Cost-effective optimization of unified power quality conditioner in wind energy conversion systems using a hybrid EnHBA-GWO algorithm

Shaziya Sultana, Umme Salma
Department of Electrical Engineering, GITAM (Deemed to be University), Visakhapatnam, India

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ABSTRACT

The rapid integration of wind energy conversion systems (WECS) into modern power networks has led to pressing power quality concerns, including voltage instability, harmonic distortion, and reactive power imbalance. To address these challenges, this study introduces a hybrid optimization strategy that combines the global search capabilities of the enhanced honey badger algorithm (EnHBA) with the local exploitation strengths of the grey wolf optimizer (GWO) for the best operational parameters of a unified power quality conditioner (UPQC). Extensive simulations in MATLAB Simulink demonstrate significant improvement in performance. The proposed method achieves 95% energy efficiency, a power factor of 0.99, and total harmonic distortion (THD) down to 5%, meeting IEEE 519-2022 standards. This outcome reflects an effective balance between cost and power quality performance, highlighting the potential of hybrid optimization to improve grid stability and efficiency in renewable energy environments.

Corresponding Author:

Shaziya Sultana
Department of Electrical Engineering, GITAM (Deemed to be University)
Visakhapatnam, Andhra Pradesh, India
Email: shaziya.2kn@gmail.com

1. INTRODUCTION

As global energy demands grow and the transition to sustainable resources accelerates, wind energy conversion systems (WECS) have become a vital component of modern power grids. However, the intermittent and variable nature of wind introduces significant power quality (PQ) issues, such as voltage fluctuations, harmonic distortions, and reactive power imbalances. These disturbances challenge the reliability, efficiency, and stability of grid-connected systems. Capable of both series and shunt compensation, the unified power quality conditioner (UPQC) has grown to be a valuable instrument for addressing such issues. Because UPQCs may lower harmonics, stabilize voltage, and raise power factor, they are especially helpful in renewable-integrated systems. Maintaining power quality at the point of common coupling (PCC), calls for the best UPQC performance as WECS penetration rises. Traditional optimization approaches, like the whale optimization algorithm (WOA), sine cosine algorithm (SCA), and particle swarm optimization (PSO), have been employed to change UPQC settings. These methods often fail in dynamic environments like WECS, where even with certain advances, in dynamic environments like WECS, where maintaining a consistent balance between performance and cost is complex. In response, this paper suggests a new combined optimization method that uses the enhanced honey badger algorithm (EnHBA) to explore globally and the grey wolf optimizer (GWO) to fine-tune local solutions. This combined approach aims to enhance UPQC control in WECS by improving key factors like energy efficiency (EE), voltage stability index (VSI), total harmonic distortion (THD), power factor improvement (PFI), system reliability (RIS), and operational cost, all at once. The broader context of this work builds on previous research into bio-inspired and AI-based optimization techniques for power system applications. Earlier studies developed algorithms like HBA and GWO, and later research investigated using neural networks, fuzzy logic, and evolutionary strategies to smartly adjust UPQC settings. Recent studies have explored advanced metaheuristic algorithms for power quality (PQ) control and optimization in renewable energy systems [1]–[3], intelligent UPQC tuning strategies using hybrid techniques [4]–[6], and AI-based control frameworks including neural networks and ANFIS controllers [7]–[10]. These efforts collectively demonstrate the potential of adaptive and intelligent solutions in mitigating PQ issues such as harmonics, voltage fluctuations, and non-linear load effects in smart grids. Building on this foundation, the present study proposes a unified control framework leveraging hybrid optimization and machine learning to enhance PQ in RES-integrated microgrids. The following sections detail the system configuration, control methodology, and performance validation. Other efforts have investigated hybrid energy integration [11]–[14], advanced controller design [15]–[20], and comprehensive metaheuristic frameworks [21]–[26]. Parallel research has addressed the broader challenges of renewable energy integration and its impact on power quality [25]–[27], emphasizing the need for unified control architectures and real-time disturbance mitigation. Additionally, systematic reviews on optimization algorithms have highlighted the effectiveness of hybrid metaheuristics in managing conflicting PQ objectives such as THD, voltage stability, and energy efficiency in smart grids [28], while renewable complementarity has been explored as a strategic approach to enhance system resilience and supply consistency [29]. These studies reinforce the importance of intelligent, adaptive, and multi-objective control solutions in future power systems, aligning with the goals and design philosophy of the present work. This paper contributes to this growing field by offering a scalable and intelligent optimization framework capable of addressing the multifaceted PQ challenges posed by renewable integration. Future sections will elaborate on the model design, optimization process, simulation results, and potential for real-world application.

