import/export exclusivity and anti-chattering, matching the discrete actuation structure of practical EMS [11]-[13], [24], [29], [37].

A multi-objective formulation balancing cost, CO₂, import reliance, and network quality (voltage/SOC), with policy-parameter sensitivities instead of assuming a fixed carbon price, consistent with emerging decarbonization analyses and policy diversity [2], [5]-[8].

A realistic digital twin of a Saharan hybrid microgrid (Boujdour) used for training and evaluation under seasonal scenarios and unseen stresses (PV derating, demand surges, battery/PCC outages), reflecting field constraints documented in prior work [9]-[11], [13].

A comparative evaluation against a PSO baseline and a single-agent DQN ablation to quantify gains in cost, emissions, reliability, and voltage compliance, bridging the gap between planning-oriented metaheuristics and real-time learning-based EMS [16], [19], [20], [23], [27].

3. Microgrid Description and Operating Environment

3.1. Site and Grid Context

The studied microgrid is located in Boujdour, a coastal town in the Moroccan Sahara (26.13° N, 14.32° W). The site couples high solar irradiance with persistent wind regimes - particularly nocturnal winds - under relatively mild ambient temperatures, providing favorable conditions for hybrid, decentralized generation. Conversely, geographic remoteness and a quasi-linear radial low-voltage (LV) feeder impose stringent requirements on voltage regulation, service continuity, and cost-effective dispatch [7]-[13].

The LV distribution network supplies 218 households, two commercial facilities, and **two** industrial consumers (with peak demands of 15 kW and 20 kW), and extends 2 170 m in a radial topology. The microgrid can operate in islanded or grid-connected mode via an MV/LV substation equipped with a 250 kVA transformer, automated switchgear, and a bidirectional advanced metering interface to the national ONEE grid. This interconnection enables dynamic import/export in response to local generation and tariff signals.

Asset Portfolio and Electrical Interface

The Boujdour microgrid is built around a 31-node radial low-voltage (LV) feeder interconnected with the national grid via a bidirectional point of common coupling (PCC). Local

generation and storage include three PV arrays (44 kW, 10 kW, and 6 kW), a 90 kW wind turbine, a 50 kVA diesel genset, and three lead-acid battery banks co-located with the PV plants. Direct PV–battery coupling enables localized charge/discharge, reduces feeder losses, and enhances resilience to generation or network contingencies. A supervisory layer of smart meters and controllers monitors active-power flows, bus voltages, and battery state-of-charge (SOC) to support coordinated control across the LV network. This architecture is consistent with well-established solar-hybrid system practices [39].

PCC operation and rules

The PCC at the MV/LV substation allows seamless islanded or grid-connected modes. Imports bridge renewable deficits; exports evacuate surplus, limiting diesel use. To stabilize grid interaction, we enforce: (i) import/export exclusivity (never both at once); (ii) a zero-crossing deadband around $PG=0$; and (iii) a dwell-time before any sign inversion (anti-chattering). PCC set-points are tiered $\{-50, -25, 0, +25, +50\}$ kW to match field actuation.

(a) Evidence (24 h test)

With $\Delta t=15$ min, deadband $\zeta=5$ kW, and the above tiers, the controller (vs. a tiers-only baseline) blocked 13 sign-change attempts, increased neutral intervals by +13 steps

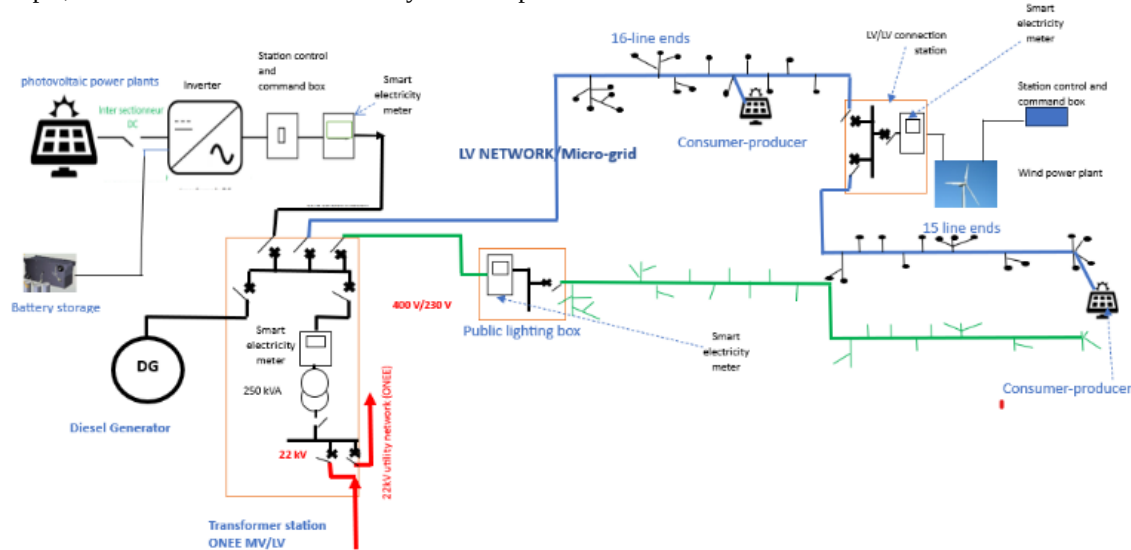


Fig. 1. Electrical single-line diagram of the studied microgrid integrating photovoltaic systems, wind generation, diesel generator, battery storage, and grid interconnection.

3.2. Climatic Conditions and Renewable Resources

a) Wind

ERA5T reanalysis indicates average speeds of ≈ 14 m/s in January and ≈ 17 m/s in July at 80 m hub height, with north-northeast winds dominating $> 60\%$ of the time at speeds exceeding 20 km/h.

b) Solar

Year-round high insolation with mild temperatures ($\approx 17^\circ\text{C}$ in January, $\approx 22^\circ\text{C}$ in July) favors PV conversion efficiency by limiting thermal losses.

(18 $\rightarrow$ 31), and reduced gross import 375.0 $\rightarrow$ 350.0 kWh (-6.7%) and gross export 243.75 $\rightarrow$ 181.25 kWh (-25.6%). This reflects fewer micro-oscillations around zero and less superfluous energy shuttling, while preserving import during deficits and export during surplus.

(b) Network feasibility

Voltages are in p.u. with an LV compliance band $\pm 10\%$ at all monitored buses. Batteries respect SOC bounds $[\text{SOC}_{\min}, \text{SOC}_{\max}]$ and power/ramp limits. At each step a fast power-flow screen masks any action that would violate SOC, device limits, or the LV voltage band, ensuring feasible-by-construction decisions.

(c) Data granularity

Demand and renewable inputs are processed at hourly resolution using summer/winter scenarios aligned with the 24-h horizon and discrete actuation.

Single-line diagram. Fig. 1. shows the LV network and asset interconnections (PV–wind–diesel–BESS–PCC). The full technical specification table is provided in Supplementary S1.

These stable yet hourly intermittent resources provide a robust basis for hybrid operation, while motivating intelligent scheduling and storage control to accommodate short-term fluctuations [7], [8].

3.3. Aggregate Load Profile

The aggregated demand exhibits pronounced diurnal variability and seasonal shifts [40]. Off-peak nighttime load (02:00–06:00) drops to approximately 9.2 kW. Two distinct peaks are observed:

A morning peak around 10:00, reaching ≈ 64.2 kW, driven mainly by commercial and light industrial activity. A

dominant evening peak between 20:00–22:00, peaking at ≈ 110 kW, largely residential (lighting, cooking, entertainment).

Fig. 2. illustrates the typical hourly demand profile, highlighting the sharp evening peak and low nighttime consumption. The evening peak coincides with minimal PV

output, increasing reliance on battery discharge and, if storage is insufficient, on the diesel generator. Mid-day surplus PV can be stored or exported via the PCC. This temporal mismatch between generation and demand motivates adaptive EMS strategies capable of load shifting and storage scheduling in real time [25], [41].

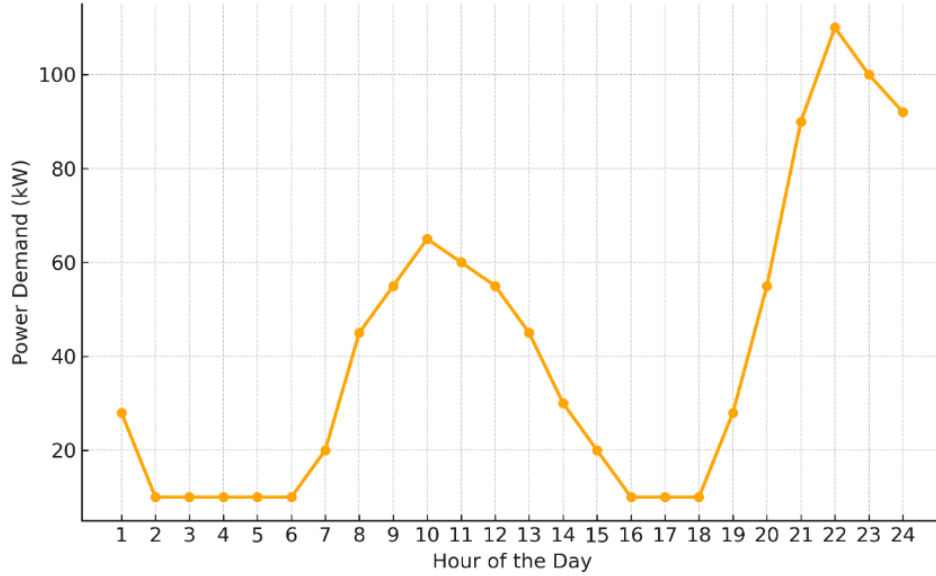


Fig. 2. Hourly profile of power demand in the studied microgrid.

3.4. PCC and Grid-Interaction Constraints

Let $P_G(t)$ denote the net power exchange at the PCC (positive for **import**, negative for **export**). The interface capacity bounds the exchange,

$$-|P_G^{\max}| \leq P_G(t) \leq |P_G^{\max}| \quad (1)$$

and simultaneous import and export are forbidden. Equivalently, with $P_{\text{imp}}(t) \geq 0$, $P_{\text{exp}}(t) \geq 0$,

$$P_G(t) = P_{\text{imp}}(t) - P_{\text{exp}}(t) \quad (2)$$

$$P_{\text{imp}}(t) P_{\text{exp}}(t) = 0 \quad (3)$$

which enforces mutual exclusivity at each time step. In practice, anti-chattering is implemented via a small deadband around $P_G(t)=0$ and a dwell time before mode reversal; formal design and parameterization are provided with the control logic in Section 4 (CTDE multi-agent framework).

3.5. Network Topology and Power-Quality Considerations

The linear LV feeder exhibits non-negligible impedance; under peak loading, end-node voltage drops can approach operational limits. Maintaining power quality therefore requires coordinated action from PV inverters, wind generation, diesel dispatch, and storage management. In all operating modes, the EMS targets a $\pm 10\%$ voltage band at LV nodes, while respecting SOC envelopes, ramp-rate limits, and PCC import/export exclusivity. The detailed enforcement of these constraints (penalties and feasibility checks) is embedded in the control problem and will be specified alongside the objective/reward alignment (Section 4).

3.6. Sensing, Communication, and Data Layer

An IoT-based sensing layer (smart meters, local controllers) continuously monitors generation outputs, nodal voltages, battery SOC, and PCC exchanges. These real-time measurements form the state vector consumed by the EMS. While the CTDE multi-agent design is introduced in Section 4, we note here that (i) independent local learners per resource (PV, wind, diesel, batteries) leverage locally available signals, and (ii) lightweight PCC coordination enforces exclusivity and anti-chattering without centralized actuation at execution time, consistent with the site's constraints and communication reliability [11]–[13], [24], [29], [37].

Based on this system description and operating constraints, the proposed control strategy is developed in the following section.

4. Control Strategy and Optimization Framework

This section presents the proposed CTDE multi-agent DQN framework, designed to ensure coordinated, grid-compliant and real-time operation.

Operating a hybrid microgrid in the Saharan context entails coping with volatile renewable resources, stochastic demand, and strict network-feasibility requirements on a long LV radial feeder. We adopt a decentralized, multi-objective control strategy under a centralized-training, decentralized-execution (CTDE) multi-agent design that targets economic, environmental, and power-quality objectives in real time [6], [11], [13], [17], [24], [27]–[29], [36], [37].

4.1. Control Objectives and Composite Optimization

The supervisory objective combines (i) monetary operating cost, (ii) CO₂ emissions from fossil units, (iii)

$$\min_{\{at\}} J = \sum_{t=1}^H \left[\underbrace{c_{imp}(t) [P_G(t)]^+ \Delta t + C_{DG} P_{DG}(t) \Delta t}_{\text{monetary cost}} + \underbrace{\beta e_D P_D(t) \Delta t}_{\text{CO}_2} + \underbrace{\gamma |P_G(t)| \Delta t}_{\text{grid exchange}} + \underbrace{\delta \Phi(t)}_{\text{power quality}} \right] \quad (4)$$

Here $[x]^+ = \max(x, 0)$ (only imports are billed via $c_{imp}(t)$), and

$$\Phi(t) = \rho_V V_{viol}(t) + \rho_{SOC} SOC_{viol}(t) \quad (5)$$

which aggregates per-step violations (in p.u.·h) of the LV voltage band ($\pm 10\%$) and the battery SOC envelope (see Sec. 3). The weights β, γ, δ are policy parameters explored in sensitivity studies (carbon, autonomy, power quality); by convention we set $\alpha=1$ to anchor monetary units. This formulation is strictly aligned with the stepwise reward in Sec. 4.4 (the objective equals the negative cumulative reward) and is enforced under the physical and PCC constraints detailed in Sec. 3 and Sec. 4.3 (import/export exclusivity, deadband, dwell-time). See [4], [6]–[8] for treating the carbon term as a policy knob rather than a fixed national carbon price.

Conventions : $P_G(t) > 0$: import; $P_G(t) < 0$: export. The term $\gamma |P_G(t)|$ symmetrically penalizes reliance on the grid (autonomy), while $c_{imp}(t) [P_G(t)]^+$ captures the billing of imports. Δt is the time step (hours).

4.2. CTDE Multi-Agent Architecture (Decentralized Execution)

We adopt a Centralized Training with Decentralized Execution (CTDE) design with independent DQN learners per resource (PV, wind, diesel, batteries) and parameter sharing across homogeneous devices when applicable.

Training uses a centralized replay and joint state features (team context); execution is fully decentralized with per-agent greedy policies under action masking to enforce network feasibility.

(a) Agents.

- PV plants (3 agents). Each agent supervises one PV unit and selects discrete curtailment tiers and inverter modes, coordinating with local voltage/SOC/network constraints to avoid unnecessary exports during high-PV/low-load periods.
- Wind (1 agent). Selects discrete set-point/curtailment tiers consistent with feasible pitch/torque envelopes.
- Batteries (3 agents). Operate in {charge | hold | discharge} with discrete power tiers, subject to SOC bounds and converter ratings.
- Diesel (1 agent). Manages on/off commitment and discrete set-point tiers under ramp-rate limits and minimum up/down-time surrogates.

reliance on the main grid at the PCC, and (iv) network-quality penalties (voltage/SOC). Over a horizon H (here $H=24$ steps), we minimize:

- PCC coordinator (1 agent, “policy-light”). Enforces import/export exclusivity, a zero-crossing deadband ζ , and dwell-times $T_{imp}^{min}, T_{exp}^{min}$ (Eqs. (1)–(3), (18)–(19a and 19b)); selects tiered import/export levels within interface capacity and tariff logic.

(b) State composition (s_t)

Each agent observes (i) local signals (on-site generation estimate/forecast, local voltage, SOC, converter headroom), and (ii) broadcast context (aggregated demand, tariff, PCC mode, weather features). We use the following compact representation:

$s_t = [\text{demand forecast slice}, P_{PV}(t), P_{WT}(t), SOC(t), P_G(t-1), V_p(t), V \text{ summary}, \text{time-of-day}, \text{season}, \text{prices } c_{imp}(t)]$.

with all features scaled; $V_{summary}$ denotes a reduced-order voltage descriptor (tail-bus proxy or PCA component).

(c) Actions at

Discrete, network-feasible choices per agent; invalid actions are masked (removed from the DQN argmax) to prevent violation-seeking behavior. Concretely:

- Diesel: {0,1} (off/on).
- Battery mode: {charge, hold, discharge} with clipped power.
- PCC: tiered import/export $\in \{-P_2, -P_1, 0, +P_1, +P_2\}$ (levels within interface capacity, $P_G > 0$ = import, $P_G < 0$ = export).

(d) Feasibility & masking.

We mask actions that would violate: (i) exclusivity + deadband ($|P_G| < \zeta \Rightarrow P_G = 0$), (ii) dwell-time (sign of P_G cannot flip before T_{dwell} ; implemented via $T_{imp}^{min}, T_{exp}^{min}$), (iii) SOC bounds, device limits and ramp rates, and (iv) the LV voltage band (pre-check via a fast power-flow surrogate).

This keeps all executed actions network-feasible by construction and directly reflects field constraints [11], [13], [24].

(e) Why discrete DQN here?

Diesel on/off, battery modes (charge/hold/discharge) and tiered PCC exchange form a naturally discrete action space. DQN provides stable, sample-efficient, and edge-friendly learning under CTDE, with straightforward action masking for feasibility [23], [37].

Continuous-action DRL (DDPG/SAC/PPO) remains future work for set-point smoothing without altering the supervisory logic [28], [27], [38].

(f) *Note on PCC rules (consistency with Section 3.2b)*

The exclusivity/deadband/dwell logic used here matches the simulation evidence reported in Sec. 3.2(b): enforcing ζ and T_{dwell} significantly reduces sign-flip attempts and micro-oscillations around zero exchange, stabilizing grid interaction while preserving import during deficits and export during surpluses.

This CTDE design mitigates the curse of dimensionality while retaining implementable local policies and a policy-tunable interaction with the main grid [27], [29], [36].

4.3. Embedded Physical and Network Models

4.3.1. Battery dynamics and health safeguards

State-of-charge (SOC) evolves as:

$$SOC(t+1) = SOC(t) + \frac{\eta_c \cdot P_{ch}(t) - \frac{P_{dis}(t)}{\eta_d}}{E_{batt}} \cdot \Delta t \quad (6)$$

Where:

- $P_{ch}(t)$ and $P_{dis}(t)$ are the charging and discharging powers at time t (in W),
- η_c and η_d are the charging and discharging efficiencies, respectively,
- E_{batt} is the nominal energy capacity of the battery (in Wh),
- Δt is the time step duration (in hours).

Charging and discharging powers are bounded as follows:

$$0 \leq P_{ch}(t) \leq P_{ch}^{max} \quad (7)$$

$$0 \leq P_{dis}(t) \leq P_{dis}^{max} \quad (8)$$

To preserve lifetime and reserve, the SOC must remain within a secure operational range:

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \quad (9)$$

4.3.2. LV feeder and voltage model

In hybrid microgrids, ensuring high-quality service is not limited to supply–demand matching: voltage stability at all

nodes must also be guaranteed. Excessive voltage deviations degrade sensitive equipment, reduce efficiency, and jeopardize reliability, issues amplified in Saharan feeders where distances are long and renewable injections are intermittent [12], [13].

We adopt a realistic nodal topology consistent with prior work on downstream DER integration in distribution networks [12], [13]. Node voltages are computed by aggregating voltage drops along feeders as functions of active/reactive flows, segment lengths, and line parameters. Compliance with national practice is enforced by constraining voltages within $\pm 10\%$ of nominal across all operating conditions [12], [13].

Fig. 3. illustrates the simplified single-line diagram used to index consumers and Distributed Energy Resource (DERs). Let n_1 denote the number of consumers upstream of DER_j ; n_j the consumers between DER_{j-1} and DER_j ; n_{M-1} those between DER_{M-2} and DER_{M-1} ; and n_M the consumers between DER_{M-1} and the feeder tail (a fictitious DER_M with zero output is assumed if none is installed). With N the total consumers and M the number of DERs, we have

$$N = \sum_{j=1}^M n_j \quad (10)$$

For a line segment of length L (m), linear resistance r (Ω/m) and reactance x (Ω/m), supplying active power P (W) and reactive power Q (VAR) at voltage U (V), the voltage drop is:

$$\Delta U = \frac{L}{U} (rP + xQ) \quad (11)$$

with nodal compliance:

$$U_{min} \leq U_{j,i}(t) \leq U_{max} \quad (12)$$

$$\text{with } \frac{U_{min}}{U_{max}} = (1 \mp 0.10)U_s$$

Where, U_s denotes the contractual (service) nominal voltage at the relevant supply level

These relations are embedded in the environment and in the penalty structure so that learned policies remain network-feasible [12], [13], [24], [37].

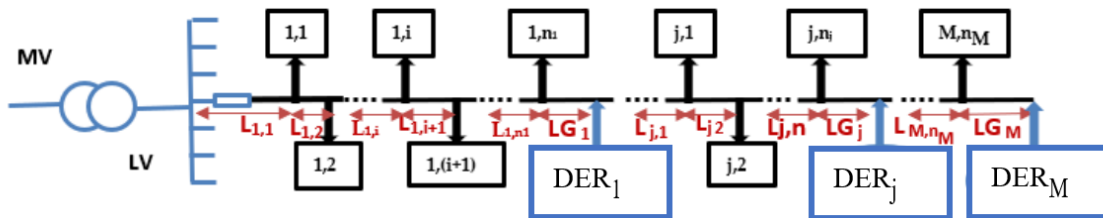


Fig. 3. Simplified line diagram showing network nodes, consumer connection points, and distributed generation units [13].

4.4. Economic Cost, Emissions and Instantaneous Reward

a) Monetary cost (per step, $\Delta t = 1$ h)

$$C_{total}(t) = \Delta t (|P_B(t)| C_B(t) + P_{DG}(t) C_{DG}(t) + [PG(t)]^+ C_{imp}(t) + C_{sec}(t)) \quad (13)$$

Where, $[x]^+ = \max(x, 0)$ charges import only; $P_B(t)$ is the signed battery power (discharge/charge), $P_G(t)$ the PCC exchange (positive = import), $P_{DG}(t)$ the diesel generator output, $C_{imp}(t)$ the grid tariff, and $C_{sec}(t)$ aggregates penalty costs due to curtailment, unserved energy, and power-quality

violations (units: MAD per time step Δt). $C_{DG}(t)$ denotes the diesel generator marginal cost (fuel + variable O&M) and $C_B(t)$ the battery cycling cost per unit throughput.