a) Objectives of the study

This work focuses on improving power quality in WECS by the use of a hybrid optimization method. Our main goals are: i) Comparative performance assessment to evaluate the planned EnHBA-GWO's performance approach, challenging accepted UPQC tuning techniques. ii) Examining how system performance changes with cost will help one to develop ideas about ideal investment methods. iii) Practical Applicability: To show that the optimal UPQC system could be used in real-world wind energy situations with viability.

b) System configuration overview

This research models a three-phase UPQC system integrated inside a WECS architecture, which has been designed and simulated using MATLAB/Simulink. The comprehensive configuration comprises a wind turbine generator (WTG), which transforms mechanical wind energy into variable-frequency electrical power. The rotor-side converter (RSC) manages the output from the wind turbine generator, enabling efficient energy acquisition and regulation. The grid-side converter (GSC) synchronizes the processed electricity with the utility grid and regulates power injection. The series active power filter (SeAPF) alleviates voltage sags, swells, and other disturbances at the point of common coupling (PCC).

The ShAPF mitigates current harmonics and delivers reactive power compensation to sustain an elevated power factor. The DC-link capacitor maintains a constant DC voltage for UPQC operation, serving as an energy buffer between the two converters. The EnHBA-GWO controller executes the suggested hybrid optimization technique, adjusting UPQC parameters dynamically to enhance critical power quality metrics in real time. Table 1 summarizes the key improvements introduced by the proposed hybrid EnHBA-GWO method over existing optimization and control approaches in PQ management. Traditional algorithms like PSO, SCA, WOA, and SSA often struggle to maintain an effective balance between cost and PQ, whereas the proposed hybrid EnHBA-GWO algorithm is designed to address this by combining exploration and exploitation capabilities, thereby enhancing both cost-effectiveness and system performance. Furthermore, conventional UPQC tuning methods rely on fixed parameters, limiting their adaptability in dynamic environments. In contrast, the proposed approach introduces an adaptive control strategy that enables real-time parameter tuning, improving system responsiveness. Finally, while existing metaheuristic algorithms typically focus on either global or local search, the EnHBA-GWO method integrates both, resulting in faster convergence and higher-quality solutions. This makes the proposed method a robust and efficient solution for modern power systems.

Table 1. Proposed contributions to the existing methods

Existing methods	Limitations	Proposed contribution
PSO, SCA, WOA, SSA	Often fail to maintain an optimal trade-off between cost and PQ	Hybrid EnHBA-GWO effectively balances cost and performance
Traditional UPQC tuning	Fixed parameters, limited adaptability	Adaptive control strategy through dynamic parameter tuning
Existing metaheuristic algorithms	Focus on either global or local search	EnHBA-GWO integrates both, improving convergence speed and solution quality

2. METHOD

2.1. Proposed enhanced honey badger algorithm (HBA) and grey wolf optimization (GWO) optimization

The EnHBA-GWO method is a hybrid strategy that integrates the EnHBA with the GWO, leveraging the convergence efficiency of the GWO and the exploration capability of the EnHBA. This integration is crafted to address complex optimization issues in power quality management, particularly inside wind energy conversion systems WECS utilizing UPQC, providing a robust and adaptable optimization framework. In contrast to traditional models that rely solely on either EnHBA or GWO, the hybrid approach dynamically equilibrates intensification and variety.