In our setting, grid export is not remunerated; therefore, only imports are billed via $[PG(t)]^+ C_{imp}(t)$. If an export tariff applies, include a revenue term $-P_{exp}(t) C_{exp}(t)$.

b) Emissions (per step)

$$E_{CO_2}(t) = e_{DG} P_{DG}(t) \Delta t \quad (14)$$

With, $e_{DG}=0.8$ kg/kWh as the diesel emission factor (consistent with the 24-hour energy and 272.5 kg CO₂ balance reported later).

c) Reward shaping (instantaneous)

$$R_t = -(\alpha C_{total}(t) + \beta E_{CO_2}(t) + \gamma [P_G(t)]^+ \Delta t) - \delta \Phi(t) \quad (15)$$

$$\Phi(t) = \rho_V V_{viol}(t) + \rho_{SOC} SOC_{viol}(t) + \rho_{curt} Curt(t) + \rho_{uns} Unserved(t) \quad (16)$$

The planning objective over horizon T is :

$$J = \sum_{t=1}^T (\alpha C_{total}(t) + \beta E_{CO_2}(t) + \gamma ([PG(t)]^+). \Delta t + \delta \Phi(t)) \quad (17)$$

Maximizing the cumulative return $\sum_{t=1}^T R_t$ is equivalent to minimizing the objective J. Training optimizes the normalized, unitless reward defined in Eqs. (22)–(28). The economic objective in Eq. (4) is for reporting and interpretation only and is numerically equal to the negative cumulative return; hence, Eqs. (15)–(17) are **not** used during training to avoid unit inconsistencies. In short, Eqs. (15)–(17) provide a raw, dimensional multi-objective formulation for reporting, whereas learning is driven by the scale-normalized reward in Eqs. (22)–(28), which prevents unit coupling, stabilizes training, and clarifies trade-offs across scenarios.

d) Time step convention.

Unless otherwise stated, all per-step quantities use $\Delta t=1h$. PCC-specific toggling metrics in Table 1 are computed at 15-min granularity for finer chattering diagnosis.

4.5. Grid Interaction: PCC Coordination and Feasibility

Let $P_G(t)$ denote net PCC exchange (>0 import, <0 export). Capacity and mutual exclusivity:

$$\triangleright -|P_G^{max}| \leq P_G(t) \leq |P_G^{max}| ;$$

$$\triangleright P_G(t) = P_{imp}(t) - P_{exp}(t) ;$$

$$\triangleright P_{imp}(t) P_{exp}(t) = 0; \quad P_{imp}(t) \geq 0; \quad P_{exp}(t) \geq 0.$$

(a) Anti-chattering deadband and dwell times:

$$|PG(t)| \in \{0\} \cup [\zeta, P_G^{max}] \quad (18)$$

with a small deadband $\zeta > 0$ around zero exchange to prevent rapid import/export toggling.

and binary mode flags $z_{imp}(t), z_{exp}(t) \in \{0,1\}$ with $z_{imp}(t) + z_{exp}(t) \leq 1$ minimum up/down times $T_{imp}^{min}, T_{exp}^{min}$ enforce dwell-time (UC-style) to limit switching wear and oscillations:

once a mode is entered, it must persist for at least T_{mode}^{min}

(b) Reactive exchange / power factor:

$$PF(t) = \frac{|P_G(t)|}{\sqrt{P_G(t)^2 + Q_G(t)^2}} \geq PF_{min} \quad (19a)$$

With ,

$$|Q_G(t)| \leq \tan(\arccos(PF_{min})) \cdot |P_G(t)| \quad (19b)$$

These rules are implemented by the PCC coordinator and shared as state flags, ensuring grid-compliant exchange [11]–[13], [24]. Their stabilizing effect (reduced sign flips, fewer micro-oscillations near zero) matches the simulation evidence reported in Sec. 3.2(b).

(c) Power Balance and Operational Constraints

$$P_{PV}(t) + P_{WT}(t) + P_{DG}(t) + P_G(t) + P_B(t) = P_{load}(t) + Curt(t) + P_{loss}(t) \quad (20)$$

with device nameplate/rating limits, diesel ramp-rates, and battery constraints (Eqs. (5)–(8), (20)). Any violation triggers the corresponding terms in $\Phi(t)$, steering the policy toward secure dispatch.

Table 1 quantifies the impact of the deadband ζ and dwell time τ on PCC behavior over a 24 h episode ($\Delta t = 15$ min).

Table 1. PCC exclusivity metrics with and without enforcement of deadband and dwell-time ($\Delta t = 15$ min)

Metric	Tiered only	Enforced (deadband + dwell)
Sign toggles ($\pm$)	2	2
Blocked sign-change steps (dwell)	0	13
Import energy (kWh)	375	350
Export energy (kWh)	243.8	181.2
Zero steps (count)	18	31

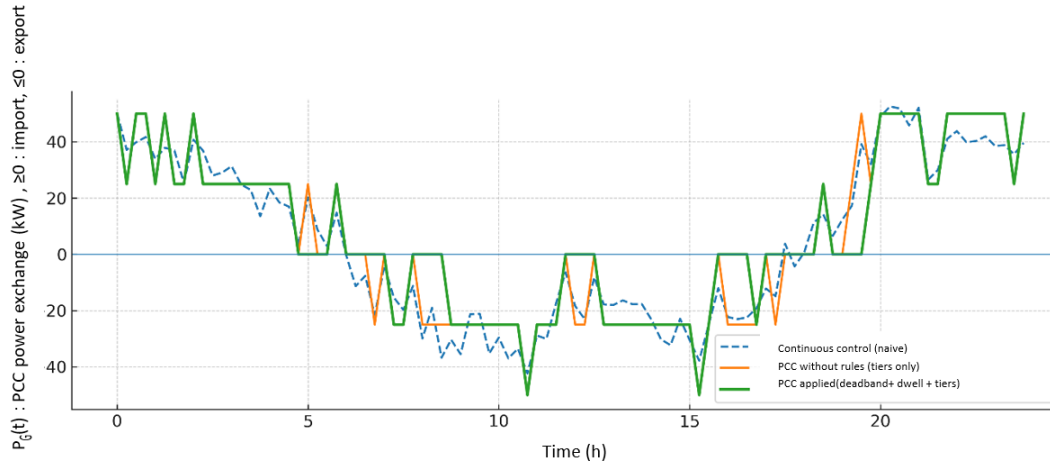


Fig. 4. Effect of the deadband ζ around zero PCC exchange.

Fig. 4. illustrates how the deadband ζ around zero and the dwell time τ suppress sign flips and enforce import/export exclusivity at the PCC.

4.6. Stochastic Environment, Episodes and Training Protocol

We simulate hourly steps over 24-h episodes, under summer/winter weather regimes (irradiance, wind) and stochastic demand with realistic diurnal structure. The agent uses experience replay and a target network; exploration follows decaying ϵ -greedy; the Q-network is an MLP with ReLU activations, optimized with Adam [13], [23], [25], [27], [37], [38].

5. Methodology Based on Deep Q-Network (DQN)

5.1. DQN Overview

The supervisory controller builds on the Deep Q-Network (DQN) paradigm, which couples value-based reinforcement learning with deep function approximation to learn near-optimal dispatch policies in high-dimensional, partially uncertain environments without requiring explicit analytic models of full system dynamics [17], [20], [28]. A neural approximator $Q_\theta(s,a)$ represents the action-value function, where the state s encodes the instantaneous microgrid condition and the action a maps to a physically admissible control decision. The optimality equation is

$$Q^*(s, a) = E[r + \gamma_{RL} \max_{a'} Q^*(s', a')] \quad (21)$$

with discount factor $\gamma_{RL} \in [0,1]$ trading off immediate and future returns. In practice, DQN updates θ by minimizing the squared temporal-difference error between $Q_\theta(s,a)$ and a target $y = r + \gamma_{RL} \max_{a'} Q_{\bar{\theta}}^*(s', a')$, where $\bar{\theta}$ denotes a slowly updated target network, a stabilization device widely adopted in power-system DRL [21], [24], [25]. Together with experience replay (random mini-batches from a transition buffer), these mechanisms decorrelate updates and mitigate divergence, enabling generalization under the non-stationary regimes typical of renewable-dominated microgrids [6], [13], [27], [28], [29].

5.2. CTDE Multi-agent Architecture, Data Flow, and Environment Loop

The proposed control framework follows a Centralized Training, Decentralized Execution (CTDE) paradigm, combining independent deep reinforcement-learning agents with a lightweight Point of Common Coupling (PCC) coordinator.

During training, agents exploit global information - including electricity tariffs, grid availability, nodal voltages, and short-term forecasts - whereas during execution, decisions rely strictly on local observations, in accordance with realistic field deployment constraints.

The PCC coordinator enforces import/export exclusivity, zero-crossing deadbands, and minimum dwell times, ensuring grid-compliant operation without compromising decentralized autonomy.

Figs. 5-7 collectively illustrate the CTDE architecture and its data flow.

Fig. 5 depicts the centralized training pipeline, where global signals are aggregated to construct the joint state. Exploration is handled via an ϵ -greedy policy, transitions are stored in a replay buffer, and policy updates are performed using minibatch stochastic gradient descent (SGD) with target networks for stabilization.

Fig. 6 details the CTDE coupling mechanism, emphasizing the separation between global information available during training and the local-only observations accessible at execution time. Feasibility checks and action masking are systematically applied to prevent violations of device and network constraints.

Fig. 7 summarizes the decentralized execution layer, in which independent local agents - associated with PV, wind, diesel, and battery resources - select discrete control actions. A policy-light PCC coordinator enforces interface rules and exposes operational mode flags, while device-level enforcement enables low-latency edge inference [11]-[13], [24], [27], [37].

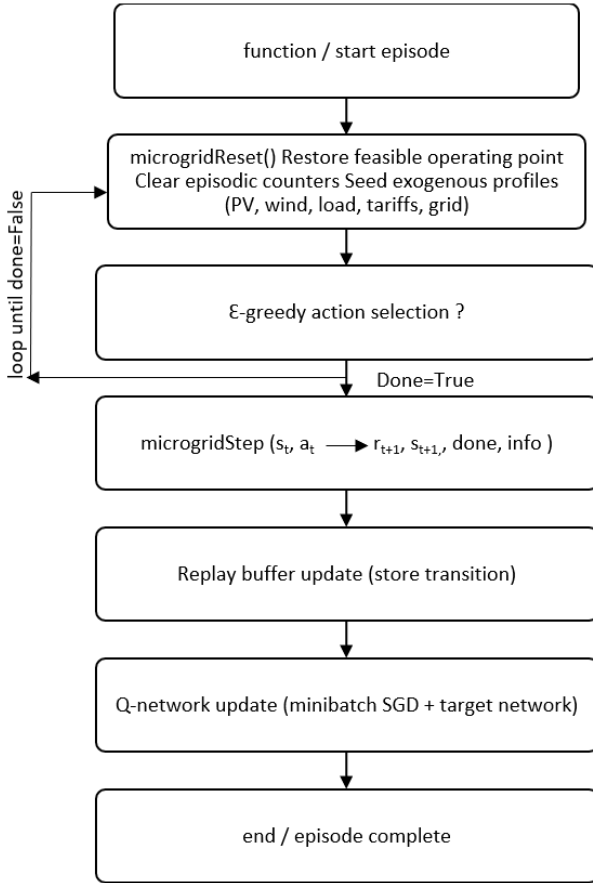


Fig. 5. Centralized training pipeline with global signals (tariffs, grid, voltages, forecasts); replay/target networks and minibatch SGD

The environment dynamics are governed by the microgrid-Step routine illustrated in Fig. 8. At each time step, the current state s_t is read, the selected joint action a_t is applied, and device-, battery-, and network-level limits are enforced through feasibility filtering and action masking. A scalar reward r_{t+1} is then computed, and the system transitions to the next state s_{t+1} , with terminal flags indicating episode completion when applicable.

Episode initialization and lifecycle management are handled by the microgrid-Reset procedure shown in Fig. 9. This routine restores a feasible operating point, clears episodic counters, and seeds all exogenous profiles, including PV generation, wind availability, load demand, dynamic tariffs, and grid connection status. The resulting episodic loop underpins both centralized training and decentralized execution.

Regarding agent roles, three PV agents actuate discrete inverter and curtailment tiers, while the wind agent selects feasible set-point or curtailment levels. Three battery agents operate over the discrete action set {charge | hold | discharge}, subject to state-of-charge and converter constraints, with tiered power levels. The diesel agent manages on/off commitment and discrete set-point tiers, incorporating ramping limits and minimum up/down-time surrogates. Throughout operation, the PCC coordinator applies exclusivity rules, deadband constraints, and dwell-time

enforcement at the interface level via environment-level constraints and action masking. This design preserves decentralized decision-making while ensuring stable, grid-compliant power exchanges [11]-[13], [24], [27], [37].

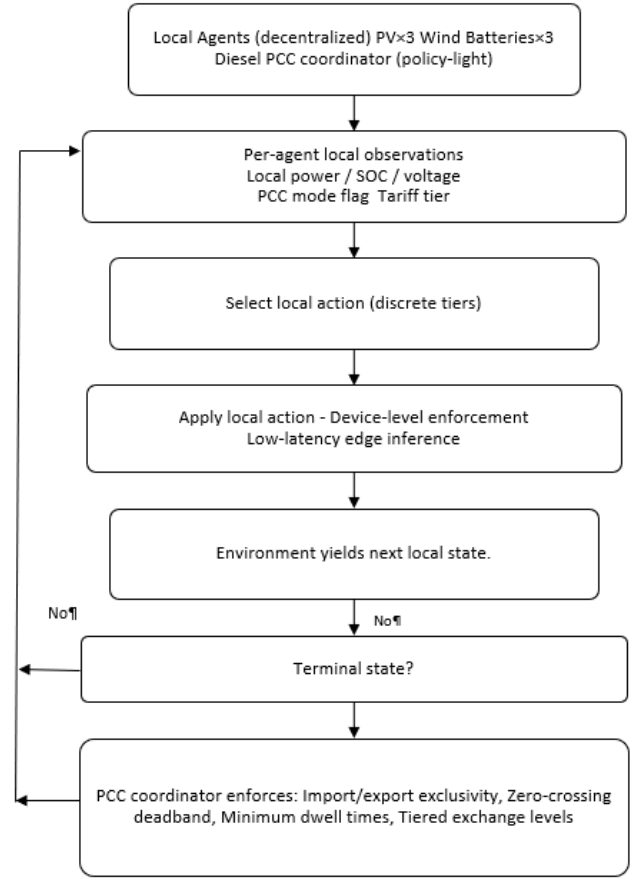


Fig. 6. CTDE coupling: global information for training vs. local-only observations at execution; feasibility checks and action masking.

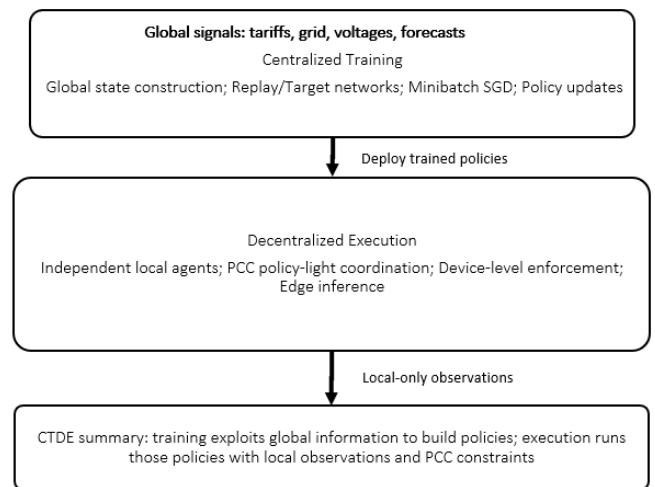


Fig. 7. Decentralized execution: independent local agents plus PCC coordination; device-level enforcement; edge inference.

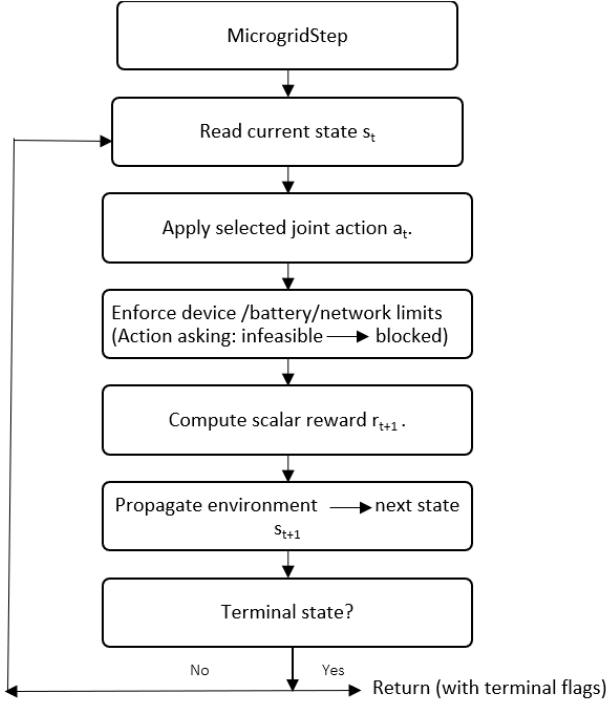


Fig. 8. microgrid-Step: read state → apply joint action → enforce limits (mask if infeasible) → compute reward → propagate to next state with terminal flags.

5.3. State, Action, and Reward Design

We adopt a CTDE multi-agent design with independent DQN learners per resource. The interface is defined as follows:

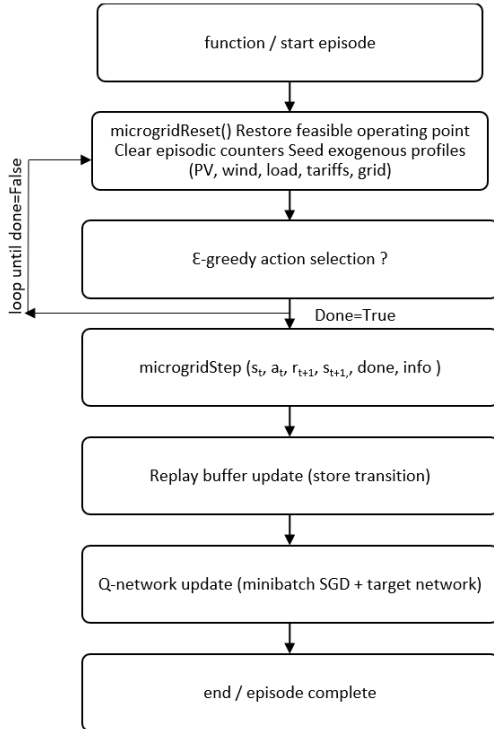


Fig. 9. Microgrid-Reset and episodic loop: restore feasible operating point, clear counters, seed exogenous profiles.

a) State vector

Joint state aggregates measured/estimated variables: PV and wind outputs (and forecasts when available), aggregate and nodal loads, battery SOC, node-wise voltages along the 31-node feeder, PCC import/export status and tariff tier, and device headrooms. Each agent receives its local slice plus a compact broadcast context (e.g., tariff tier and PCC mode).

b) Action space

Discrete, hardware-consistent actuation: diesel on/off; battery mode tiers (charge/hold/discharge within ratings); PV/wind curtailment tiers; tiered grid exchange at the PCC. This discreteness matches contactor-level logic and tariff steps and motivates a DQN family over continuous-action methods; continuous DRL (DDPG/SAC/PPO) is reserved for future fine set-point tuning. [21], [24], [26], [27].

c) Reward shaping

$$R_t = -\left(\alpha \tilde{C}(t) + \beta \tilde{E}_{CO_2}(t) + \gamma \tilde{P}_G(t) + \delta \tilde{V}_{viol}(t)\right) \quad (22)$$

With

$$\tilde{C}(t) = \frac{C_{total}(t)}{C_{ref}}; \tilde{E}_{CO_2}(t) = \frac{E_{CO_2}(t)}{E_{ref}}; \tilde{P}_G(t) = \frac{|P_G(t)|}{P_{ref}}; \tilde{V}_{viol}(t) = \lambda_V \Psi_V(t) + \lambda_{SOC} \Psi_{SOC}(t) \quad (23)$$

where C_{ref} , E_{ref} , P_{ref} normalize heterogeneous units (MAD, tCO₂, kW) for learning stability, and $\tilde{V}_{viol}(t)$ aggregates voltage and SOC penalties using internal weights λ_V , λ_{SOC} (not policy weights).

d) Voltage and SOC penalties follow

$$\Psi_V(t) = \sum_i [\max(0, \frac{|V_i(t) - V_{nom}|}{V_{nom}} - \Delta_{tol})]^2 \quad (24)$$

$$\Psi_{SOC}(t) = [\max(0, SOC_{min} - SOC(t)) + \max(0, SOC(t) - SOC_{max})]^2 \quad (25)$$

With, $\Delta_{tol} = 0.10$ p.u. ($\pm 10\%$).

e) Degradation & autonomy notes

Battery degradation is not double-counted: it is monetized via $C_B(t)$ inside $C_{total}(t)$ (Section 4, Eq. (13)) rather than a separate reward term. Likewise, an extra autonomy penalty $\Phi_{pcc}(t)$ is omitted by default because import is already captured by the $\gamma \tilde{P}_{import}(t)$ term; it can be activated in dedicated autonomy-first experiments [8], [11], [14], [24], [37].

5.4. Training Protocol and Hyperparameters

A physics-constrained digital twin calibrated to Boujdour reproduces stochastic PV/wind resources, the hourly demand structure, battery round-trip efficiencies and SOC envelopes, and node-wise voltages along the feeder [10], [11], [14], [15]. Training uses two representative 24-h episodes (summer / winter), each with 24 steps, repeated 500–1000 times under a decaying ϵ -greedy exploration ($1.0 \rightarrow 0.01$). Experience is stored in a replay buffer of 10 000 transitions; i.i.d (independent and identically distributed). minibatches of 64 are sampled at each update. The Q-approximator is a 2-layer MLP (64/32, ReLU) optimized with Adam (learning rate 5×10^{-4}). Stabilization relies on a target network (periodic hard

syncs or equivalent soft updates) and the replay mechanism; the discount is $\gamma_{RL} = 0.99$ [6], [13], [21], [24], [25], [27]. Unless stated otherwise, per-step quantities use $\Delta t = 1$ h; both seasonal scenarios are shuffled within the training loop. (Full per-agent action spaces are identical except for device-specific tiers; the complete configuration can be found in Supplementary S3.)

5.5. Reward Formulation and Normalization

At each time step t , we compute three raw metrics: the monetary cost $C(t)$ (MAD), the instantaneous CO_2 emissions $E(t)$ (kg), and a power-quality/constraint metric $\Phi(t)$ (e.g., p.u.·h for voltage violations or a composite score). To avoid unit inconsistencies and to stabilize learning, we train the agent with a unitless reward obtained by normalizing each raw metric by a positive calibration scale:

$$\tilde{C}(t) = \frac{C(t)}{S_C}; \quad \tilde{E}(t) = \frac{E(t)}{S_E}; \quad \tilde{\Phi}(t) = \frac{\Phi(t)}{S_\Phi}$$

where S_C (MAD), S_E (kg), and S_Φ (p.u.·h or dimensionless) are fixed scales defined below.

a) *The training reward is then*

$$R_t = -(\beta_1 \tilde{C}(t) + \gamma_1 \tilde{E}(t) + \delta_1 \tilde{\Phi}(t)) \quad (26)$$

with $\beta_1, \gamma_1, \delta_1 \geq 0$ dimensionless trade-off weights. The agent maximizes the discounted return

$$G_t = \sum_{k=0}^{T-t-1} \rho^k R_{t+k+1}; \quad 0 < \rho \leq 1 \quad (27)$$

where ρ is the discount factor (we deliberately avoid using γ here to prevent confusion with the emission weight γ above).

b) *Calibration of normalization scales.*

We adopt a pragmatic calibration to make unitless quantities interpretable:

➤ *Option A (baseline-relative):*

$S_C = C_{\text{baseline}}, S_E = E_{\text{baseline}}, S_\Phi = \Phi_{\text{baseline}}$, where “baseline” denotes a non-RL policy (e.g., heuristic or PSO). This makes $\tilde{\cdot} \approx 1$ represent baseline performance.