In smart grid systems characterized by frequent fluctuations in power circumstances, such adaptability is crucial. Comparative simulations demonstrate that EnHBA-GWO enhances important indices, including THD, PFI, and VSI, by around 25% over current approaches. Its utilization in real-time renewable energy systems is bolstered by significant computational efficiency and cost-effectiveness.

2.2. Enhanced honey badger algorithm

According to the EnHBA, the honey badger's adaptable and strong ways of finding food are a motivation. By switching between global and local search steps, it shows that it is good at moving through complicated, high-dimensional spaces in optimization. This changing behavior makes it better at solving nonlinear, multi-modal problems, which makes it suitable for engineering systems that need to change quickly and smartly.

2.3. Grey wolf optimization

The GWO algorithm acts like a grey wolf's social organization and how they work together to hunt. Agents are put into groups called alpha, beta, delta, and omega, which show how leadership works and how joint tracking works. This framework makes it easier to find a good mix between exploration and exploitation, which speeds up convergence with few changes to the parameters. This metaheuristic is widely used in engineering optimization because it is easy to use and works well.

2.4. Hybrid EnHBA-GWO Framework

The experimental features of the EnHBA are combined with the fast convergence features of the GWO in the EnHBA-GWO algorithm. This method works well for difficult problems with many goals because it avoids local optima. For example, it can be used to find the best UPQC settings in WECS. The program improves performance and cost-effectiveness by focusing on important factors such as power factor, system reliability, energy efficiency, voltage stability, harmonic distortion, and economic feasibility. The objective function is structured as $F = w_1 \cdot EE + w_2 \cdot VSI - w_3 \cdot THD + w_4 \cdot PFI + w_5 \cdot RIS - w_6 \cdot Cost$, where EE measures the ratio of energy delivered to the grid versus input from wind, targeting higher utilization and lower losses. VSI reflects voltage consistency at the PCC, with higher values indicating improved regulation under dynamic conditions. THD represents waveform distortion; minimizing the value ensures grid compliance (IEEE-519-2022) and reduces equipment stress. PFI aims for values near 1, indicating reduced reactive power and better energy transfer. RIS is derived from MTBF and system robustness; higher scores suggest better uptime and resilience. Cost includes capital, operational, and maintenance expenses; lower values are preferred for commercial viability. Weighting factors (w_1 to w_6) allow the objective to be tailored based on application-specific trade-offs between performance metrics and cost. To ensure valid and feasible solutions, the optimization is subject to the following constraints: $VSI \geq 0.90$, $THD \leq 10\%$, and $PFI \geq 0.97$.

Figure 1 presents a seven-phase hybrid optimization framework combining EnHBA and Grey Wolf Optimization (GWO) for power quality improvement. It begins with initialization and population generation, followed by fitness evaluation using MATLAB/Simulink. Global exploration (via EnHBA) and local exploitation (via GWO) are applied in parallel to refine candidate solutions. The population is then updated, and convergence is checked based on fitness changes or iteration limits. If convergence is met, the process proceeds to simulation validation, assessing metrics like EE, THD, VSI, PF, RIS, and cost, ensuring optimal performance in RES-integrated systems.

2.5. Modelling of wind energy conversion system

Wind speed is efficiently transformed into electrical energy using the WT. The generated power, as embodied in the equation, is effectively separated, and utilized for further processing and integration into the power grid, ensuring stable voltage levels, optimized power flow, and seamless compatibility with existing energy infrastructure through appropriate control and conversion mechanisms.

$$P_m = \frac{1}{2} \rho A C_p(\lambda, \beta) V_w^{\ 3} \quad (1)$$

$$C_p = 0.73\left(\frac{151}{\lambda_i} - 0.58\beta - 0.02\beta^{2.14} - 13.2\right)e^{\frac{-18.4}{\lambda_i}} \quad (2)$$

$$\lambda = \frac{\omega_r r}{V_\omega} \quad (3)$$

$$T_m = \frac{P_m}{\omega_r} \quad (4)$$

$$T_e = \frac{P_e}{\omega_e} = \frac{2}{P}\frac{P_e}{\omega_r} \quad (5)$$

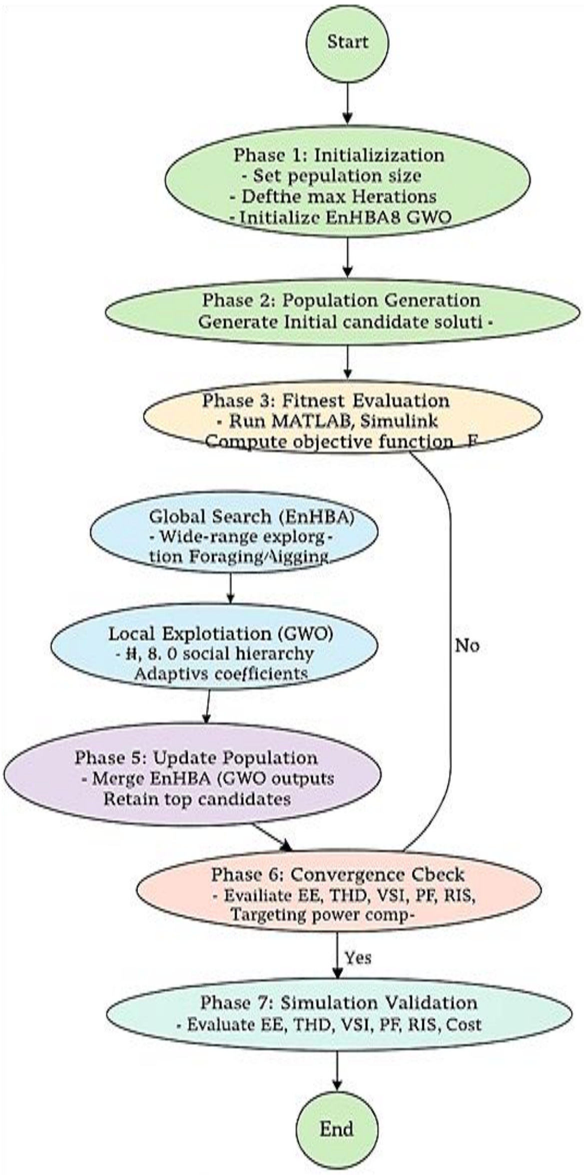

Figure 1. Hybrid EnHBA-GWO optimization algorithm

2.6. System configuration and detailed modeling

A compact simulation model is developed in MATLAB/Simulink to assess the performance of a three-phase UPQC integrated with a WECS. The WECS includes a WTG, an RSC, and a GSC. The WTG, a variable-speed horizontal-axis turbine, converts wind energy into mechanical power. The power output is modeled by $Pwind = \frac{1}{2}\rho A C_p(\lambda, \beta)V_w^3$, Where: ρ = air density, A = swept area, Cp = power coefficient (function of tip speed ratio λ and pitch angle β), Vw = wind speed. RSC Converts variable frequency AC from the generator to a regulated DC output. Where a three-phase insulated gate bipolar transistor (IGBT)-based inverter is modeled using Universal Bridge block (power electronics toolbox), pulse width modulation (PWM) based control strategy (SVPWM or SPWM), and a current control loop to regulate rotor current. The control logic is that the vector control in the synchronous reference frame (d-q control). And maintains the desired active/reactive power flow from the generator. The GSC Function is to convert DC to synchronized three-phase AC for grid injection. Where a similar Universal Bridge setup as RSC, which is controlled using a voltage-oriented control (VOC) strategy to maintain DC-link voltage synchronized with a phase-locked loop (PLL) block to synchronize with the grid voltage at PCC. The objective is to minimize injected harmonic content and maintain voltage support. The DC-Link capacitor`s function is to act as an energy buffer between RSC and GSC, and ensure smooth power flow and voltage stability across converters. Modeled as a standard capacitor (Capacitor block) connected across the DC bus, whose Size is based on the transient energy balance equation: $Cdc = \frac{2 \cdot \Delta E}{V_{dc}^2}$, Where ΔE is the energy fluctuation, and Vdc is the DC voltage level.