➤ *Option B (bounded by physics/limits):*

S_C, S_E, S_Φ chosen as credible per-step upper bounds (e.g., tariff-at-peak, diesel at rated power, maximum allowed violation). This typically yields $\tilde{\cdot} \in [0, 1]$.

In our experiments, we use option A and report the actual values of S_C, S_E, S_Φ in the Appendix/Experimental Setup for reproducibility.

c) *Constraints handling.*

Physical and network-feasibility constraints - including PCC power limits, battery state-of-charge (SOC) bounds, voltage and power-factor requirements, as well as dwell-time and deadband constraints for power sign changes - are enforced through a dual mechanism: (i) action masking to prevent infeasible decisions whenever applicable, and (ii) a bounded penalty term incorporated into the reward function $\Phi(t)$ to account for any residual constraint violation. A generic composite formulation is given by

$$\Phi(t) = w_V \Phi_V(t) + w_{PF} \Phi_{PF}(t) + w_{PCC} \Phi_{PCC}(t) \quad (28)$$

where each penalty component $\Phi_i(t) \geq 0$ is equal to zero when the corresponding constraint is satisfied and increases monotonically with the magnitude and/or duration of the violation. The weighting coefficients w_i regulate the relative contribution of each constraint term and are kept constant across all policies and simulation scenarios to ensure fair comparison.

d) *Reporting vs. raining*

Training minimizes the unitless aggregate $\beta\tilde{C} + \gamma\tilde{E} + \delta\tilde{\Phi}$ through reward maximization. For interpretability, all results are reported in raw KPIs: total cost $\sum_t C(t)$ (MAD), total emissions $\sum_t E(t)$ (kg), grid import/export (kWh), and voltage violation hours V_{viol} (p.u.·h). The descriptive *economic* objective -(for reporting only; training uses the normalized reward)- shown elsewhere mirrors the reward structure but is not used directly during learning.

5.6. Implementation and Co-simulation

The DQN agents are implemented in Python (TensorFlow) and co-simulated with a detailed MATLAB microgrid model to ensure consistent feeder power-flow responses and device-level constraints. This modular design clarifies constraint handling (voltage and SOC), supports edge deployment for low-latency inference, and follows recent grid-edge DRL practices [6], [24], [26], [27], [37]. Batteries are monitored with SOC-centric safeguards aligned with contemporary estimation/management practices to preserve lifetime under frequent cycling [14], [15].

6. Results and Discussion

The performance of the proposed framework is evaluated under realistic operating scenarios, as detailed in the following subsections.

Although the agent is trained with a unitless normalized reward, all performance is reported using raw KPIs for interpretability: total operating cost (MAD), CO_2 emissions (kg), grid import/export (kWh), and voltage-violation hours (p.u.·h). Unless stated otherwise, improvements are given as absolute values and relative percentages with respect to the baseline.

6.1. Evaluation Setup

We evaluate the CTDE multi-agent DQN on a 24-h digital-twin of the Boujdour microgrid (summer/winter profiles), with stochastic PV/wind and a diurnal load consistent with §3. The environment enforces device/network constraints (SOC, ramp-rates, PCC exclusivity & dwell, $\pm 10\%$ voltage band) and computes the policy reward aligned with the multi-objective formulation in Eq. (4) (cost- CO_2 -import-quality) [2], [5]-[8], [16], [18]-[20], [24], [27], [29], [37].

6.2. Baseline Multi-objective Performance (24-h)

Energy mix & autonomy. Over a 24-h horizon with total demand 991.1 kWh, the learned dispatch is renewables-first: PV 559.4 kWh (56.4 %), diesel 340.6 kWh (34.4 %), and main-grid exchange 91.2 kWh (9.2 %). The batteries act as

shallow buffers with a throughput of ± 7.6 kWh, indicating that most balancing is achieved via coordinated PV curtailment tiers, diesel commitment tiers, and tiered PCC exchange, rather than deep cycling.

Emissions. With a diesel factor of 0.8 kg kWh^{-1} , total CO_2 amounts to 272.5 kg, i.e., an intensity of $\approx 275 \text{ g kWh}^{-1}$ across the day: consistent with the reductions typically reported for learning-based EMS in hybrid systems [4], [6].

Takeaway. PV is prioritized; diesel covers edge hours (early morning/evening); the grid remains tertiary. This mix delivers limited grid reliance and restrained cycling while maintaining feasibility and service quality. (A full numeric breakdown formerly shown in Table 4 is retained in Supplementary S4.)

6.3. Temporal Dispatch and Interpretability

Overview. A single multi-panel view (Figs. 10–13) summarizes source-wise dispatch, balance with demand, carbon effects, and battery behavior over 24 h.

Source-wise dispatch (fig. 10). The three PV arrays dominate at mid-day; wind ramps in late afternoon; the diesel unit covers early/late deficits with short, targeted runs.

Generation vs. load (Fig. 11). Two demand peaks ($\approx 11:00$; $20:00$ – $22:00$) are aligned with selective diesel commitment and shallow battery support, limiting over-production and import spikes.

Emissions profile (Fig. 12). Hourly CO_2 remains low during PV-rich periods; controlled battery discharge mitigates evening emissions by shaving peaks.

SOC dynamics (Fig. 13). All three units stay within $[\text{SOC}_{\min}, \text{SOC}_{\max}]$, with heterogeneous roles: one daily cyclist, one peak-shaver, and one buffer, a merit-order pattern typical of value-based DRL policies [24], [37].

The panels collectively show a renewables-first dispatch with restrained cycling, grid stability at the PCC, and interpretable battery roles that generalize across operating conditions.

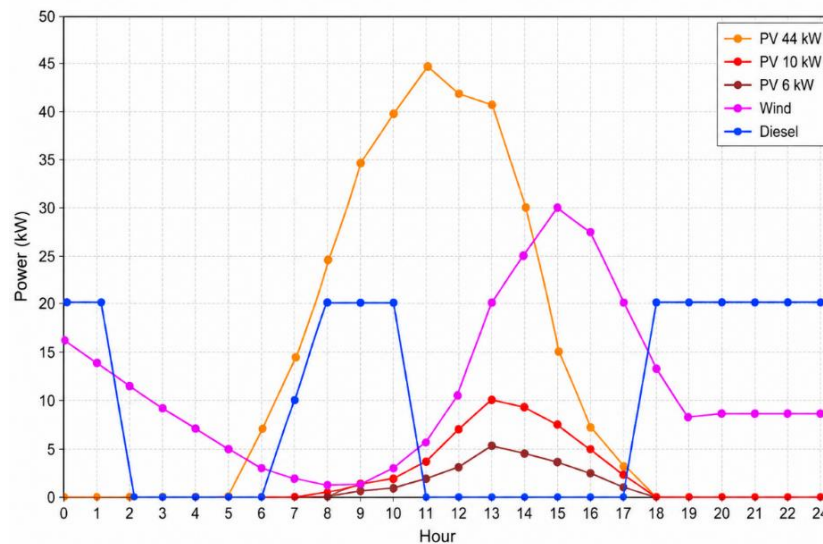


Fig. 10. Source-wise power (PV-44 kW, PV-10 kW, PV-6 kW, wind, diesel).

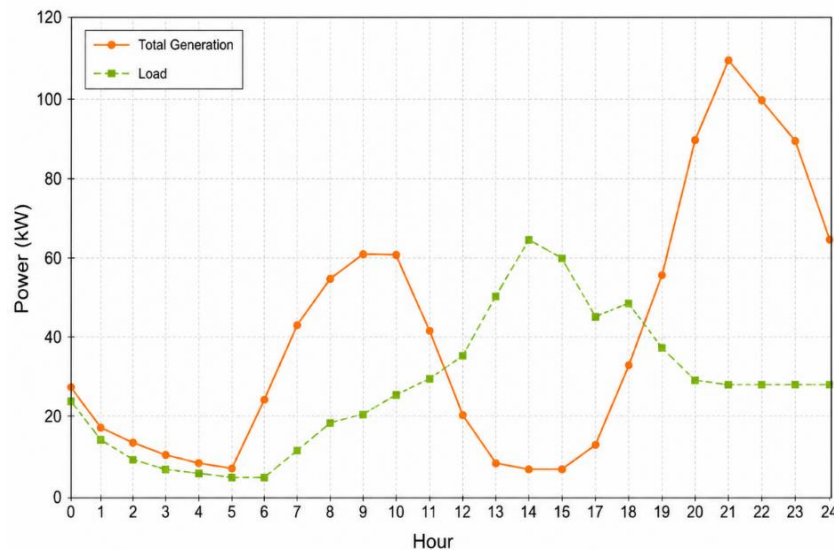


Fig. 11. Total generation vs. load.

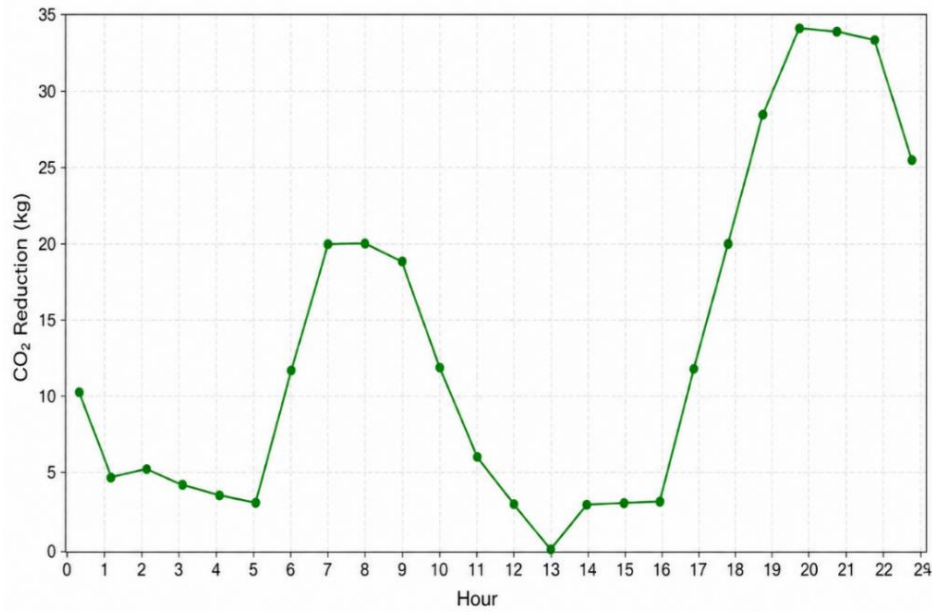


Fig. 12. Hourly CO₂ reduction attributable to the learned policy (relative to diesel-centric operation)

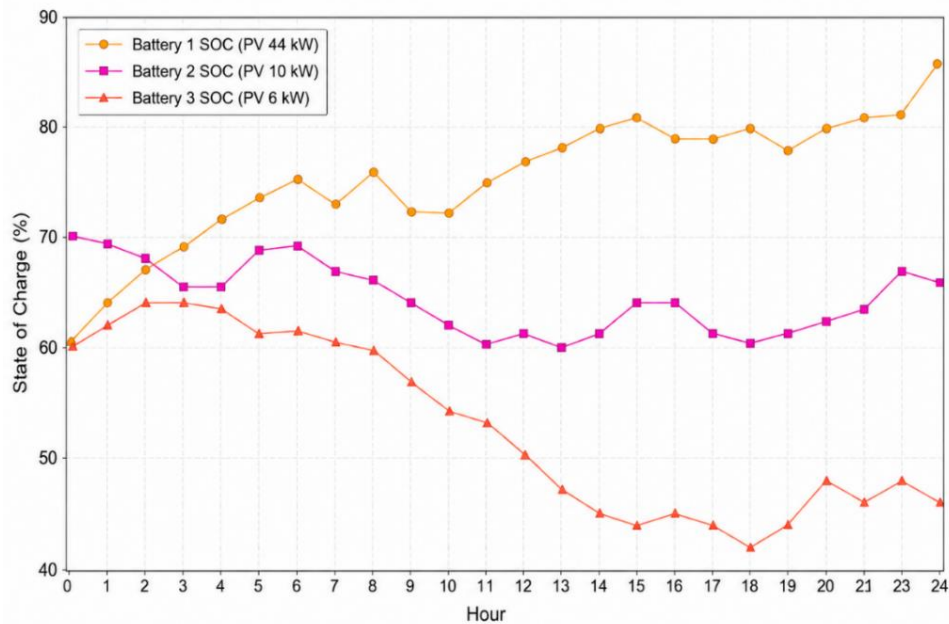


Fig. 13. Battery SOC trajectories (three PV-coupled units), all within operational bounds; roles emerge as daily cycler, peak-shaver, buffer [24], [37].

6.4. Grid-interaction Behavior (PCC)

The PCC coordinator enforces import/export exclusivity, a zero-crossing deadband and dwell times, which together suppress near-zero oscillations and prevent chatter. In practice we observe few reversals and stable tiered exchanges aligned with tariffs and local balance, an expected result of coupling cost/import weights with voltage-penalty terms in the reward and feasibility masks [11]-[13], [24]. Quantitative effects (blocked sign-change attempts, increase in zero-exchange steps, reduced gross import/export) are reported in Sec. 3.2(b) and visualized in Fig. 4.

6.5. Voltage-quality Compliance on the LV Feeder

Voltage profiles along the low-voltage (LV) feeder remain fully compliant with the $\pm 10\%$ admissible band, despite the presence of long radial sections and intermittent power injections from distributed energy resources [12], [13]. The time-series voltage trajectories observed at representative buses - namely nodes 1, 15, and 31 - exhibit smooth and stable behavior throughout the 24-hour horizon, with no noticeable excursions beyond the allowable limits, as illustrated in Fig. 14.

This behavior is further confirmed by the spatio-temporal voltage surface spanning all monitored nodes and hourly time

steps. As shown in Fig. 15, voltage variations evolve gradually across both space and time, without abrupt drops or deep localized sags, indicating a well-regulated feeder under the proposed control strategy.

Consistently, the aggregated voltage-violation metric $V_{\text{viol}}(t)$ remains close to zero over the entire horizon. This

outcome reflects the effectiveness of the enforced power-factor constraint and the voltage-aware penalty structure embedded in the learning process, which together internalize network feasibility and ensure stable LV operation during both training and execution phases [12], [13], [24], [37].

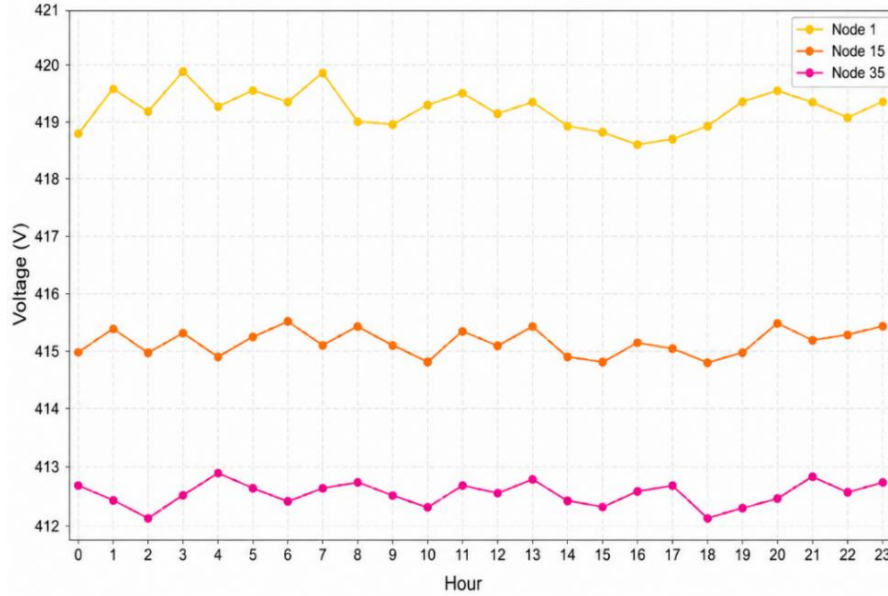


Fig. 14. LV voltage quality assessment.

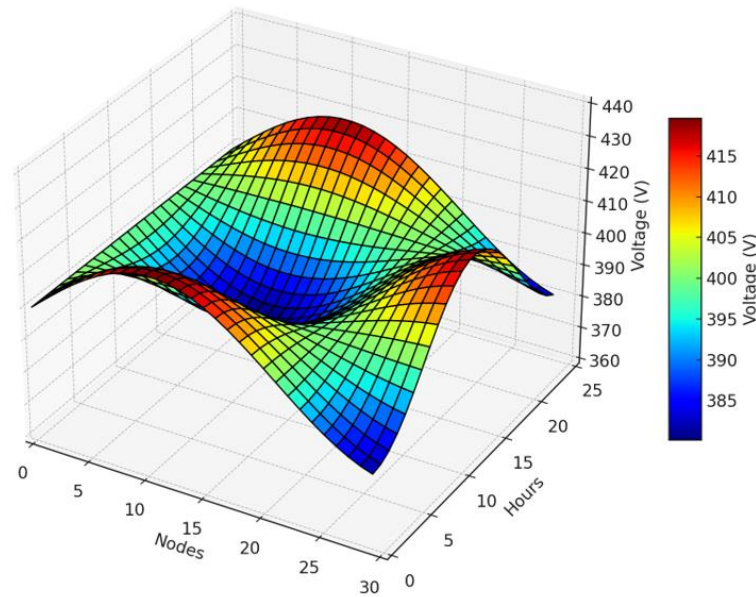


Fig. 15. LV voltage quality assessment.

Voltage at selected nodes (1, 15, and 31) over 24 h, remaining within the $\pm 10\%$ compliance band.

Spatio-temporal voltage surface (nodes $\times$ hours), showing smooth voltage variations and the absence of deep sags.

6.6. Sensitivity to Policy Weights

6.6.1. CO_2 penalty weight β

We sweep $\beta \in \{0.1, 0.5, 1.0, 2.0\}$ with the other weights fixed. The trend is monotonic: a larger β reduces diesel use and CO_2 at the expense of higher cost. Concretely, for the same 24-h load (991.1 kWh):

- Cost (MAD): $1100 \rightarrow 1135 \rightarrow 1180 \rightarrow 1270$ (+15.5%)
- CO_2 (kg): $310 \rightarrow 290 \rightarrow 265 \rightarrow 240$ (−22.6%), i.e., $\approx 313 \rightarrow \approx 242 \text{ g kWh}^{-1}$

➤ Diesel (kWh): 360 → 340 → 320 → 290 (−19.4%)

This behavior reflects the reward trade-off encoded by β and aligns with policy-tuning effects reported for value-based DRL in hybrid systems [24], [37].

6.6.2. Import reliance γ and quality weight δ

The sensitivity of the proposed control framework to the import-reliance weight γ and the power-quality weight δ is investigated through systematic parametric sweeps. These analyses aim to clarify how grid dependency, emissions, voltage quality, and operational cost trade off against one another under multi-objective reinforcement learning.

Across the (β, γ) sweep, increasing the import-reliance weight γ progressively penalizes grid exchanges, resulting in a marked reduction of the absolute grid power $|P_G|$. This shift forces a greater reliance on local balancing resources - namely diesel generation and battery storage - which slightly increases the total operating cost. However, within a moderate γ range, this cost increase remains limited while grid dependency is significantly reduced.

Similarly, across the (β, δ) sweep, increasing the power-quality weight δ enforces stricter voltage-compliance constraints, reflected by lower accumulated voltage-violation severity V_{viol} . This improvement is typically achieved through additional curtailment or more conservative dispatch decisions, again with only modest cost penalties when δ is tuned within a practical range [24], [37].

A coherent and practically relevant operating region emerges around $\beta \approx 0.5$ -1.0 and $\gamma \approx 0.1$ -0.2, where total cost remains moderate while both grid imports and CO₂ emissions are effectively reduced. This region represents a balanced compromise between economic performance, autonomy, and environmental impact.

Table 2 summarizes three Pareto-efficient operating points selected from the combined (β, γ, δ) sweeps, each emphasizing a different operational priority: carbon reduction, grid autonomy, or voltage quality. For each point, the table reports the total cost (MAD), CO₂ emissions (kg), absolute grid exchange $|P_G|$ (kWh), and voltage-violation severity V_{viol} (p.u.h.).

Table 2. Pareto-efficient operating points (β, γ, δ) .

(β, γ, δ)	Cost (MAD)	CO ₂ (kg)	$ P_G $ (kWh)	V_{viol} (p.u.·h)	Notes
(2.0, 0.10, 100)	1278	241	122	0.28	Carbon-lean (minimum emissions at moderate grid use)
(0.5, 0.30, 100)	1186	289	102	0.34	Autonomy-lean (low grid exchange with moderate cost)
(0.5, 0.10, 400)	1142	292	128	0.21	Power-quality-lean (tight voltage via higher δ)

Figs.16-18 present two-dimensional sweeps over (β, γ) for total operating cost, CO₂ emissions, and absolute grid exchange, respectively. In all three maps, a consistent operating region - highlighted by a black rectangle - can be

identified around $\beta \approx 0.5$ -1.0 and $\gamma \approx 0.1$ -0.2. Within this region, cost escalation is limited while both emissions and grid reliance are noticeably reduced, confirming the robustness of this parameter range.

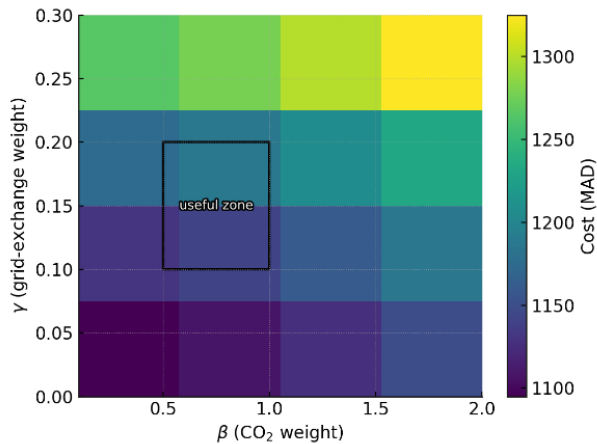


Fig. 16. Cost (MAD) over a $\beta \times \gamma$ sweep. The marked rectangle highlights a useful operating zone ($\beta \approx 0.5$ –1.0, $\gamma \approx 0.1$ –0.2) where costs remain moderate while import reliance is curtailed.

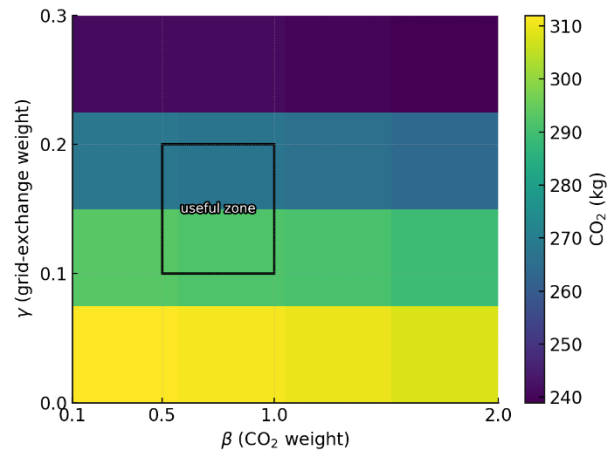


Fig. 17. CO₂ emissions (kg) across the $\beta \times \gamma$ sweep. The annotated “useful zone” ($\beta \approx 0.5$ –1.0, $\gamma \approx 0.1$ –0.2) achieves lower emissions while maintaining improved autonomy with limited cost penalties.

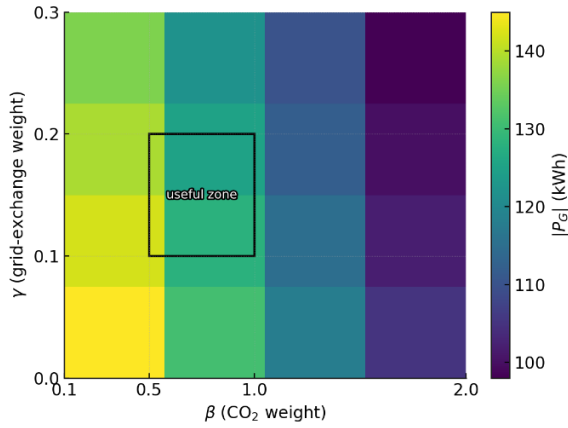


Fig. 18. Absolute grid exchange $|P_G|$ (kWh) across the $\beta \times \gamma$ sweep. Reduced grid dependency is observed in the same operating region, confirming the consistency of the identified trade-off.

Table 3. DQN vs PSO

Criteria	DQN-Based Control	PSO-Based Control	% Δ vs PSO
Control strategy type	Model-free, learning-based	Metaheuristic, population-based	-
Action space	Discrete, learned policies	Continuous, search-based	-
Adaptability to real-time variations	High (real-time reactive)	Low (offline only)	-
CO ₂ emissions (kg)	272.5	318.9	-14.6%
Total cost (MAD)	1120	1250	-10.4%
Voltage compliance	All nodes within $\pm 10\%$	Occasional violations at distant nodes	Better
Battery SOC range maintained	Yes (30–95%)	Partially maintained	Better
Computation time (per episode)	≈ 2.1 s	≈ 12.8 s	-83.6%
Deployment feasibility (edge devices)	Yes	Limited (requires central computation)	Better

DQN reduces emissions from 318.9 to 272.5 kg CO₂ (-14.6%) and lowers total cost from 1250 to 1120 MAD (-10.4%). Control latency per episode drops from about 12.8 s to 2.1 s (-83.6%), making edge implementation practical. Voltage compliance is consistently better under DQN (no violations at distant nodes). PSO remains a solid planning baseline but struggles in real-time operation (search latency, premature convergence), whereas DQN learns tiered, network-feasible responses that generalize under variability, [6], [16], [19], [20], [27], [28].

6.7.2. DQN-MA vs DQN-SA ablation

a) Objective.

Quantify the benefit of decentralized execution under CTDE versus a single centralized DQN, normalized reward Eq. (26), action discretizations, and all constraints Eqs. (1)–(3), (6), (18)–(20)) strictly identical.

b) Compared configurations.

- DQN-SA (centralized): one policy outputs the full joint action $(a_t^{PV1}, a_t^{PV2}, a_t^{PV3}, a_t^{WT}, a_t^{DG}, a_t^{B1}, a_t^{B2}, a_t^{B3}, a_t^{PCC})$

Taken together, these results demonstrate that careful tuning of γ and δ enables the controller to navigate smoothly between competing objectives. The radar plot in panel (d) synthesizes these trade-offs by contrasting the three Pareto-efficient operating points of Table 2 - carbon-lean, autonomy-lean, and quality-lean - highlighting the flexibility of the proposed framework to accommodate different operational priorities without compromising feasibility or stability.

6.7. Comparative evaluation

6.7.1. DQN vs PSO (same microgrid)

Table 3 compares the proposed DQN against the previously implemented PSO [11]. DQN reduces CO₂ from 318.9 kg to 272.5 kg (-14.6 %), and cost from 1250 to 1120 MAD (-10.4 %). Control latency per episode improves from 12.8 s to 2.1 s (-83.6 %), enabling edge deployment. Voltage compliance is consistently better under DQN (no distant-node violations).

input is a global state (generation/load aggregates, PCC indicators, summarized nodal voltages).

- DQN-MA (CTDE): independent learners (PV $\times$ 3, Wind, DG, Batt $\times$ 3) trained centrally with global signals and executed locally; a lightweight PCC coordinator enforces import/export exclusivity, zero-crossing deadband, and dwell times.

c) Experimental design.

Same hyperparameters and training budget as Table 4. Episodes of 24 h, summer/winter scenarios, plus unseen stressors: PV -20 %, evening-peak +20 %, PV2 outage (4 h), PCC unavailability (2 h). Report means $\pm$ std over 5 seeds.

d) Key performance indicators (to be reported).

Total cost (MAD); (ii) CO₂ (kg); (iii) grid import/export (kWh); (iv) V_{viol} (p.u.·h, Eq. 19); (v) PCC toggling rate (zero-crossings/day); (vi) diesel runtime (h); (vii) SOC-window adherence (% steps within $[SOC_{min}, SOC_{max}]$); (viii) battery throughput (kWh/day); (ix) episode latency (s) and compute footprint (MB/model or total).

Table 4. Ablation: MA-DQN vs SA-DQN (mean $\pm$ std, 5 seeds)

Metric	SA-DQN (Summer)	MA-DQN (Summer)	SA-DQN (Winter)	MA-DQN (Winter)
Total cost (MAD)	1128 $\pm$ 14	1115 $\pm$ 12	1176 $\pm$ 16	1162 $\pm$ 15
CO ₂ (kg)	279 $\pm$ 6	271 $\pm$ 5	296 $\pm$ 7	287 $\pm$ 6
P _G (kWh)	138 $\pm$ 12	121 $\pm$ 10	162 $\pm$ 14	138 $\pm$ 12
V _{viol} (p.u. · h)	0.46 $\pm$ 0.06	0.31 $\pm$ 0.05	0.52 $\pm$ 0.07	0.37 $\pm$ 0.06
SOC violation (p.u. · h)	0.20 $\pm$ 0.05	0.11 $\pm$ 0.03	0.24 $\pm$ 0.06	0.14 $\pm$ 0.04
PCC sign toggles (count)	27 $\pm$ 6	12 $\pm$ 3	31 $\pm$ 7	15 $\pm$ 4
Diesel runtime (h)	14.1 $\pm$ 0.8	13.0 $\pm$ 0.7	15.6 $\pm$ 0.9	14.5 $\pm$ 0.8
Battery throughput (kWh/day)	205 $\pm$ 11	191 $\pm$ 10	215 $\pm$ 12	198 $\pm$ 11
Episode latency (s)	2.2 $\pm$ 0.1	2.0 $\pm$ 0.1	2.2 $\pm$ 0.1	2.0 $\pm$ 0.1
Compute footprint (MB)	14.2 $\pm$ 0.6	17.8 $\pm$ 0.8	14.2 $\pm$ 0.6	17.8 $\pm$ 0.8

e) *Expected patterns (to be confirmed numerically).*

Network quality: Compared with the single-agent DQN, the multi-agent DQN reduces the voltage-violation metric and decreases PCC toggling, owing to local observability and PCC arbitration with deadband and dwell constraints.

Energy & cost: DQN-MA achieves comparable or lower cost and CO₂, often with fewer diesel hours and smoother imports.

Storage behavior: fewer SOC-window violations and more balanced battery throughput (healthier cycling).

Compute & deployment: similar or lower latency; distributed memory footprint compatible with edge deployment.

6.8. *Robustness and Generalization (unseen stressors)*

We test three unseen scenarios without retraining: (i) PV profile depression (cloud cover), (ii) PV2 outage (4 h), (iii) +20 % evening peak. In all cases the agent adapts PCC imports, diesel tiers, and battery modes to keep SOC within bounds and preserve supply; voltage remains compliant except a minor spike on node 31 under the load surge.

The quantitative results under these stress scenarios are summarized in Table 5.

The learned policy maintains service continuity and voltage compliance under significant perturbations, key for weakly interconnected Saharan microgrids [11], [13], [24], [37].

Table 5. Robustness under unforeseen operating conditions (your values; unchanged)

Scenario	Total Cost (MAD)	CO ₂ Emissions (kg)	Diesel Usage (kWh)	Grid Import (kWh)	SOC Range Maintained	Voltage Violation
Baseline (Normal Day)	1120	272.5	340.6	91.2	Yes	None
Unusual PV Profile (Cloud Cover)	1245	298.1	370.2	108.5	Yes	None
Partial PV Outage (PV2 disconnected 4h)	1290	322.4	388.7	120.1	Yes	None
Unexpected Load Surge (+20% peak)	1375	349.7	402.9	133.0	Yes	Minor spike at node 31

7. Conclusion

We proposed and validated a CTDE multi-agent DQN controller for a Saharan hybrid microgrid, combining independent learners (PV, wind, batteries, diesel) with a PCC-aware coordination policy that enforces import/export exclusivity, a zero-crossing deadband, and dwell-time constraints. The formulation aligns the objective and the reward via common policy weights α (cost), β (CO₂), γ (import), and δ (power quality), while embedding network feasibility (± 10 % voltage band, SOC envelopes, ramp-rates) directly in learning.

On a 24-h digital twin of Boujdour, the learned policy achieves a renewables-first energy mix (PV 56.4 %, grid 9.2

%) and 272.5 kg CO₂ (≈ 275 g/kWh), with voltage compliance across representative nodes. Relative to a PSO baseline, the controller lowers total cost by 10.4 % and CO₂ by 14.6 %, while cutting control latency by 83.6 %, making the approach suitable for edge hardware. A systematic policy-weight sensitivity confirms carbon-aware tunability: raising β from 0.1 to 2.0 reduces emissions 22.6 % at a 15.5 % cost increase. Robustness under unseen perturbations (cloud-induced PV depression, a 4-h PV2 outage, +20 % peak load) preserves supply continuity, SOC safety, and voltage limits, with only a minor voltage excursion at the feeder tail.

Implications. The results indicate that grid-interactive, voltage-aware DRL can deliver policy-tunable cost–carbon–

autonomy trade-offs in weakly interconnected microgrids, reducing operator intervention while respecting distribution-level constraints.

Limitations. The present controller uses discrete actuation tiers; continuous set-point refinement is delegated to device-level controllers. Exogenous uncertainty (weather/load) is handled implicitly; explicit probabilistic forecasting is not yet integrated. Battery degradation is approximated by throughput-based costs.

Future work. (i) Extend to continuous-action DRL (DDPG/SAC/PPO) to refine set-points without changing supervisory logic; (ii) couple with probabilistic forecasts and distributionally robust training; (iii) add multi-season and multi-year evaluation with realistic outages; (iv) conduct an ablation versus a single-agent DQN and, where available, a MILP benchmark; (v) integrate explainability (policy saliency, action attribution) and cyber-safety constraints for field deployment; (vi) explore multi-microgrid coordination and policy co-design of α , β , γ , δ with local carbon and reliability targets.

These findings position CTDE multi-agent DQN as a credible, edge-deployable supervisory layer for Saharan microgrids, capable of delivering quantifiable gains in cost, carbon, and power quality under operational uncertainty, while remaining tunable to evolving policy priorities.

Acronyms

Acronym	Definition
CTDE	Centralized Training, Decentralized Execution
MA	Multi-Agent
EMS	Energy Management System
PCC	Point of Common Coupling
BESS	Battery Energy Storage System
RES	Renewable Energy Sources
DER	Distributed Energy Resources
DG	Diesel Generator
RL/DRL	(Deep) Reinforcement Learning
DQN/DDQN	(Double) Deep Q-Network
DDPG/SAC/PPO	Actor-critic DRL methods (future continuous-action refinements)
MDP	Markov Decision Process
UC	Unit Commitment
KPI	Key Performance Indicator
LV/MV	Low Voltage / Medium Voltage
PF	Power Factor
MAD	Moroccan Dirham
CO ₂	Carbon dioxide

Main symbols

Symbol	Definition
t	Time index (h)
Δt	Time step (h); default $\Delta t = 1$ h unless stated
$P_G(t)$	Net PCC exchange (kW); $P_G > 0$ import, $P_G < 0$ export
$P_{DG}(t)$	Diesel-generator power (kW)
$P_{BP}(t)$	Battery power (kW); positive for discharge, negative for charge (sign follows manuscript)
$SOC(t)$	State of charge (p.u.)
$V_i(t)$	Voltage at bus i (p.u.)
$C_{total}(t)$	Operating cost at time t (MAD)
$E_{CO_2}(t)$	Emissions at time t (kg)
$V_{viol}(t)$	Voltage-violation severity aggregator (p.u.h)
$\alpha, \beta, \gamma, \delta$	Policy weights for cost / CO ₂ / grid import / power-quality terms
ρ_V, ρ_{SOC}	Internal penalty coefficients (reward-shaping, not policy weights)
ζ	PCC zero-crossing deadband (kW)
$T_{imp}^{min}, T_{exp}^{min}$	Minimum up/down (dwell) times for import/export modes (steps)
γ_{RL}	RL discount factor (default 0.99)

Acknowledgment

The authors would like to thank the Faculty of Sciences Ain Chock (FSAC), Hassan II University of Casablanca, for providing the academic and research environment that supported this work.

Author Contributions

All authors contributed to the study conception and design.

Redouane Mihramane: Conceptualization, Methodology, Software, Validation, Writing – original draft, Visualization, Supervision.

Sidi Salah Ech-Charqaouy: Conceptualization, Methodology, Software, Validation, Writing – original draft, Visualization, Supervision.

Abdelkader Boulezhar: Project administration, Resources, Supervision, Validation.

Nizar Ech-Charqaouy: Data curation, Resources, Writing – review & editing.

Amjad Ech-Charqaouy: Software, Formal analysis, Investigation, Writing – review & editing.

All authors read and approved the final manuscript.

Conflict of Interests

The authors declare that they have no competing financial or non-financial interests related to the work reported in this manuscript.

References

- [1] Q. Liu, K. Kamoto, and X. Liu, "Microgrids-as-a-service for rural electrification in Sub-Saharan Africa," *Computers, Materials & Continua*, vol. 63, pp. 1249–1261, 2020, doi: 10.32604/cmc.2020.05598.
- [2] A. Giedraityte, S. Rimkevicius, M. Marciukaitis, V. Radziukynas, and R. Bakas, "Hybrid renewable energy systems: a review of optimization approaches and future challenges," *Applied Sciences*, vol. 15, no. 4, pp. 1744, 2025, doi: 10.3390/app15041744.
- [3] J. Hirwa, A. Zolan, W. Becker, T. Flamand, and A. Newman, "Optimizing design and dispatch of a resilient renewable energy microgrid for a South African hospital," *Applied Energy*, vol. 348, pp. 121438, 2023, doi: 10.1016/j.apenergy.2023.121438.
- [4] Q. Hassan, S. Algburi, A. Z. Sameen, H. M. Salman, and M. Jaszczur, "A review of hybrid renewable energy systems: solar and wind-powered solutions: challenges, opportunities, and policy implications," *Results in Engineering*, vol. 20, pp. 101621, 2023, doi: 10.1016/j.rineng.2023.101621.
- [5] H. Al-Rawashdeh, O. A. Al-Khashman, J. T. Al Bdour, M. R. Gomaa, H. Rezk, A. Marashli, L. M. Arrfou, and M. Louzazni, "Performance analysis of a hybrid renewable-energy system for green buildings to improve efficiency and reduce GHG emissions with multiple scenarios," *Sustainability*, vol. 15, no. 9, pp. 7529, 2023, doi: 10.3390/su15097529.
- [6] M. Ali, K. Prakash, M. A. Hossain, and H. R. Pota, "Intelligent energy management: evolving developments, current challenges, and research directions for sustainable future," *Journal of Cleaner Production*, vol. 314, pp. 127904, 2021, doi: 10.1016/j.jclepro.2021.127904.
- [7] International Energy Agency, "Global Energy Review 2025: CO₂ Emissions," IEA, Paris, France, 2025. <https://www.iea.org/reports/global-energy-review-2025/co2-emissions>.
- [8] R. Thapa-Parajuli, R. Neupane, M. Timsina, B. Pokharel, D. Poudel, M. Maharjan, S. P. KC, and S. Shrestha, "Global CO₂ emission reduction disparities after and before COVID-19," *Sustainability*, vol. 17, no. 14, pp. 6602, 2025, doi: 10.3390/su17146602.
- [9] I. T. Halidou, H. O. R. Howlader, M. M. Gamil, M. H. Elkholy, and T. Senjyu, "Optimal power scheduling and techno-economic analysis of a residential microgrid for a remotely located area: A case study for the Sahara Desert of Niger," *Energies*, vol. 16, no. 8, pp. 3471, 2023, doi: 10.3390/en16083471.
- [10] L. Richard, C. Boudinet, S. A. Ranaivoson, J. O. Rabarivao, A. E. Befeno, D. Frey, M.-C. Alvarez-Hérault, B. Raison, and N. Saincy, "Development of a DC microgrid with decentralized production and storage: From the lab to field deployment in Rural Africa," *Energies*, vol. 15, no. 18, pp. 6727, 2022, doi: 10.3390/en15186727.
- [11] R. L. Mihramane, S. S. Ech-Charqaouy, D. Saifaoui, N. Ech-Charqaouy, and A. Ech-Charqaouy, "Management and optimization of a renewable energy hybrid system integrated into a microgrid, considering constraints related to voltage stability and service continuity," *IJRER*, vol. 15, no. 2, pp. 213–225, 2025, doi: 10.20508/ijrer.v15i2.14781.g9042.
- [12] S. S. Ech-Charqaouy, D. Saifaoui, O. Benzohra, and A. Lebsir, "Integration of decentralized generations into the distribution network smart grid downstream of the meter," *IJSmartGrid*, vol. 4, no. 1, pp. 17–27, 2020, doi: 10.20508/ijsmartgrid.v4i1.92.g78.
- [13] S. S. Ech-Charqaouy, D. Saifaoui, O. Benzohra, and A. Lebsir, "Impact of integrating renewable energies into distribution networks on the voltage profile," *IJRER*, vol. 10, no. 1, pp. 143–154, 2020, doi: 10.20508/ijrer.v10i1.10204.g7848.
- [14] E. Sutanto, P. E. Astawa, F. Fahmi, M. I. Hamid, M. Yazid, W. Shalannanda, and M. Aziz, "Lithium-ion battery state-of-charge estimation from the voltage discharge profile using gradient vector and support vector machine," *Energies*, vol. 16, no. 3, Art. no. 1083, 2023, doi: 10.3390/en16031083.
- [15] J. A. Braun, R. Behmann, D. Schmider, and W. G. Bessler, "State of charge and state of health diagnosis of batteries with voltage-controlled models," *Journal of Power Sources*, vol. 544, Art. no. 231828, 2022, doi: 10.1016/j.jpowsour.2022.231828.
- [16] L. Yi, P. Langlotz, M. Hussong, M. Glatt, F. Sousa, and J. C. Aurich, "An integrated energy management system using double deep Q-learning and energy storage equipment to reduce energy cost in manufacturing under real-time pricing condition: A case study of a scale-model factory," *CIRP Journal of Manufacturing Science and Technology*, vol. 38, pp. 844–860, 2022, doi: 10.1016/j.cirpj.2022.07.009.
- [17] E. Foruzan, L.-K. Soh, and S. Asgarpour, "Reinforcement learning approach for optimal distributed energy management in a microgrid," *IEEE Transactions on Power Systems*, vol. 33, no. 5, pp. 5749–5758, 2018, doi: 10.1109/TPWRS.2018.2823641.
- [18] D. Liu, C. Zang, P. Zeng, W. Li, X. Wang, Y. Liu, and S. Wang, "Deep reinforcement learning for real-time economic energy management of microgrid system considering uncertainties," *Frontiers in Energy Research*, vol. 11, Art. no. 1163053, 2023, doi: 10.3389/fenrg.2023.1163053.
- [19] T. Levent, P. Preux, E. Le Pennec, J. Badosa, G. Henri, and Y. Bonnassieux, "Energy Management for Microgrids: A Reinforcement Learning Approach," in *Proc. IEEE PES, Bucharest, Romania, 2019*, pp. 1–5, doi: 10.1109/ISGTEurope.2019.8905538.
- [20] J. Terven, "Deep reinforcement learning: A chronological overview and methods," *AI*, vol. 6, no. 3, Art. no. 46, 2025, doi: 10.3390/ai6030046.

- [21] U. K., K. Gurunadh, N. K. S. Keerthan, N. K. Musunuru, and A. J., "Energy management system-deep reinforcement learning based dueling DQN (Deep Q-Networks)," in Proc. Asia Pacific Conference on Innovation in Technology (APCIT), Mysore, India, 2024, pp. 1–7, doi: 10.1109/APCIT62007.2024.10673561.
- [22] E. O. Arwa and K. Folly, "Reinforcement learning techniques for optimal power control in grid-connected microgrids: A comprehensive review," IEEE Access, vol. 8, pp. 227747–227766, 2020, doi: 10.1109/ACCESS.2020.3038735.
- [23] M. Ahmed, C. P. Lim, and S. Nahavandi, "A deep Q-network reinforcement learning-based model for autonomous driving," in Proc. IEEE International Conference on Systems, Man, and Cybernetics (SMC), Melbourne, Australia, 2021, pp. 739–744, doi: 10.1109/SMC52423.2021.9658892.
- [24] G. Custodio, L. F. Ochoa, T. Alpcan, F. C. L. Trindade, and R. A. de Godoy Rosolen, "Using dueling double Q-learning for voltage regulation in PV-rich distribution networks," in Proc. IEEE Madrid PowerTech, Madrid, Spain, 2021, pp. 1–6, doi: 10.1109/PowerTech46648.2021.9494903.
- [25] H. Qiu and F. Liu, "A state representation dueling network for deep reinforcement learning," in Proc. IEEE 32nd International Conference on Tools with Artificial Intelligence (ICTAI), Baltimore, MD, USA, 2020, pp. 669–674, doi: 10.1109/ICTAI50040.2020.00107.
- [26] P. Kiran and K. R. M. Vijaya Chandrakala, "New interactive agent based reinforcement learning approach towards smart generator bidding in electricity market with microgrid integration," Applied Soft Computing, vol. 97, Art. no. 106762, 2020, doi: 10.1016/j.asoc.2020.106762.
- [27] S. Mischos, E. Dalagdi, and D. Vrakas, "Intelligent energy management systems: A review," Artificial Intelligence Review, vol. 56, pp. 1–40, 2023, doi: 10.1007/s10462-023-10441-3.
- [28] D. M. S. Zekrifa, R. D. Prakash, M. Dhanalakshmi, R. Puviarasi, C. S. Sundar Ganesh, J. Samson Isaac, P. Duraipandy, and A. Rajaram, "Optimized controller design for renewable energy systems by using deep reinforcement learning technique," IJRER, vol. 14, no. 1, pp. 101–110, 2024, doi:10.20508/ijrer.v14i1.14273.g8866.
- [29] P. I. N. Barbalho, A. L. Moraes, V. A. Lacerda, P. H. A. Barra, R. A. S. Fernandes, and D. V. Coury, "Reinforcement Learning Solutions for Microgrid Control and Management: A Survey," IEEE Access, vol. 13, pp. 1–31, 2025, doi: 10.1109/ACCESS.2025.3546578.
- [30] C. Sauer, F. J. D. Lange, M. Thurow, I. Dormuth, and A.-L. Boulesteix, "Statistical parametric simulation studies based on real data," Statistics Methodology, 2025, doi: 10.48550/arXiv.2504.04864.
- [31] N. Singh, A. Agarwal, and J. Kumar, "A decentralised power management strategy in a hybrid energy storage supported islanded residential sustainable DC microgrid system," IJETP, vol. 18, no. 1, pp. 1–22, 2022, doi: 10.1504/IJETP.2022.10045782.
- [32] A. Iosifidis and A. Tefas, Deep learning for robot perception and cognition. Cambridge, MA, USA: Academic Press, 2022.
- [33] H. Alavizadeh, H. Alavizadeh, and J. Jang-Jaccard, "Deep Q-learning based reinforcement learning approach for network intrusion detection," Computers, vol. 11, no. 3, Art. no. 41, 2022, doi: 10.3390/computers11030041.
- [34] J. Kumar, A. Agarwal, and N. Singh, "A Cost-Effective DC microgrid system for resilient power supply to grid-connected societies," International Journal of Numerical Modelling: Electronic Networks, Devices and Fields, vol. 36, no. 5, pp. 1–24, 2023, doi: 10.1002/jnm.3097.
- [35] T. Nakabi and P. Toivanen, "Deep reinforcement learning for energy management in a microgrid with flexible demand," Sustainable Energy, Grids and Networks, vol. 25, Art. no. 100413, 2021, doi: 10.1016/j.segan.2020.100413.
- [36] S. Stavrev and D. Ginchev, "Reinforcement learning techniques in optimizing energy systems," Electronics, vol. 13, no. 8, Art. no. 1459, 2024, doi: 10.3390/electronics13081459.
- [37] H. Song, Y. Liu, J. Zhao, J. Liu, and G. Wu, "Prioritized replay dueling DDQN based grid-edge control of community energy storage system," IEEE Transactions on Smart Grid, vol. 12, no. 6, pp. 4950–4961, 2021, doi: 10.1109/TSG.2021.3099133.
- [38] E. Samadi, A. Badri, and R. Ebrahimpour, "Q-learning approach for optimal power dispatch of microgrid," in Proc. 28th Iranian Conference on Electrical Engineering (ICEE), Tabriz, Iran, 2020, pp. 1–5, doi: 10.1109/ICEE50131.2020.9260722.
- [39] A. Aktaş and Y. Kırçiçek, Solar Hybrid Systems. Cambridge, MA, USA: Academic Press, 2021.
- [40] A. Kumari and S. Tanwar, "Reinforcement learning for multiagent-based residential energy management system," in Proc. IEEE Globecom Workshops (GC Wkshps), Madrid, Spain, 2021, pp. 1–6, doi: 10.1109/GCWkshps52748.2021.9682182.
- [41] M. K. Perera, K. T. M. U. Hemapala, and W. D. A. S. Wijayapala, "Developing a reinforcement learning model for energy management of microgrids in python," in Proc. International Conference on Computational Intelligence and Knowledge Economy (ICCIKE), Dubai, United Arab Emirates, 2021, pp. 68–73, doi: 10.1109/ICCIKE51210.2021.9410754.

Intelligent ExDoGBoost-Enabled UPFC System for Power Quality Enhancement in Grid-Connected PV System

J. P. Srividhya ^{*}, D. Meena ^{**}, S. Tamil Selvi ^{***}, R. Suresh ^{****}

^{*}Associate Professor, Department of Electrical and Electronics Engineering, KCG College of Technology, Karapakkam, Chennai, Tamilnadu, India.

^{**}Assistant Professor, Department of Electrical and Electronics Engineering, SRM Institute of Science and Technology, Ramapuram Campus, Chennai-600089, India.

^{***}Assistant Professor, Department of Electrical and Electronics Engineering, Erode Sengunthar Engineering College, Perundurai, Erode, Tamilnadu, India.

^{****}Associate Professor, Department of Electrical and Electronics Engineering, Arunai Engineering College (Autonomous), Velunagar, Tiruvannamalai-606 603, Tamilnadu, India.

(sriviprakash2007@gmail.com, meenad@srmist.edu.in, stmlselvi9@gmail.com, kasturisuresh43@gmail.com)

^{*†}Corresponding Author: J. P. Srividhya; sriviprakash2007@gmail.com

Received: 09.12.2025 Accepted: 26.01.2026

Abstract- With increasing use of Renewable Energy Sources (RES) such as Photovoltaic (PV) systems, power quality has become a major challenge in modern grids. Harmonic distortions, voltage sag/swell, and load demand variations significantly affect stability and efficiency of power delivery. A Unified Power Flow Controller (UPFC) connected to a solar PV system is introduced as a sophisticated control scheme for enhancing power quality. The UPFC consists of a series and shunt converter working together to regulate voltage, manage power flow, and suppress harmonics. To ensure constant DC-link voltage under unpredictable PV conditions, an Extended Double Gain Step-Up Boost Converter (ExDoGBoost) is proposed, enabling high voltage gain and efficient energy conversion. For stable converter operation, a PI controller optimized using the Giant Trevally Optimization Algorithm (GTOA) provides effective DC voltage regulation, while a Decoupled Neural Network (DNN) generates adaptive reference currents to improve responsiveness under dynamic grid conditions. The integration of AI-based control with high-gain conversion significantly enhances the UPFC's ability to mitigate voltage sag/swells, reduce Total Harmonic Distortion (THD) to 1.71%, and support reactive power adjustment. MATLAB simulations validate the proposed system, achieving 96% converter efficiency and appreciable power quality improvement, making it suitable for renewable-integrated distribution networks.

Keywords: Unified power flow controller, ExDoGBoost converter, giant trevally optimization algorithm, decoupled neural network.

1. Introduction

The global demand for electrical energy continues to rise steadily. Although fossil fuels remain abundant, growing environmental concerns are accelerating the transition toward renewable energy sources. Among these, PV technology stands out as a leading form of distributed renewable energy and is projected to become dominant contributor to electricity generation [1]. PV systems are environmentally sustainable, generating power without releasing harmful emissions. As a result, their adoption is expanding rapidly across the globe. A significant portion of PV-generated electricity is now being fed into Low Voltage (LV) distribution networks. However, these networks were originally designed without anticipating widespread PV integration [2]. Most LV systems follow a radial configuration, where electricity flows from medium voltage transformers downstream to end users. High PV penetration disrupts this flow, causing substantial voltage fluctuations that must be carefully managed to stay within acceptable limits. In certain scenarios, when PV output surpasses local demand, the direction of power flow reverse within segments of the network [3]. This reversal, along with changes in voltage profiles, represents major power quality challenges in LV networks with distributed generation. Issues such as voltage imbalance, overvoltage, and phase unbalance become more pronounced and require advanced control strategies to mitigate. To address these challenges, Flexible AC Transmission System (FACTS) devices powered by solid-state electronics offer rapid response capabilities for voltage regulation. Key FACTS technologies include the Static Compensator (STATCOM), Dynamic Voltage Restorer (DVR), and UPFC [4].

Current research in LV networks with PV integration focuses on optimizing voltage control, balancing phases, reducing line losses, correcting voltage profiles, and implementing active filtering. Deployment of FACTS devices is being extensively explored as a solution to these emerging issues. DVR is a series-connected power electronic device designed to safeguard sensitive or critical electrical loads from common supply-side disturbances excluding complete outages [5]. It operates as a Voltage Source Inverter (VSI), with its output linked in series to the distribution feeder. The primary role of DVR is to maintain stable voltage at load terminals, regardless of fluctuations such as voltage sag/swells, distortions, or imbalances in the incoming supply [6]. It achieves this by injecting a compensating voltage with the appropriate magnitude and frequency. While the DVR is capable of adjusting the load voltage to any desired level and phase angle, its performance is constrained by the energy storage capacity available at the DC bus. DSTATCOM is a parallel-connected device designed for voltage regulation in distribution systems [7]. It utilizes a solid-state voltage source inverter and typically relies on energy stored in a DC capacitor to operate. When linked to a specific load, the DSTATCOM inject corrective current to ensure that the overall power demand aligns with utility standards. However, a considerable amount of this current continues to flow through the input terminal, meaning the device does not effectively compensate for zero-sequence components at that point [8].

1.1. Research Gap

Although FACTS controllers are well-established in transmission network control, their deployment in distribution systems remains relatively rare. There is a noticeable lack of comprehensive studies focusing on the use of FACTS devices for voltage regulation in radial distribution networks, particularly those with high levels of PV integration [9]. Current research in exploring the potential of fast-acting power electronic controllers to address voltage-related challenges at the consumer level. Among the FACTS technologies, DSTATCOM is the most straightforward to implement as a shunt-connected device [10]. However, the conventional three-leg DSTATCOM design has limitations, especially in compensating for harmonic and neutral currents, often requiring additional components. These shortcomings are addressed by four-leg DSTATCOM configurations. Meanwhile, the UPFC has demonstrated the ability to perform multiple functions simultaneously, including regulating positive sequence voltage, correcting voltage imbalance, and compensating for both neutral and harmonic currents, as well as improving power factor all without the need for auxiliary devices [11].

1.2. Motivation

As lifestyles transform and traditional energy sources dwindle, alongside shifting supply-demand patterns, importance of integrating RES into conventional power systems continues to grow. This integration is essential to meet rising energy needs in a more sustainable and eco-friendly way [12]. However, incorporating RES like solar PV systems presents notable challenges to maintaining system frequency due to their variable output. This calls for the development of sophisticated control mechanisms to satisfy Load Frequency Control (LFC) requirements. Devices like UPFC play a vital role in absorbing or releasing excess energy. These systems help reduce unnecessary fluctuations in frequency and tie-line power, thereby enhancing stability and responsiveness of overall grid operations [13].

Beyond regulating line power flows, the UPFC also plays a vital role in mitigating power oscillations. Most existing control strategies rely on conventional PI or lead-lag feedback controllers, which offer adequate damping performance near a specific operating point. However, since PI controllers operate with fixed parameters, their effectiveness diminishes when system operating conditions vary [14]. To address this, a sliding-mode control method is introduced as a more robust alternative. Yet, its performance hinges on the system's transfer function an element that is challenging to derive accurately in power systems integrated with UPFC due to their inherent complexity [15]. According to [16], a UPFC equipped with an ANN controller was shown to effectively regulate active power flow within the power system network. However, ANN-based UPFC approach is that the ANN is applied only to the shunt controllers, restricting its ability to fully optimize the dynamic power flow across the entire system. Decoupled neural network based UPFC controller is integrated, for enhancing the performance of the power system by independently managing shunt and series control actions.

1.3. Related Works

The DC link is powered by PV system, the serving as an energy buffer that enables power exchange between the shunt and series converters. The energy attained from the PV system is highly dependent on the environmental conditions, resulting in low and unreliable DC power. The PV power generation is enhanced by employing converters and control approaches explored below. DC-to-DC boost converter plays a crucial role in elevating input voltage to a level suitable for further processing. In solar photovoltaic (SPV) systems, this converter facilitates efficient energy harvesting and precise voltage regulation [17]. The Interleaved Boost Converter (IBC) utilizing an interleaved configuration, the system effectively minimizes conduction losses while significantly reducing Input Current Ripple (ICR) and Output Voltage Ripple (OVR), thereby enhancing the overall power handling capability [18]. The Quadratic Boost Converter (QBC) architecture enables substantial voltage gain even at relatively low duty cycles. This design effectively reduces voltage stress on primary power switch, thereby improving converter's reliability and extending its operational lifespan [19]. Yet, the conventional converters exhibit sensitivity to dynamic load variations and environmental fluctuations, leads to instability or reduced efficiency without robust real-time control mechanisms.

Converter's operation is fine-tuned through control algorithms that dynamically adjust switching duty cycle, thereby achieving desired output voltage and enhancing overall system performance. The converter operations are regulated by a closed loop control mechanism, PI controller where a PI controller optimized using bio-inspired algorithms continuously adjusts the system response to maintain voltage stability and ensure precise regulation of power flow under varying grid and load conditions. The Flower Pollination Algorithm (FPA) is employed to enhance performance of a PI control scheme integrated with a solar PV system. The combined FPA-PI controller, when used alongside a UPFC, capable of generating sufficient electrical energy, significantly improve when the solar PV system supplies power to the system [20]. The Moth Flame Optimization (MFO) algorithm inspired by the natural navigation behaviour of moths, this algorithm mimics their tendency to maintain a fixed angle relative to moonlight during nocturnal flight. This nature-inspired approach enables dynamic adjustment of control parameters, improving system response and stability [21]. However, these existing algorithms are highly dependent on the quality of optimization and system tuning, its effectiveness may diminish under poorly modelled or highly variable thermal-thermal system conditions. The Table 1 reviews PV based UPFC systems.

Table 1. Related works

Author/ Year/ Reference	UPQC System	Converter	Controller	Functionality
Koganti Srilakshmi <i>et al</i> (2024) [22]	Shunt Active Power Filter (SHAPF) integrated with Solar and Energy Storage System (ESS)	Boost converter	Fuzzy Logic Controller (FLC) optimized using Golden Ball Optimization Algorithm (GBOA)	Stabilizes DC-link capacitor voltage, dynamic response with THD reduction from 11.36% to 2.24%; performance highly dependent on accurate tuning of fuzzy membership functions and optimization parameters, which reduce robustness under poor operating conditions
Chilakapati Lenin Babu <i>et al</i> (2025) [23]	Solar-PV coordinated UPQC	DC-DC boost converter	PI controller optimized using Adaptive Leakage Least Mean Square (AL-LMS) algorithm	Improves PQ in grid connected PV system, further research is required to extend the approach with novel converter topologies and advanced optimization techniques for PI regulation
Ramesh Rudraram <i>et al</i> (2023) [24]	PV-integrated UPQC	DC/DC Interleaved Cuk Converter interfaced with common DC-link	d-q theory-based control with PI controller.	System performance under large PV arrays and grid disturbances remains untested.
Mangalapuri Sravani <i>et al</i> (2025) [25]	Grid-PV based UPQC	Boost converter	Deep Reinforcement Learning (DRL)-based PI controller	Provides adaptive DC-link voltage regulation. DRL-PI controller demands high computational resources and stable training environments, which challenge real-time converter control in embedded systems
Alireza Rostamipour <i>et al</i> (2024) [26]	PV based UPQC system	Boost converter	Synchronisation Reference Frame (SRF)	Effectively reduces voltage drop and current harmonics in distribution systems; reliance on SRF requires precise tuning and introduce delays in fast-changing grid conditions.

The proposed intelligent UPFC system in PV based grid system is listed below:

- UPFC effectively controls active and reactive power flow and improves voltage stability and damps power oscillations of the grid-connected PV system.
- Decoupled neural network offers adaptive control through independent management of shunt and series converter operations to achieve dynamic response to grid disturbances with high precision.
- The DC link is energized by the PV system, providing clean and sustainable power supporting efficient power flow control within the UPFC framework.
- ExDoGBoost Converter effectively enhances the low power attained from the PV system, achieving solid performance under diverse system conditions.
- GTOA-PI controller optimizes converter switching by having optimized PI parameters that ensure constant voltage and current output from the PV system to efficiently convert the energy.

1.4. Organization

The rest of the article is organized as follows: Section 2 details proposed modelling PV systems based UPFC system description for LFC. Section 3 covers modelling frameworks for the PV, DC converter, controller, UPFC based system modelling. With Section 4 presenting a comprehensive analysis of the results. The article concludes with final remarks in Section 5.

2. Proposed System Description

The proposed intelligent ExDoGBoost-enabled UPFC system, illustrated in Figure 1, presents an advanced architecture designed to address power quality challenges in grid-connected PV environments through sophisticated power electronic control strategies.

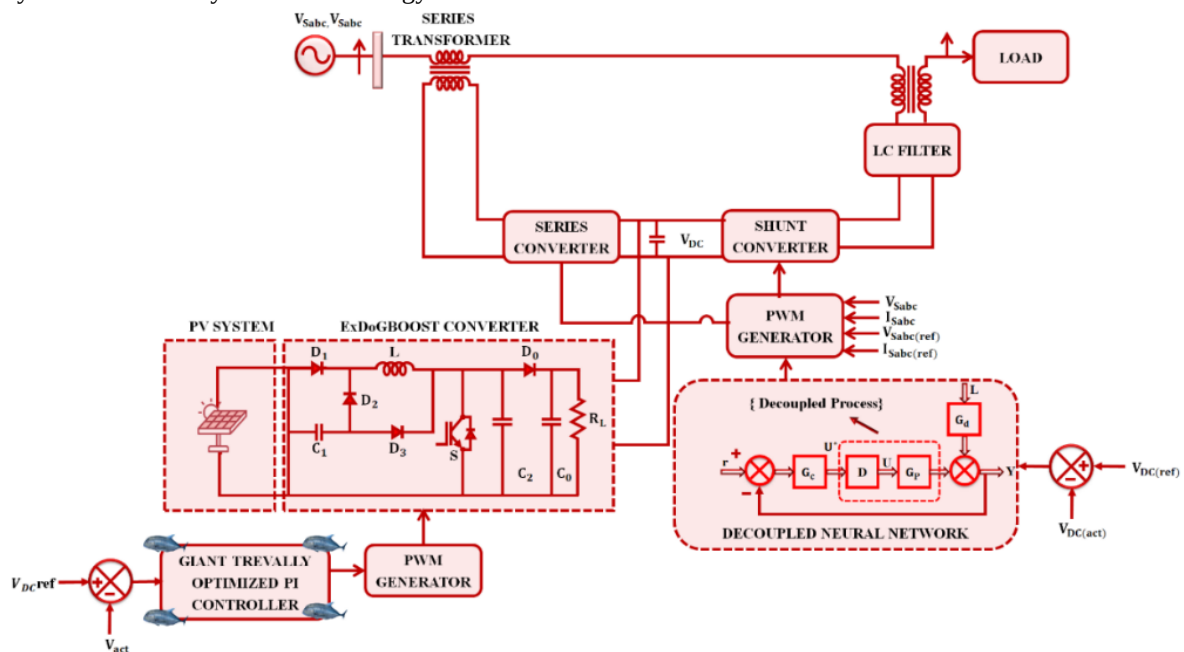


Fig. 1. Proposed UPFC based system.

The PV source serves as the primary renewable energy input; however, due to the intermittent nature of solar irradiance, the output power is inherently variable, leading to voltage and current fluctuations that degrade power quality. To overcome this, the system incorporates an ExDoGBoost, which elevates the low-voltage DC output from the PV array to a higher, grid-compatible level. The converter topology is optimized to achieve high voltage gain at relatively low duty cycles, thereby enhancing conversion efficiency and reducing stress on switching components.

Control of the converter is achieved through a GTOA-based PI controller, a bio-inspired technique that dynamically tunes PI parameters for optimal voltage regulation and maximum power extraction. This controller interfaces with a Pulse Width Modulation (PWM) generator to produce precise switching signals for the converter. The regulated DC output is then fed into the DC bus, maintaining a stable DC-link

voltage essential for consistent system operation. The converter also facilitates seamless bidirectional energy exchange between the series and shunt converters, enabling dynamic voltage regulation and flexible power flow control.

A Decoupled Neural Network (DNN) is employed to manage the real-time behaviour of the UPFC. It receives inputs such as reference and actual DC voltages ($V_{DC(ref)}$) and actual voltage ($V_{DC(act)}$), and generates adaptive reference currents for the shunt converter. The decoupling strategy allows the neural network to independently control the series and shunt components of the UPFC, enhancing the system's responsiveness, accuracy, and adaptability under varying grid conditions. This integrated control framework ensures robust voltage support, harmonic suppression, and improved power quality in renewable-integrated distribution networks.

3. Proposed System Modelling

3.1. UPFC

The UPFC is seen as the most versatile and potent member of the FACTS family and can control voltage, power flow, and system stability in transmission systems. In contrast to traditional FACTS devices that regulate a single variable, the UPFC, Figure 2, offers three degrees of freedom voltage magnitude control, phase angle control, and line impedance control hence regulating both real and reactive power simultaneously.

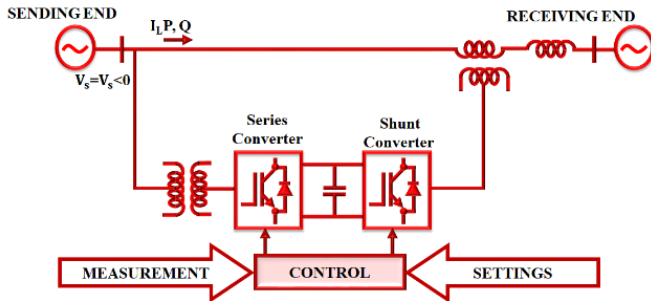


Fig. 2. Fundamental structure of UPFC.

Basic Configuration

Two Voltage Source Converters (VSCs) in UPFC are:

Shunt Converter: Normally connected in shunt to the transmission line via a shunt transformer, maintains bus voltage through controlled injection of reactive current and supplies DC power to the series converter as needed.

Series Converter: In series with transmission line via a series transformer. It introduces a controlled voltage of adjustable magnitude and phase angle into line, thus controlling power transfer.

Two converters are connected via a shared DC link capacitor, which allows active power transfer between them. Energy storage capability of this capacitor is usually small, and therefore the active power supplied by shunt converter should be equal to active power supplied by series converter. Reactive power exchange of each converter is controlled independently, though.

When the DC link switches are not closed, the two converters are independent, the shunt converter acts as a STATCOM and the series converter as an Static Synchronous Series Compensator (SSSC), regulating reactive current and injected series voltage respectively. When they are closed, active power transfer is established, and the UPFC is able to regulate simultaneously both real and reactive power recorded at receiving end of the transmission line. This intensive effort thus quickly stabilizes the system, diminishes the oscillations, and brings back the steady operation. As a result, the UPFC is capable of maintaining stable voltage, improving power factor, and ensuring the grid performance is reliable under the dynamic conditions.

The UPFC principle of operations are explained in Appendix A, as UPFC needs to be controlled by improved control mechanism for ensuring synchronized operation

between them, managing the exchange of active power via the DC link and independently regulating reactive power.

3.2. Decoupled Network

In grid-connected PV systems with a UPFC integrated into them, the control problem is naturally multivariable and very tightly coupled. Injected series voltage, shunt current, and reactive power compensation are not standalone actions, but rather are interdependent to the extent that a control action for regulating one parameter, e.g., bus voltage, tends to affect other performance metrics like harmonic distortion or reactive power balance. This intercoupling makes it difficult to design traditional controllers and leads to suboptimal performance in dynamic operating environments. To address these interactions, a DNN model is proposed, Figure 3. The fundamental rule of this model is to create synthetic manipulated inputs that control the effect on just a single output variable at a time, thus converting the original Multi-Input Multi-Output (MIMO) problem to a sequence of independent Single-Input Single-Output (SISO) subsystems. This enables every control channel, like voltage regulation or current harmonic suppression, to be treated independently without cross-interference.

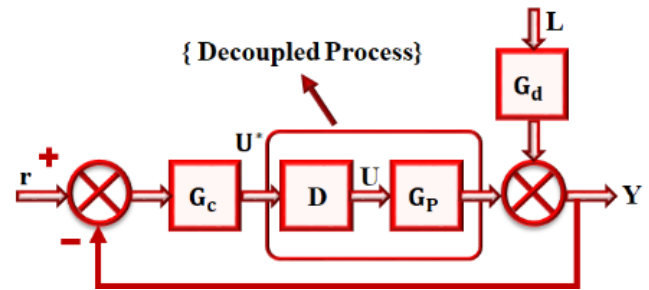


Fig. 3. Decoupled network controller.

The detailed mathematical expressions for decoupled network is given in Appendix B. As the system to energize the DC-link capacitor, a renewable energy input, the photovoltaic (PV) source is integrated.

3.3. PV System Modelling

To energize the DC link, PV module is employed by connecting multiple solar cells, which are basic devices that convert sunlight into electricity without causing pollution. These modules are further arranged in series and parallel configurations to create PV arrays that generate environmentally friendly and sustainable energy. Each solar cell functions as a component within an electrical circuit, comprising a diode and a photocurrent generator responsible for converting light into electrical energy. Additionally, the circuit includes two resistors one in series and one in parallel that represent the Joule heating effect and recombination losses, respectively.

The fundamental circuit layout of a solar panel is illustrated in Figure 4.

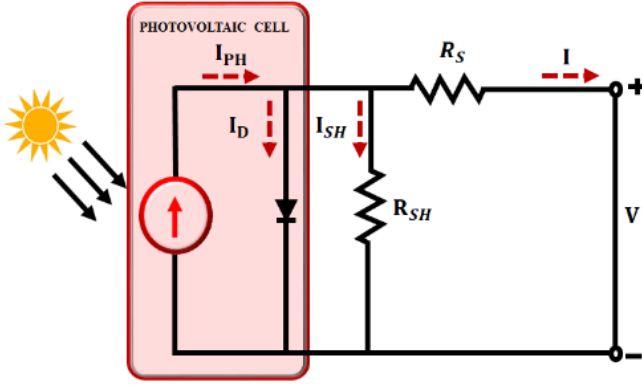


Fig. 4. Solar panel equivalent circuit.

According to Kirchhoff's law, current output of a PV cell is governed by the following expression:

$$I = I_{PH} - I_D - I_{SH} \quad (1)$$

The shunt current is defined as:

$$I_{SH} = \frac{V + R_S I}{R_{SH}} = \frac{V_D}{R_{SH}} \quad (2)$$

Where, (I) denotes output current of PV cell, (I_{PH}) and (I_D) represent the photocurrent and diode current, (I_{SH}) and (R_{SH}) refer to the shunt current and shunt resistance, (V) and (R_S) indicate the terminal voltage and series resistance.

The diode current is described by following equation:

$$I_D = I_S \left(e^{\frac{V_d}{nV_T}} - 1 \right) \quad (3)$$

Here, (I_S) is the reverse saturation current, (n) is the diode ideality factor, (V_T) is the thermal voltage, calculated as:

$$V_T = \frac{N_S k T_C}{q} \quad (4)$$

Where, (k) is Boltzmann constant, (q) is elementary charge, (N_S) is number of series-connected cells.

The reverse saturation current (I_S) is determined using the following relation:

$$I_S = I_{SN} \left(\frac{T_C}{T_{ref}} \right)^3 e^{\left(\frac{E_{go} \left(\frac{1}{T_n} - \frac{1}{T_C} \right)}{nk} \right)} \quad (5)$$

In this formula, eqn (5), (I_{SN}) is reverse saturation current at reference temperature (T_{ref}), (E_{go}) is energy band gap of semiconductor.

The short-circuit current (I_{CC}) and open-circuit voltage (V_{CO}) are used to express (I_{SN}) as:

$$I_{SN} = \frac{I_{CC}}{e^{\left(\frac{V_{CO}}{nV_T} \right)} - 1} \quad (6)$$

The photocurrent (I_{PH}) for any given irradiance (G) and cell temperature (T_C) is calculated by:

$$I_{PH} = \frac{G}{G_{ref}} I_{CC} + k_i (T_C - T_{ref}) \quad (7)$$

Where, (G_{ref}) and (T_{ref}) are the reference irradiance and temperature, (k_i) is the temperature coefficient of current.

Consequently, output current I of PV system is expressed as:

$$I = I_{PH} - I_S \left(e^{\frac{V_d}{nV_T}} - 1 \right) - \frac{V_D}{R_{SH}} \quad (8)$$

PV systems are designed to supply power to electrical loads. However, fluctuations in environmental conditions such as overcast skies or rainfall significantly impact the output voltage. To address this issue, the proposed system incorporates a high-efficiency converter aimed at boosting the output voltage and ensuring stable performance, as elaborated in the following section.

3.4. ExDoGBoost Converter

The proposed ExDoGBoost converter is developed for boosting the PV power with enhanced voltage gain, as depicted in Figure 5. The main concept of the ExDoGBoost converter is to utilize an additional capacitor–diode branch (C_1, D_2, D_3) combined with the boost inductor (L) and diode (D_1) to form an enhanced energy transfer cell, which doubles the voltage boosting capability.

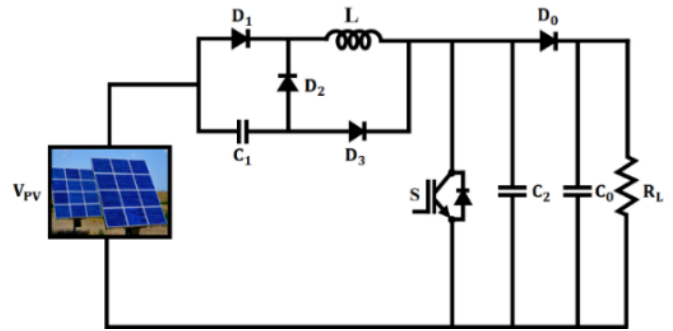


Fig. 5. ExDoGBoost converter.

In this configuration, the boost network is composed of (L), (C_1), switch (S), and diodes (D_1) and (D_3). The extended voltage cell consists of capacitor (C_1) and diodes (D_2) and (D_3). During the ON-state of switch (S), the inductor (L_1) stores energy from PV source (V_{PV}), while capacitor (C_1) is charged through (D_2). When switch (S) turns OFF, (L_1) releases its stored energy in series with (C_1), transferring it through (D_0) to charge (C_2) and (C_0), thereby supplying the load (R_L). This coordinated energy transfer charging capacitors in parallel and discharging them in series enables the converter to achieve a significantly higher voltage gain compared to a conventional boost converter, while maintaining continuous input current and reduced voltage stress across the switch and diodes.

Proposed converter operates in two distinct switching modes within each switching -cycle, as illustrated in Figure 6 (a) and Figure 6 (b).

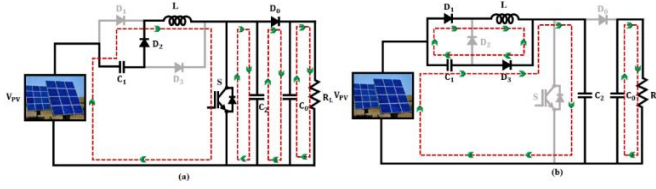


Fig. 6. (a) Mode 1 (b) Mode 2 operation of proposed ExDoGBoost converter.

Operating principle of proposed ExDoGBoost converter.

To simplify analysis, all components in the converter are assumed ideal. Inductor (L), capacitors (C_1, C_2, C_0) diodes (D_0, D_1, D_2, D_3) and load (R_L) are considered linear, time-invariant, and frequency-independent. Converter is analyzed under Continuous Conduction Mode (CCM), where inductor current never falls to zero during switching period T_s .

Mode 1: Switch ON State (S Conducting)

When main switch S is turned ON, diodes (D_1) and (D_3) are reverse-biased, while (D_2) and (D_0) becomes forward-biased, allowing capacitor (C_1) to be charged from the input PV source (V_{PV}). During this mode, Inductor (L) stores energy directly from (V_{PV}), capacitor (C_1) is charged via (D_2). Load (R_L) is supplied by discharge of capacitors (C_2) and (C_0) in parallel.

The inductor voltage during this interval is expressed as:

$$V_{L,ON} = V_{PV} \quad (9)$$

Capacitor (C_1) voltage increases as it charges.

Mode 2: Switch OFF State (S Open)

When switch S is turned OFF, energy stored in inductor (L) is released. Diodes (D_1) and (D_3) conduct, allowing inductor current to flow through (C_1) and in series with (V_{PV}). During this mode, inductor (L) discharges energy, which adds to (V_{PV}) and charges (C_2) and (C_0) through diode (D_0). Capacitor (C_1) discharges through (D_3), boosting the total transferred energy.

The effective series connection of (V_{PV}) and (C_1) produces a higher voltage at the output, providing a double-boost effect.

The inductor voltage during this interval becomes:

$$V_{L,OFF} = V_{PV} + V_{C1} - V_{C2} \quad (10)$$

The load is continuously powered by (C_0) during this phase, ensuring smooth voltage output.

Voltage Gain Derivation:

Applying the volt-second balance on the inductor (L):

$$V_{L,ON} \cdot DT_s + V_{L,OFF} \cdot (1 - D)T_s = 0 \quad (11)$$

Substituting $V_{L,ON}$ and $V_{L,OFF}$ and solving for V_{C1} and V_0 ,

$$V_{C1} = \frac{D}{1-D} V_{PV} \quad (12)$$

$$V_0 = V_{C2} = V_{PV} + V_{C1} = \frac{V_{PV}}{1-D} \quad (13)$$

Thus, the overall voltage gain of the ExDoGBoost converter is:

$$G = \frac{V_0}{V_{PV}} = \frac{1+D}{1-D} \quad (14)$$

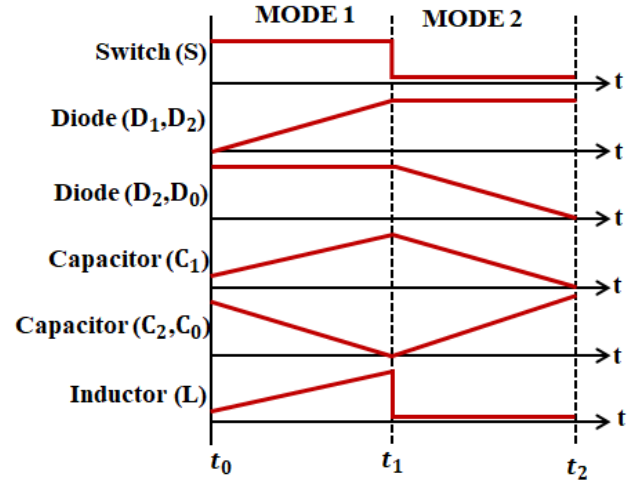


Fig. 7. Timing diagram.

Figure 7 displays the timing diagram, shows that the proposed converter achieves higher step-up capability compared to a conventional boost converter, while maintaining continuous current and reduced switch stress.

3.5. Giant Trevally Optimized PI Controller

For smooth converter operation in the proposed ExDoGBoost-based UPFC system, a PI controller is used for efficient DC voltage control. PI controller, works on the principle of smoothly controlling the system response after a fault or deviation from the reference is detected. The control sequence starts with the calculation of error signal, which is difference between desired set point and system's actual output. The Proportional (P) term is immediate in its action by multiplying the error with a proportional gain (K_p). Thus, it takes a corrective action proportional to the size of the deviation. This ensures an immediate response. The Integral (I) term, however, adds the history of past errors through the process of integration with an integral gain (K_i). This block removes steady-state error by ensuring persistent deviations are increasingly reduced.

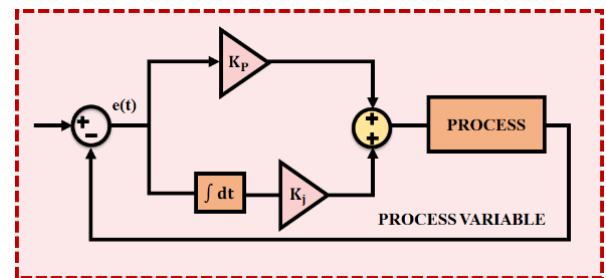


Fig. 8. PI controller circuit diagram.

Through the integration of the proportional and integral actions, the PI controller produces a control output signal that constantly leads the system to the reference value. The

generated control signal is given as a summation of the error and its integral, which guarantees inaccuracies decrease over time and the set point is held consistently. The overall structure is depicted in Figure 8, where the generated control signal is utilized to control the DC-link voltage and stabilize converter operation.

For further improvement in the controller robustness, the PI controller gains (K_p, K_i) are optimized by the GTOA, a population-based metaheuristic motivated by the intelligent and adaptive predatorial tactics of the giant trevally fish (also referred to as giant kingfish). Members of the jack family of predatory sea creatures, giant trevallies dominate their environments through highly adaptive predatorial methods. They are able to hunt singly or as coordinated hunting groups, with the dominant predator within a group typically being the most successful at catching prey.

One outstanding feature of the hunting tactic of giant trevallies is their prowess in jumping out of the water to ambush seabirds, thus showing intelligence, flexibility, and opportunism. This novel tactic has been mathematically formalized into the GTOA for optimization problem solving.

Like other metaheuristic methods, GTOA starts by generating a random population of potential solution candidates known as giant trevallies. Each candidate is a potential solution vector in the search space. The population matrix is written as,

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,Dim} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,Dim} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,j} & \cdots & x_{N,Dim} \end{bmatrix} \quad (15)$$

Here, X_i denotes the i^{th} candidate solution, N is the population size, Dim represents the number of decision parameters, and $x_{i,j}$ stands for value of j^{th} variable of i^{th} candidate solution. After initialization, population size and dimensions are fixed throughout optimization.

Every member is initially given a random position within the assigned search space to ensure complete coverage of feasible regions. This random initialization is controlled by:

$$X_{i,j} = Minimum_j + (Maximum_j - Minimum_j) \times R \quad (16)$$

Where, R is a uniformly distributed random number between $[0, 1]$, $Minimum_j, Maximum_j$ are lower and upper limits of the search space in the j^{th} dimension.

The performance of every candidate is assessed based on an objective function, in this study pertaining to reducing voltage deviation and control error. The objective function value vector is presented as:

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N \times 1} \quad (17)$$

Where, F_i is the fitness of the i^{th} candidate.

Exploration and Exploitation Phases of GTOA:

Hunting behaviour of the giant trevallies is simulated in three primary steps that are evenly balanced between exploration (global search) and exploitation (local tuning):

- Levy flight search on large scale
- Hunting ground selection
- Jumping exploit attack on prey

The broad-scale searches of trevallies for seabirds during the exploration phase are modelled by Levy flights, which enable large jumps and avoid premature convergence. This is represented as:

$$X(t+1) = Best_p \times R + ((Maximum - Minimum) \times R + Minimum) \times Levy(Dim) \quad (18)$$

Where, $X(t+1)$ is position at iteration $t+1$, $Best_p$ is best position so far, and $Levy(Dim)$ simulates random steps with heavy-tailed step lengths.

The Levy function is given as:

$$Levy(Dim) = step \times \frac{u \times \sigma}{|v|^{1/\beta}} \quad (19)$$

Where, $step = 0.01$, β is the Levy flight index (set to 1.5), and u, v are normally distributed random numbers between 0 and 1. The scaling parameter (σ) is calculated as:

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin(\frac{\pi\beta}{2})}{\Gamma(1+\beta) \times \beta \times 2^{\frac{\beta-1}{2}}} \right) \quad (20)$$

In the second stage, trevallies choose the most favourable hunting area based on prey concentration. This adaptiveness is modelled mathematically as:

$$X(t+1) = BestP \times A \times R + MeanInfo - X_i(t) \times R \quad (21)$$

Where, A is a parameter (0.3–0.4) that governs position changes, and $MeanInfo$ is the population-average positional information, computed by:

$$MeanInfo = \frac{1}{N} \sum_{i=1}^N X_i(t) \quad (22)$$

Lastly, during exploitation, the attacking mechanism is emulated by simulating trevallies jumping out of the water and catching seabirds. This includes random distortions simulating visual refraction effects encountered during striking, to provide additional variability in the solution space.

Figure 9 visualizes flowchart of GTOA-PI control strategy depicts a biologically inspired method which adjusts the PI controller parameters in real time so as to control the DC, link voltage in the given power system. After measuring the actual DC, link voltage $V_{DC(act)}$ and setting a reference voltage $V_{DC(ref)}$, the error $e(t)$ is calculated as the difference between these two values. If the error goes beyond a predetermined threshold ϵ , the optimization procedure is activated. Starting PI parameters K_p and K_i are considered, and a population of individuals is created according to GTOA rules. The quality of each individual is determined through an objective function that reflects the performance, usually the minimization of voltage deviation and overshoot. At this point, the algorithm moves to the exploration phase, where it performs a global search using Levy flight operations to widen

the search area. If the number of iterations is not yet at the maximum, the process returns to the exploration again. After reaching the iteration limit, the algorithm goes to the exploitation phase, which includes the operations of hunting ground selection and jump attack in these trevally fish hunting behaviour is simulated, and local search is done by the PI parameters adjusting. The candidate solution with the highest fitness is chosen and the optimized K_p and K_i values are used to produce the final PI output. Such an adaptive tuning method ensures excellent voltage regulation, making it very appropriate for real-time power quality improvement in the envisaged smart UPFC system.

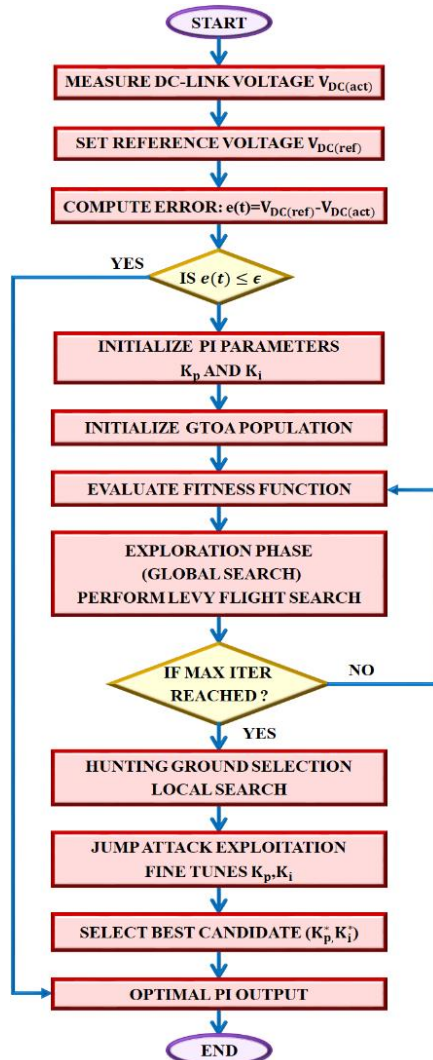


Fig. 9. Flowchart of GTOA-PI control algorithm.

4. Result and Discussion

This section presents a detailed account of the results obtained through MATLAB/Simulink simulation and experimental validation of the proposed framework. A comparative evaluation is also conducted against conventional methods, to demonstrate the superiority of the proposed topology. Furthermore, Table 2 outlines the parameter specifications used in the development and implementation of the system.

Table 2. Parameter specifications

Parameters	Values
PV System	
Open Circuit voltage	37.25V
Short Circuit current	8.95A
Number of cells connected in series	17
Number of cells connected in parallel	5
Rated Power	20kW
ExDoGBoost Converter	
Switching Frequency	10kHz
Inductor (L)	4.7mH
Capacitor (C_1, C_2)	22 μ F
Capacitor C_0	2200 μ F
UPFC	
Turns ratio	1:1
Resistance	0.28 Ω
Leakage Inductance	0.3mH
V_{dc}	600V
Z_{dc}	4700 μ F

Case 1: Constant Condition

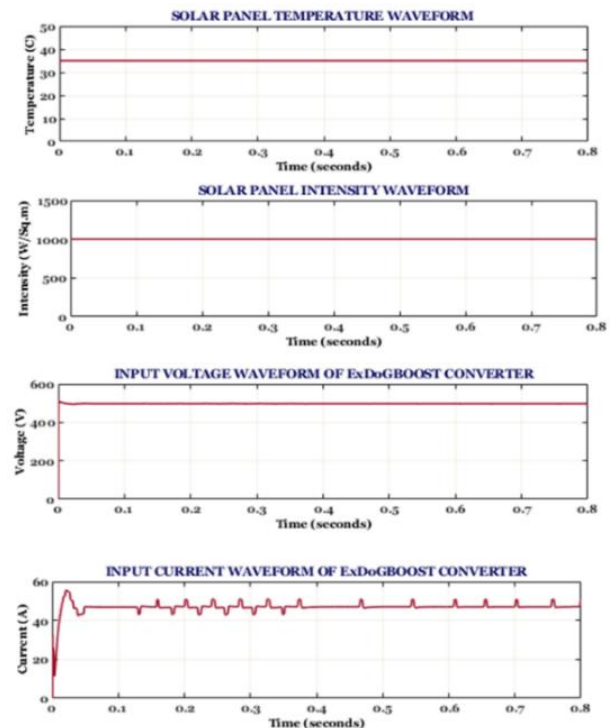


Fig. 10. PV system.

Figure 10 presents PV system response under constant temperature and intensity condition. The PV temperature waveform is constant at around 35°C during the observed time frame. This shows that the solar panel is working under constant ambient conditions without any temperature fluctuations. A constant temperature is good for PV efficiency, as high heat degrades performance. A constant level of irradiance of about 1000 W/m², which is optimum for solar panel performance. With constant irradiance, the solar panel provide a reliable power output, making it easy to design the control strategy for the UPFC system. The input voltage is

held constant at around 500V, which means that the converter is being fed a stable DC supply from the solar panel. This is what happens when temperature and irradiance are also constant, with the panel's output voltage levelling off accordingly. The input current is always approximately 50A, which shows a constant power consumption from the solar panel. This implies that the grid interaction or load demand is balanced and not changing at this time. A fixed current under constant voltage and irradiance conditions verifies that the system is operating in a steady-state mode. This is perfect for testing or baseline analysis, as the engineers can assess the behaviour of the converter without external interference.

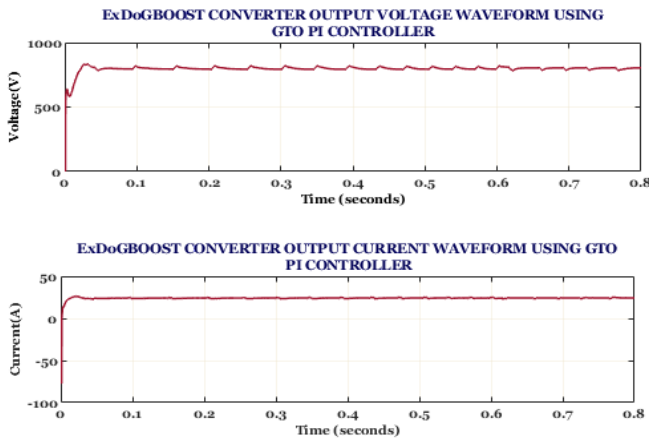


Fig. 11. ExDoGBoost converter.

Figure 11 represents the dynamic behaviour of the ExDoGBoost converter regulated by a GTO PI controller in an intelligent UPFC system for power quality improvement in a grid-connected PV system. The converter voltage graph starts with a short transient period before the output voltage settles to a constant value of 750V. When environmental conditions are kept constant the input to the converter is also constant, and the GTO PI controller rapidly drive the system to its set operating point. The transient describes the initial adjustment of the system, while the rapid settling is a demonstration to the precision and responsiveness of the controller. As with the voltage waveform, the graph of current displays a transient for a very brief moment followed by a stable output current 25A. This action verifies that the input power and load demand are balanced and that the converter is successfully controlling energy flow. The GTO PI controller makes sure the current settles at its desired value quickly and stays steady, which is vital for reliable power supply to the grid.

Case 2: Constant Temperature Varying Intensity Solar Panel Temperature Waveform

Figure 12 displays the PV array temperature, intensity, voltage and current waveform, where both temperature is maintained constant and varying intensity throughout depicted time duration of 0.8s. Temperature is kept constant at about 25°C and the irradiance starts at 800 W/m² and ramps to 1000 W/m² by approximately 0.4 seconds, then remains constant. This represents a real-world condition in which sunlight rises due to cloud movements or environmental variations. The

input voltage of the converter shows that, voltage is constantly maintained at 500V through entire time period with null fluctuations. The input current exhibits oscillating characteristics around 48A, with periodic ripples.

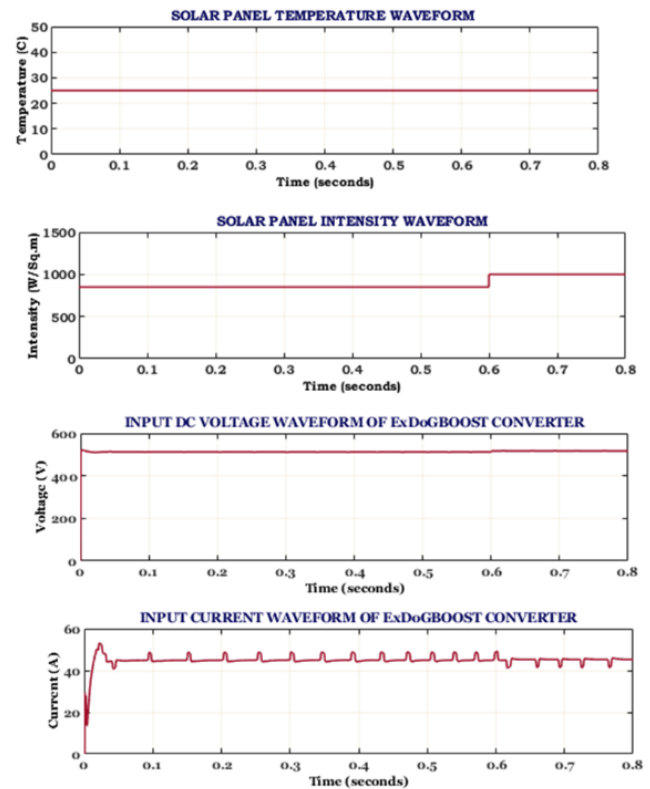


Fig. 12. PV array waveforms.

Figure 13 visualizes the behaviour of the proposed ExDoGBoost converter, controlled using GTO-PI controller, under constant temperature and varying intensity condition, for validating the converter abilities. Output voltage begins around 600V stabilizes and staying across 750V across the entire 0.8-s duration. This stability is impressive considering the fluctuating solar intensity, with temperature kept constant at 25°C, ExDoGBoost converter, driven by the GTO PI controller, effectively controls the output voltage.

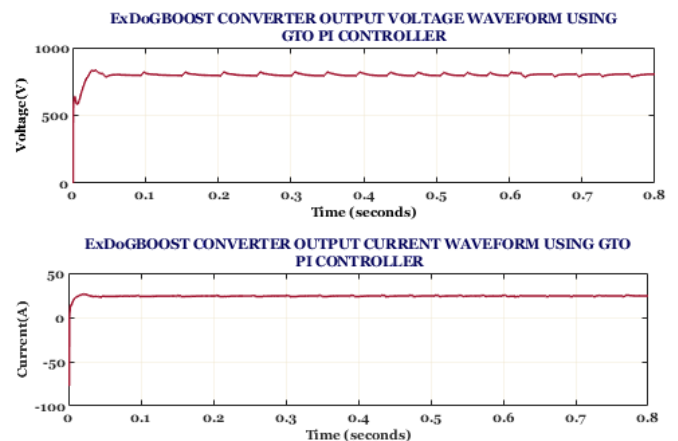


Fig. 13. Proposed ExDoGBoost converter.

The output current stays constant at 25A with minimal ripple, demonstrating the proposed converter's capacity to adjust to rising irradiance and maintain current supply smooth and consistent.

Case 3: Swell +2

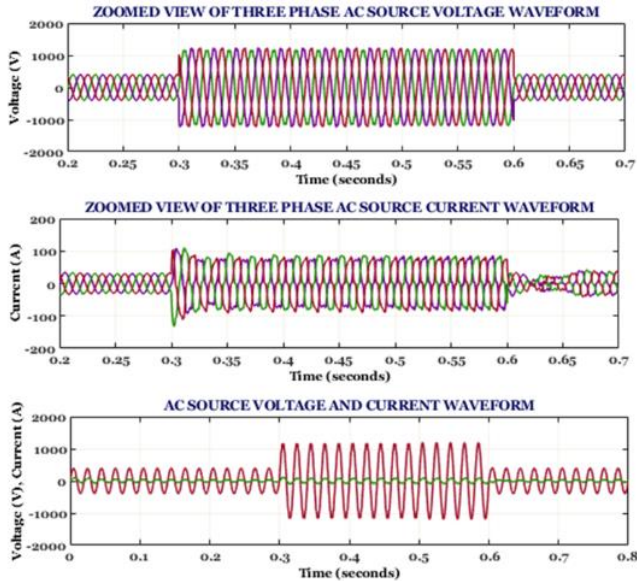


Fig. 14. Three-phase AC waveforms.

Figure 14 illustrates the behaviour of AC source voltage waveform in the swell condition. The three Phase AC source voltage and current with significant sag, which are maintained between $\pm 400\text{V}$ and $\pm 45\text{A}$ respectively. These distortions occurring is a result of the dynamic response of the converter to varying grid conditions. Nevertheless, the overall waveform is stable, indicating that the system is efficiently regulating power supply. The combined waveform indicates both voltage and current over a wider time period. In spite of the swell situation, voltage and current are closely coordinated and in phase, which is a definite indicator of power factor correction as well as harmonic suppression.

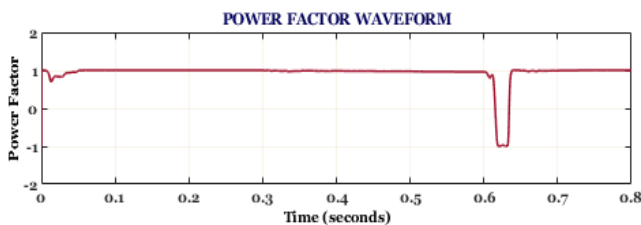


Fig. 15. Power factor.

Figure 15 demonstrates the power factor waveform describing how it behaves in swell, condition. The power factor waveform starts close to unity (1), which means the system is running efficiently with little reactive power. The beginning stability is a result of the UPFC keeping the voltage and current waveforms in synchronization under normal loads. The waveform takes a sharp drop to about -1 around 0.63 seconds, which is an indication of a transient disturbance here, the swell event. The negative indicates that the system temporarily entered a leading power factor condition, perhaps

due to overcompensation or reactive power flow reversal. The quick return of the power factor to close to unity at 0.65 seconds is due to the smarter control approach built into the UPFC.

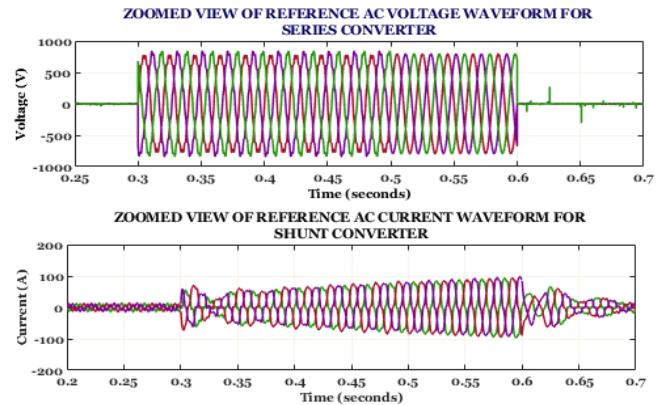


Fig. 16. Series and shunt converter.

Figure 16 indicates the reference AC voltage and current waveform of series and shunt converter under condition of swell. The reference AC voltage waveform of the series converter illustrates a high-frequency sinusoidal signal with amplitude modulation of up to $\pm 750\text{V}$, signifying that the series converter is actively injecting compensating voltage to compensate for the sag and stabilize the grid-side voltage. AC reference current waveform of the shunt converter indicates a sinusoidal waveform with amplitude fluctuations within $\pm 20\text{A}$, capturing the function of the shunt converter for reactive power assistance and harmonic reduction during sag conditions. These waveforms, illustrate the coordinated functioning of series and shunt converters, demonstrating UPFC system's ability to maintain voltage and current stability, damp disturbances, and improve overall power quality in real time.

Figure 17 shows three-phase load voltage and current waveforms in scenario SAG +2, disturbances in a grid-connected PV setup is exhibited by the system. In the three-phase load voltage waveform, sinusoidal signals with a clear disturbance around 0.3 seconds are shown. This fluctuation is equivalent to the SAG +2 event, in which the grid suffers a momentary reduction in voltage caused by external disturbances like fault conditions or rapid load changes. In spite of the sag, the waveform rapidly settles, reflecting the fact that the UPFC system, actively injecting counteracting voltage to bring load-side voltage back to normal. In three-phase load current waveform, there is a similar transient action in the same time interval. The current waveforms have a short fluctuation before they return to steady-state sinusoidal forms. The intelligent control strategy facilitates to make output change to ensure current stability, keep harmonic distortion suppressed, and assist in the dynamic demand of the load.

Figure 18 exhibits the response of the real and reactive power waveforms under voltage sag +2 condition. In the real power waveform, a steady power output initially attained followed by a sharp dip at about 0.3 seconds corresponding to the initiation of the SAG +2 event. This dip signifies a transient decrease in active power supply as a result of the

voltage dip produced by grid perturbations or load variations. In the reactive power waveform, high-frequency oscillations are observed within the same time frame, the reactive power injection to assist voltage recovery and stabilize the system.

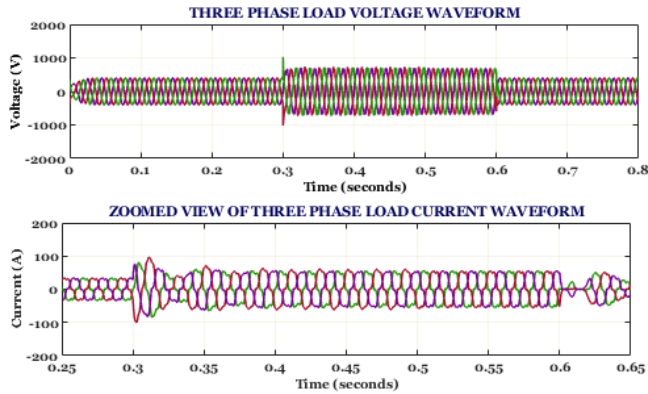


Fig. 17. Three-phase load waveforms.

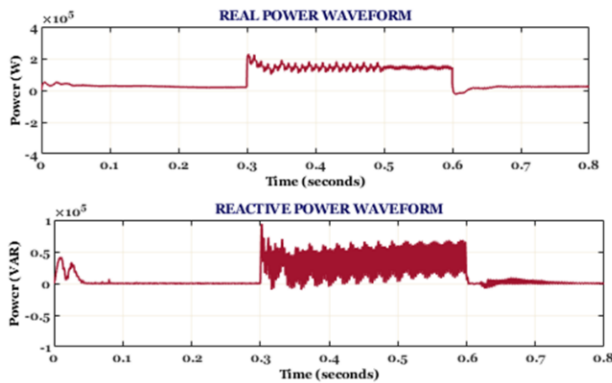


Fig. 18. Real and reactive power.

Case 4: SAG-2

Figure 19 presents the waveform of the dynamic responses of the proposed intelligent UPFC system under a voltage sag condition in a grid-connected PV setup. Three-phase AC source voltage waveform, shows a minor dip in amplitude pointing towards the initiation of the SAG-2 condition. In spite of this perturbation, the waveform is sinusoidal in shape and phase synchrony, which clearly shows the efficiency of the series converter in injecting compensating voltage. The ExDoGBoost Converter provides a stable DC-link voltage so that the series converter, react rapidly and regulate voltages. The PI controller optimized through the GTO algorithm helps improve further voltage regulation, such that there is little deviation from nominal values. The three-phase AC source current waveform demonstrates small amplitude variations across the sag interval, indicating DNN produces adaptive reference currents, enabling the shunt converter to dynamically adjust its output based on grid conditions.

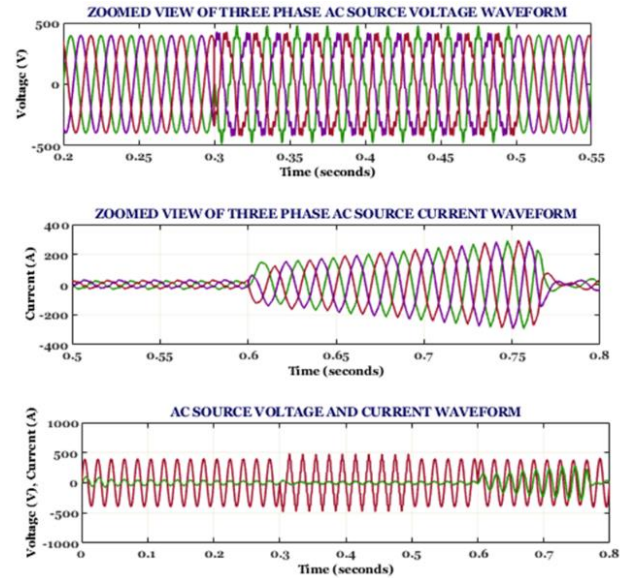


Fig. 19. AC source waveforms.

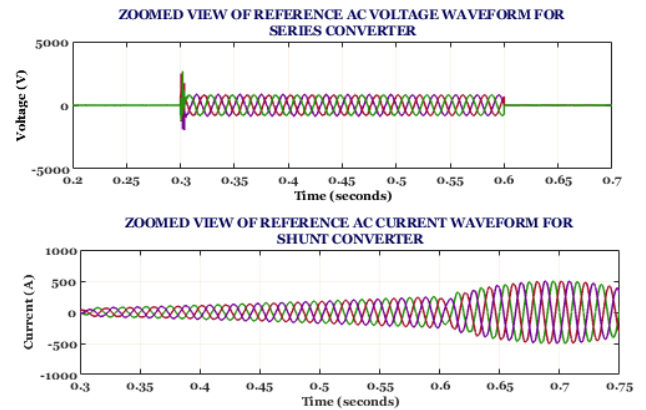


Fig. 20. Series and shunt converter waveforms.

Figure 20 represents the dynamic correction ability of the intelligent ExDoGBoost-enabled UPFC system in a grid-interfaced PV installation. Reference AC voltage waveform of the series converter, exhibits the sinusoidal waveform with high amplitude oscillations for the time period of 0.3 to 0.55 seconds. Reference AC current waveform of the shunt converter shows sinusoidal current starting off with low value and increasing over time and topping off this is in accordance with the response of the system to the SAG-2 condition when the grid voltage falls below nominal levels as a result of some disturbance. The smart control mechanism maintains the voltage waveform as sinusoidal and phase-synchronized, even under the sag occurrence, thus maintaining power supply integrity.

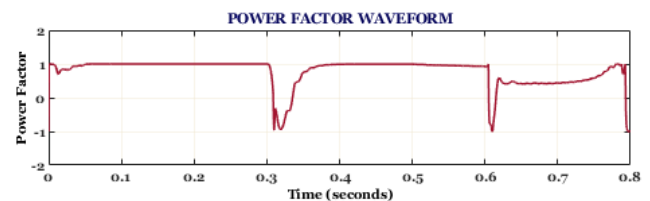


Fig. 21. Power factor.

Figure 21 displays the power factor waveform, an essential measure of the effectiveness with which electrical power is being consumed, and the oscillations under sag conditions indicate the system's capability to absorb and recover under stress. The UPFC system consisting of a series converter, shunt converter, and an ExDoGBoost is to actively control voltage and current, inhibit harmonics, and regulate reactive power. The control scheme is supplemented by a GTOA-based PI controller for DC-link voltage and a DNN for adaptive current output. In the PF waveform, steep changes are noticed and the fluctuations are highest near the sag event, showing the system attempting to compensate for the disparity between real and reactive power. The smart control system, however, learns to adapt very quickly, and the waveform starts stabilizing, showing the UPFC's ability to correct efficient use of power.

Figure 22 illustrates the impact of a voltage sag event on the three-phase electrical load and the corrective response of the Intelligent ExDoGBoost-enabled UPFC system integrated with a grid-connected PV source. In the three-phase load voltage waveform, the sinusoidal signals show clear disturbances around 0.3 and 0.7 seconds. These dips in amplitude are indicative of the SAG-2 condition, where the grid voltage momentarily drops below nominal levels. Despite these transients, the waveform quickly recovers, ensuring that the DC-link voltage remains stable and maintain voltage symmetry across all three phases. The three-phase load current waveform, similar disturbances with fluctuations in amplitude and waveform shape. The DNN generates adaptive reference currents, allowing the shunt converter to adjust its output dynamically in response to changing grid conditions. Waveform's recovery and return to a balanced sinusoidal form confirm the system's ability to suppress current distortion and maintain reliable power delivery.

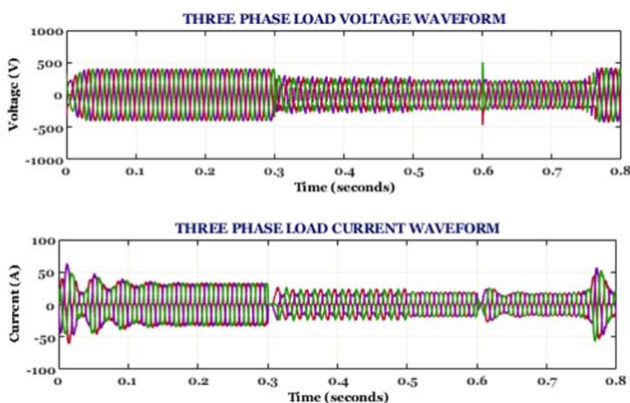


Fig. 22. Three-phase load.

Figure 23 visualizes behavior of real and reactive power waveforms during voltage sag event in a grid-connected PV environment. Voltage sag, typically caused by grid faults or sudden load changes, can significantly disrupt power flow and degrade power quality. The real power waveform, the plot initially shows a stable power output, indicating normal operating conditions. Around 0.3 seconds, a noticeable drop followed by oscillations occurs, marking the onset of the SAG-2 condition. This dip in real power is a direct

consequence of the voltage sag, which temporarily reduces the system's ability to deliver active power. In the reactive power waveform, a similar pattern is observed. The waveform begins with a steady reactive power level, followed by a drop and oscillations around 0.3 seconds. The proposed UPFC system, which integrates a ExDoGBoost, a GTOA-optimized PI controller, and a DNN, is designed to actively regulate voltage and current, suppress transients, and maintain system stability under such conditions.

Figure 24 demonstrates the analysis of harmonic distortion across three different scenarios, each represented by a frequency spectrum bar graph centered on a fundamental frequency of 50 Hz. In all three phases, the THD values are notably low 1.95%, 1.86%, and 1.71% respectively indicating effective suppression of harmonic components in the system. These results reflect the performance of the intelligent ExDoGBoost-enabled UPFC system in maintaining power quality within a grid-connected PV environment. This harmonic analysis validates the system's capability to reduce signal distortion, enhance waveform purity, and ensure stable and efficient power delivery in renewable-integrated networks.

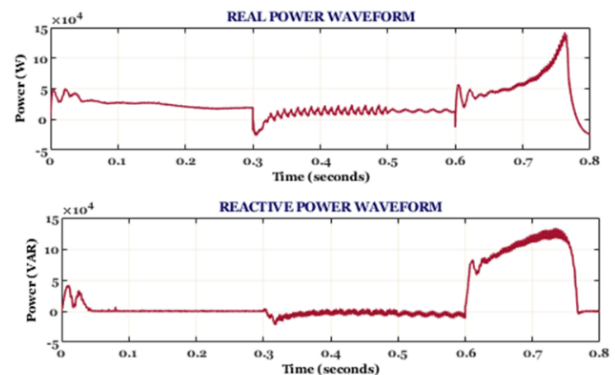


Fig. 23. Real and reactive power.

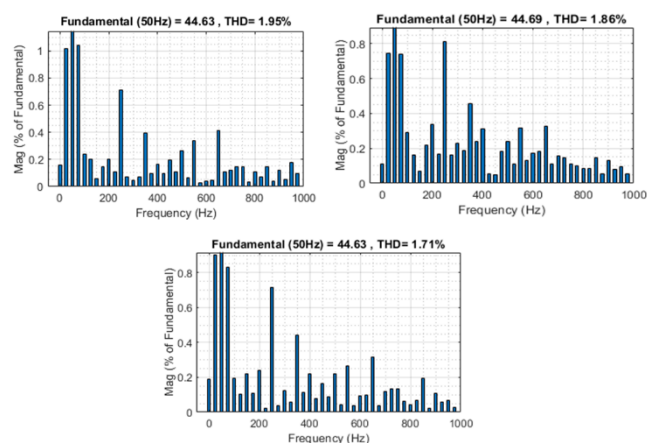


Fig. 24. THD waveforms.

5. Discussion

The simulation results presented in Section 4 vividly illustrate the outstanding functionality of the ExDoGBoost, powered UPFC as a versatile device in the power system. The

proposed system maintain steady voltage and current levels under constant solar conditions, thus acting as a reliable steady, state operation unit. In the face of a changing solar irradiance, the converter is able to keep the DC, link voltage at the desired level and delivers a current free of ripples, thus showing the fast response of the GTO, optimized PI controller. The integration of the series and shunt converters at the point of voltage swell and sag provides timely voltage compensation, reactive power support, and fast recovery of power factor. Furthermore, the low THD values at all phases attest to the effectiveness of the harmonic suppression technique. The simulation results, serve as a proof that the proposed intelligent UPFC is capable of voltage regulation, power factor, and power quality improvement, while being strongly resistant to PV and grid variations.

Figure 25 shows the comparison of the efficiency of various converter topologies, each with their respective efficiency ratings. Of all the converters listed, the proposed converter registers the best efficiency rate at 96%, indicating its superior energy conversion performance. The traditional DC-DC boost converter [27] at 92.40%, followed by the Switched Inductor Boost (S-I B) [28] converter at 94.30%, and

Interleaved Quadratic Boost (IQB) [29] converter reaches an efficiency of 94.80%.

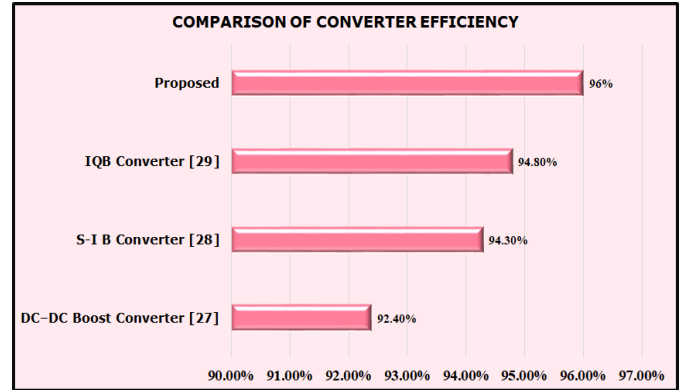


Fig. 25. Comparison of efficiency.

The enhanced performance of proposed converter is realized as a result of incorporating the extended double gain step-up into the boost converter, which ensures minimal power loss and maximum voltage gain under dynamic operating conditions.

Table 3. Comparative study of converter components

Converter Topologies	Switches	Diodes	Capacitor	Inductor	Total No.of components
DC-DC Boost [27]	2	2	5	5	14
IQB [29]	4	2	4	2	12
Proposed	1	4	3	2	10

Table 3 represents the comparison of different converter topologies in terms of number of components. Table compares the performance of DC-DC Boost [27], IQB [29] with proposed ExDoGBoost converter. The proposed converter exhibits high efficiency (96%) with fewer components and

provides high voltage gain with the use of soft-switching for minimizing losses. Such an efficient design performs better than the conventional techniques, highlighting its superiority for enhancing power quality in grid-connected PV based UPFC applications.

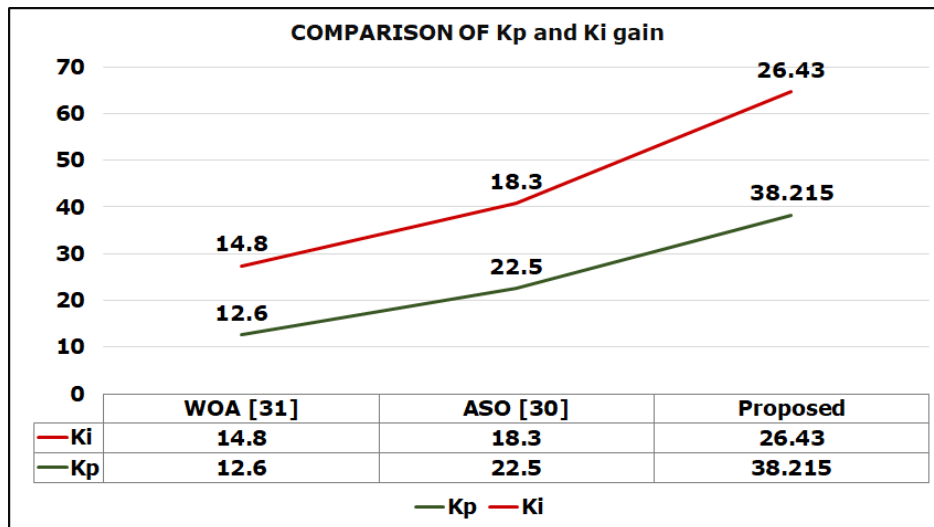


Fig. 26. Comparison of gain parameters.

Figure 26 exhibits the comparison of proportional (K_p) and integral (K_i) gains for different optimization control methods: WOA [26], ASO [25], and the proposed method. As indicated, the proposed method maximizes gain values at $K_p = 38.215$ and $K_i = 26.43$, demonstrating a more sensitive

and well-adjusted control system. Conversely, Atomic Search Optimization (ASO) [30] and Whale Optimization Algorithm (WOA) [31] provides the smallest gains, indicating a reduced response and possibly a less effective dynamic regulation.

Table 4. Comparative analysis of converter topologies

Converter	Voltage gain capability	Main active devices		Passive components		Switching Frequency	Relative efficiency
		Switch	Diode	Inductor	Capacitor		
Conventional boost	Medium	1	1	1	1	10kHz	Moderate
SEPIC converter	Medium-high	1	2	2	2	10kHz	Moderate
Cuk converter	Medium-high	1	1	2	2	10kHz	Moderate
Proposed ExDoGBoost	High	1	3	1	3	10kHz	High

Table 4, the efficiency assessment accounted for conduction, switching, and passive component losses for all converters at 10 kHz. Conventional Boost, SEPIC, and Cuk converters exhibited moderate efficiency levels, which were attributed to higher device stress and passive losses. By contrast, the ExDoGBoost, achieve a higher voltage gain and also reduce the ripple to a minimum. As a result, the ExDoGBoost attain better efficiency and lower losses than the other converters, thereby making it the most appropriate one for dynamic PV, UPFC applications.

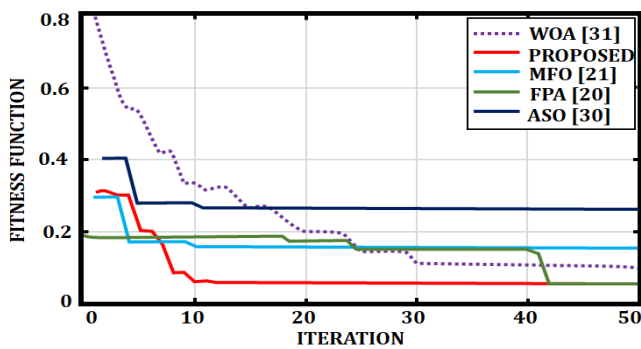


Fig. 27. Comparison of convergence.

Figure 27 displays the convergence characteristics of five optimization algorithms within 50 iterations, by comparing their fitness function values. Proposed The algorithm demonstrates the quickest and most stable convergence, as it achieves the lowest fitness value, which is a clear indication of the best optimization performance. On the other hand, WOA [31], MFO [21], FPA [20], and ASO [30] are showing slower convergence. Thus, it is concluded that the proposed method is very efficient and robust in terms of minimizing the objective function.

Figure 28 presents the dynamic performance of UPFC control methods, Fuzzy Logic Controller (FLC) [32], Fractional-Order Proportional–Integral–Derivative controller (FO-PID) [33], and the proposed DNN method on their settling time. The FLC [32] has the maximum settling time of 2.63 seconds and is indicative of slower system response and lagging stabilization. The FO-PID [33] is much better with a lesser settling time of only 0.64 seconds and is reflective of higher control accuracy and quicker convergence. The Proposed method beats both with an extremely low settling time of only 0.3 seconds. This higher performance is credited to the use of the DNN for adaptive current control in the intelligent UPFC system.

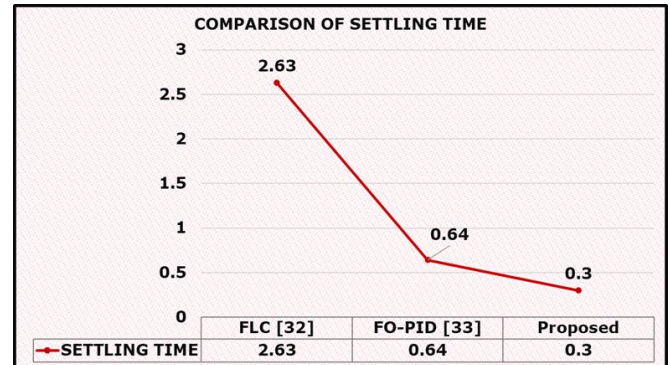


Fig. 28. Comparison of UPFC based controllers.

6. Conclusion

The proposed intelligent ExDoGBoost-enabled UPFC system provides a robust solution for mitigating critical power quality issues such as voltage sag, swell, and harmonic distortion in grid-connected PV environments. By integrating a UPFC architecture with coordinated series and shunt converters, the system achieves dynamic voltage regulation, reactive power compensation, and enhanced power flow management. The inclusion of the ExDoGBoost converter ensures high voltage gain and stable DC-link operation, even under fluctuating solar irradiance, thereby improving efficiency and reducing stress on switching devices. Furthermore, the GTOA-optimized PI controller delivers precise voltage regulation, while the DNN enhances adaptability by generating intelligent reference currents for responsive converter control. Simulation results validate the effectiveness of the proposed system, demonstrating a significant reduction in THD to 1.71%, improved power factor stability, minimized power ripple, and efficient recovery of real and reactive power during transient events. With a converter efficiency of 96% and reduced settling and rise times of 0.3 s, the system proves to be a reliable and scalable solution for renewable-integrated distribution networks. Overall, this research highlights the potential of combining advanced converter topologies with AI-driven control strategies to achieve sustainable, high-quality power delivery, paving the way for future applications in smart grids and large-scale renewable energy integration.

Acknowledgements

Not applicable.

Author Contributions

J. P. Srividhya: Conceptualization, Methodology, Writing-Original Draft.

D. Meena: Data Curation, Investigation, Validation.

S. Tamil Selvi: Formal Analysis, Visualization, Writing-Review & Editing.

R. Suresh: Supervision, Project Administration, Writing-Review & Editing.

Conflict of Interest

The authors declare no conflict of interest.

References

- [1] O. Tasdemir, M. Yesilbudak, and E. Irmak, "Day-ahead photovoltaic power production forecasting using a hybrid artificial neural network model integrated with metaheuristic algorithms", *International Journal of Smart Grid-ijSmartGrid*, vol. 9, no. 4, pp. 210-218, 2025.
- [2] S. Smonia Joe Princy, C. Hentry, N. Alharbi, H. Siddiq, M. Refaei, H. Alzahrani, M.R. Bindhu, V. Sarojini, and S. Sasi Florence, "Synergistic antimicrobial and photocatalytic properties of PVP-Ag- PEG nanocomposites for sustainable leachate treatment", *Journal of Inorganic and Organometallic Polymers and Materials*, pp. 1-19, Dec. 2024.
- [3] S.M Islam, A.A Salema, I.A Sarker, and R.F Tanima, "Design, sizing and economic analysis of grid-connected solar PV (GCPV) system for an electric bus depot in Malaysia", *International Journal of Renewable Energy Research (IJRER)*, vol. 15, no. 4, pp. 860-876, 2025.
- [4] S. Jayaraman Panneerselvam, Y. Krishnamoorthi, S. Ramamoorthy, and J. Selvaraj, "Optimal allocation of distributed generation for power flow enhancement in distribution network", *Optimal Control Applications and Methods*, vol. 44, no. 6, pp. 3168-3184, Nov. 2023.
- [5] M.A. Prabhu, G.E. Sheela, A.M. Mohammad, R.A. Hegazy, S.S. Florence, and V. Sarojini, "Biogenic synthesis of silver, gold, and palladium nanoparticles using moringa oleifera seeds: exploring photocatalytic, catalytic, and antimicrobial activities", *Advances in Natural Sciences: Nanoscience and Nanotechnology*, vol. 15, no. 1, pp. 015007, Jan. 2024.
- [6] K. Zhang, Z. Chen, J. Wang, C. Yu, H. Long, and C. Wang, "A fast- response power-flow control strategy of MMC-UPFC based on active disturbance rejection control", *IEEE Access*, vol. 12, pp. 177553-177564, Aug. 2024.
- [7] J. P. Srividhya, and D. Sivakumar, "Monitoring and analysis of PQ parameters after first order derivative function to suppress the background instability in harmonic signal", *Journal of Computational and Theoretical Nanoscience*, vol. 14, no. 7, pp. 3220-3226, Jul. 2017.
- [8] S. K. Kumar, K. A. Tebeje, A. S. Endris, and K. S. Kavin, "Power factor correction using sensorless BLDC motor for wide speed operation with bridgeless converter topology", *International Journal of Modern Trends in Engineering and Research (IJMTER)*, vol. 4, no. 6, pp. 13-23, Jun. 2017.
- [9] E Hrayshat, "Techno-economic analysis of an autonomous hybrid PV-Biomass-Battery power system", *International Journal of Renewable Energy Research (IJRER)*, vol. 15, no. 4, pp. 675-684, 2025.
- [10] A. K. Priya and A. Yazhini, "Integrating whale optimization algorithm and machine learning for efficient traffic management", *International Journal of Advanced Trends in Engineering and Management (IJATEM)*, vol. 2, no. 10, pp. 12-23, 2023.
- [11] D. Sivakumar, J. P. Srividhya, and T. Shanmathi, "A Review on power quality monitoring and its controlling techniques", In *8th International Conference on Latest Trends in Engineering and Technology*, vol. 1, no. 1, pp. 3-9, May. 2016.
- [12] P.L. Rose, V. Sarojini, and G.D. Biji, "Antibacterial and anticancer activity of green synthesised silver nanoparticles using polysaccharides extracted from the marine alga portieria hornemannii", *Journal of Applied and Natural Science*, vol. 16, no. 1, pp. 69-76, Mar. 2024.
- [13] K. S. Kavin, P. SubhaKaruvellam and P. Kavitha, "Energy Management of AC Grid by the Solar PV System Using Landsman Converter," *SSRN Electronic Journal*, 2020.
- [14] S. S. Biswal, D. R. Swain, and P. K. Rout, "Inter-area and intra-area oscillation damping for UPFC in a multi-machine power system based on tuned fractional PI controllers", *International Journal of Dynamics and Control*, vol. 10, no. 5, pp. 1594-1612, Oct. 2022.
- [15] Y. Chen, H. Wang, M. Zhu, M. Liu, J. Ma, and X. Cai, "Passive sliding mode controlled UPFC and its treatment strategy of unbalanced grid conditions", *Frontiers in Energy Research*, vol. 9, pp. 712397, Jul. 2021.
- [16] P. Jagtap, and V.K. Chandrakar, "Intelligent method for Power flow using artificial neural network with UPFC", *Journal of Physics: Conference Series*, vol. 2763, no. 1, pp. 012004, May. 2024.
- [17] R. Kassem, N.F. Ibrahim, M.M. Mahmoud, A. Alkuhayli, U. Khaled, A. Beroual, and H. Saleeb, "Enhanced multiphase interleaved boost converter interface for grid-connected PV power system", *IEEE Access*, vol. 12, pp. 134245-134258, Sep. 2024.
- [18] H. Tekin, K. Bulut, and D. Ertekin, "A novel switched-capacitor and fuzzy logic-based quadratic boost converter with mitigated voltage stress, applicable for DC micro-grid", *Electrical Engineering*, vol. 104, no. 6, pp. 4391-4413, Dec. 2022.
- [19] M. Dehghan, H. Gholizadeh, R.S. Shahrivar, S. Amini, and H. Vahedi, "Quadratic boost DC-DC converters

capable of being extended to improved topologies”, IEEE Access, vol. 13, pp. 112345–112359, Jul. 2025.

- [20] S.B. Masikana, G. Sharma, S. Sharma, and E. Çelik, “Frequency regulation in solar PV-powered thermal power system using FPA-PID controller through UPFC and RFB”, *Electrical Engineering*, vol. 107, no. 7, pp. 8665-8677, 2025.
- [21] A. Wadood, and H. Park, “A novel application of fractional order derivative moth flame optimization algorithm for solving the problem of optimal coordination of directional overcurrent relays”, *Fractal and Fractional*, vol. 8, no. 5, pp. 251, Apr. 2024.
- [22] K. Srilakshmi, D. Sundaragiri, S. Gaddameedhi, R. Vangalapudi, P. K. Balachandran, I. Colak, and S. Selvarajan, “Simulation of grid/standalone solar energy supplied reduced switch converter with optimal fuzzy logic controller using golden Ball Algorithm”, *Frontiers in Energy Research*, vol. 12, pp. 1370412, 2024.
- [23] L. B. Chilakapati, “Power quality improvement in a grid connected Solar-PV system with adaptive neuro-fuzzy controller based UPQC”, *International Research Journal of Multidisciplinary Technovation*, vol. 7, no. 1, pp. 264-279, 2025.
- [24] R. Rudraram, S. Chinnathambi, and M. Mani, “PV integrated UPQC with intelligent control techniques for power quality enhancement”, *International Journal of Electrical and Electronics Research*, vol. 11, no. 1, pp. 202-212, 2023.
- [25] M. Sravani, and P. VS Sobhan, “Deep reinforcement learning-based controller for DC-link voltage regulation and voltage sag compensation in a solar PV-integrated UPQC system”, *Scientific Reports*, vol. 15, no. 1, pp. 25800, 2025.
- [26] A. Rostamipour, M. Abdi, and A. Ghayeni, “Presenting a control method using UPQC and PV array to reduce voltage drop and current harmonics during distribution system,” *International Journal of Power Electronics*, vol. 20, no. 3, pp. 243-265, 2024.
- [27] M. Samiullah, M.D. Siddique, A. Iqbal, P.K. Maroti, and S. Banerjee, “A non-isolated symmetrical design of voltage lift switched-inductor boost converter with higher gain and low voltage stress across switches”, *IET Power Electronics*, vol. 19, Art. no. e12433, 2026.
- [28] D. Ferreira, A. Cordeiro, P. Gambôa, L. Rocha, F. Barata, J. Fernando Silva, F. J. Martins, and V. Fernão Pires, “Interleaved quadratic boost DC-DC Converter with extended voltage gain and reduced switch voltage stress for photovoltaic applications”, *Open Research Europe*, vol. 5, pp. 55, Feb. 2025.
- [29] M. Hosseinpour, E. Seifi, A. Seifi, and S. Sajedi, “A novel interleaved nonisolated high gain DC–DC boost converter based on voltage multiplier rectifier”, *Scientific Reports*, vol. 15, no. 1, pp. 26284, Jul. 2025.
- [30] M. M. Salama, M. I. Mosaad, and H. A. AbdelHadi, “Performance enhancement of grid-connected renewable energy systems using UPFC”, *Energies*, vol. 16, no. 11, pp. 4362, May. 2023.
- [31] M.I. Mosaad, H.S.M. Ramadan, M. Aljohani, M.F. El-Naggar, and S.S. Ghoneim, “Near-optimal PI controllers of STATCOM for efficient hybrid renewable power system”, *IEEE Access*, vol. 9, pp. 34119-34130, Feb. 2021.
- [32] P. Jagtap, and V. K. Chandrakar, “Advanced UPFC controllers to improve transient and dynamic stability of power system”, *Journal of Physics: Conference Series*, vol. 2763, no. 1, pp. 012003, May. 2024.
- [33] H. Ababsia, D. Dib, and A. Djeddi, “Optimal control of the UPFC for the stability of electrical networks”, *International Journal of Applied Power Engineering*, vol. 14, no. 1, pp. 180-187, Mar. 2025.

APPENDIX A:

UPQC Principle of Operation

Fundamental working principle of UPFC is to inject a series voltage (V_s) with a certain magnitude and phase angle with respect to sending-end voltage (V_1). The line voltage is thus modified to:

$$V_2 = V_1 + V_s \quad (23)$$

This changes the effective transmission angle (δ), with both transmitted real power and reactive power controllable. The basic equations that determine power flow are:

$$P = \frac{V_s V_r}{X} \sin(\alpha - \beta) \quad (24)$$

$$Q = \frac{V_r}{X} (V_s - V_r) \quad (25)$$

Where, V_s and V_r are sending and receiving end voltages, (X) is reactance of a line, and (α, β) are phase angles.

The transmitted power and reactive power with injected voltage are given by:

$$P = P \left(P - \frac{V_r}{X} \sin \delta \right), Q = Q_r \left(Q - \frac{V_r}{X} (1 - \cos \delta) \right) \quad (26)$$

For general modelling, the injected power and voltage constraints are given by:

$$V_{pq} = \Delta V + V_\sigma + V_q \quad (27)$$

$$Q_r \{Q_r(\delta) - 1\}^2 + \{P_o(\delta)\}^2 = 1 \quad (28)$$

When there is no series injection ($V_{pq} = 0$):

$$P = jQ_r = V_r \left(\frac{V_s - V_r}{jX} \right) \quad (29)$$

With series injection ($V_{pq} \neq 0$):

$$P = jQ_r = V_r \left(\frac{V_s - V_r}{jX} + \frac{V_r V_{pq}}{-jX} \right) \quad (30)$$

Sending and receiving end voltages in phasor form are:

$$V_s = V e^{j\delta/2} = V \left(\cos \frac{\delta}{2} + j \sin \frac{\delta}{2} \right) \quad (31)$$

$$V_r = V e^{-j\delta/2} = V \left(\cos \frac{\delta}{2} - j \sin \frac{\delta}{2} \right) \quad (32)$$

And the injected series voltage in phasor form is:

$$V_{pq} = V_{pq} e^{j(\delta/2 + \rho)} = V_{pq} \left(\cos \left(\frac{\delta}{2} + \rho \right) - j \sin \left(\frac{\delta}{2} + \rho \right) \right) \quad (33)$$

APPENDIX B:

DEEP COUPLED NETWORK

The dynamic relationship between the synthetic input vector $u(s)$, and the system output vector $y(s)$ is expressed as

$$y(s) = G_p(s)D(s) \cdot u(s) \quad (34)$$

Where, $G_p(s)$ is scaled process transfer function matrix of PV-UPFC system and $D(s)$ is the decoupling matrix that projects the original inputs to synthetic inputs. For a two-variable case, the relation can be expressed as:

$$\begin{bmatrix} y_1(s) \\ y_2(s) \end{bmatrix} = G_p(s)D(s) \begin{bmatrix} u_1(s) \\ u_2(s) \end{bmatrix} \quad (35)$$

Here, $y_1(s)$ and $y_2(s)$ equal to control values like bus voltage amplitude and harmonic distortion factor, whereas $u_1(s)$ and $u_2(s)$ are the control input signals extracted from UPFC converters.

A perfect decoupler is given by:

$$D(s) = \begin{bmatrix} \tilde{g}_{11}(s) & 0 \\ 0 & \tilde{g}_{22}(s) \end{bmatrix} \quad (36)$$

Which shows that every control channel is totally decoupled. In actual grid-connected systems, precise process modelling is difficult because of nonlinearities, parameter uncertainties, and time-varying disturbances. Therefore, a reduced decoupler is employed:

$$D(s) = \begin{bmatrix} 1 & d_{12}(s) \\ d_{21}(s) & 1 \end{bmatrix} \quad (37)$$

By multiplying the process transfer matrix with this reduced decoupler, the resulting decoupled process dynamics are:

$$G_p(s)D(s) = \begin{bmatrix} g_{11}^*(s) & 0 \\ 0 & g_{22}^*(s) \end{bmatrix} \quad (38)$$

Where, the decoupling terms are computed as:

$$d_{12}(s) = \frac{\tilde{g}_{12}(s)}{\tilde{g}_{11}(s)}, d_{21}(s) = \frac{\tilde{g}_{21}(s)}{\tilde{g}_{22}(s)} \quad (39)$$

The compensated diagonal terms are derived as:

$$g_{11}^*(s) = \tilde{g}_{11}(s) - \frac{\tilde{g}_{12}(s)\tilde{g}_{21}(s)}{\tilde{g}_{22}(s)}, g_{22}^*(s) = \tilde{g}_{22}(s) - \frac{\tilde{g}_{21}(s)\tilde{g}_{12}(s)}{\tilde{g}_{11}(s)} \quad (40)$$

The decoupled outputs are subsequently expressed as:

$$y_1(s) = g_{11}^*(s)u_1(s), y_2(s) = g_{22}^*(s)u_2(s) \quad (41)$$

Equation (41) evident that each synthetic input only affects its corresponding output, which forms the basis of the developed DNN strategy. This enables the UPFC to be regulated as a collection of decoupled loops instead of as a highly coupled nonlinear system, greatly easing controller design