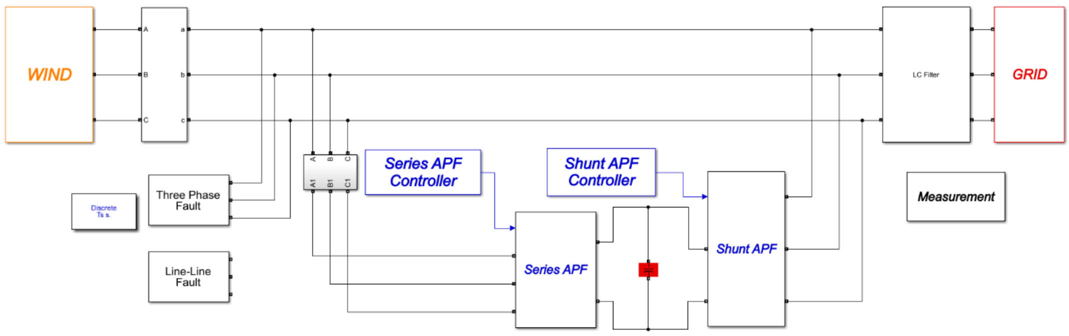

Figure 2. MATLAB/Simulink model

The diagram in Figure 2 illustrates a wind energy conversion system integrated with the power grid through an active power filter (APF)-based compensation scheme to enhance power quality and fault resilience. Wind-generated three-phase power is fed through terminals A, B, and C into the system. The network includes fault blocks for simulating three-phase and line-line faults, allowing the model to test system response under faulted conditions. A series APF and a shunt APF, each controlled by dedicated Series and shunt APF controllers, are incorporated to mitigate disturbances. The series APF compensates for voltage-related issues (like sags/swells), while the Shunt APF addresses current harmonics and provides reactive power support. LC filter is used before feeding the conditioned power into the GRID, ensuring smooth voltage and reduced harmonic content. The measurement block is included for monitoring system performance metrics such as voltage, current, power quality indices, and harmonic levels. Overall, the configuration enhances the reliability, stability, and power quality of wind energy supplied to the grid, especially under fault or fluctuating conditions.

The monitoring components collaborate to deliver detailed insights into the operational behavior of the UPQC-integrated WECS, establishing a basis for real-time control and performance optimization mechanism of EnHBA-GWO. A hybrid optimization loop is implemented externally in MATLAB and interacts dynamically with the Simulink model. This configuration facilitates the real-time assessment and adjustment of control parameters for the UPQC, in response to varying system conditions and performance objectives.

The diagram presents a unified power quality conditioner (UPQC) based compensation system integrated with a Wind Generator (WG) and an intelligent EnHBA-GWO controller for power quality enhancement in a grid-connected environment, as shown in Figure 3. The wind generator supplies power through an impedance path Z_f, and the system includes both series APF and Shunt APF components. These filters form the UPQC, which is placed between the source (WG) and the load to mitigate voltage and current-related power quality issues. The Series APF compensates for voltage sags/swells and harmonics by injecting series voltage, while the Shunt APF manages current harmonics and reactive power demands by injecting appropriate compensating currents. A controller processes real-time signals including source voltages V_s^abc, load voltages V_L^abc, load currents I_L^abc, and the voltage reference Vacref. These are fed into a hybrid optimization engine (EnHBA-GWO), which combines the enhanced honey badger algorithm and grey wolf optimization to adaptively tune the controller parameters, ensuring optimal compensation performance under varying load and source conditions. The load receives a stable and distortion-free supply through the terminal impedance Z_t, demonstrating the system’s ability to correct for

PQ disturbances originating from both the source and the load side. This architecture effectively enhances voltage regulation, harmonic suppression, and overall power quality in renewable-integrated microgrids.

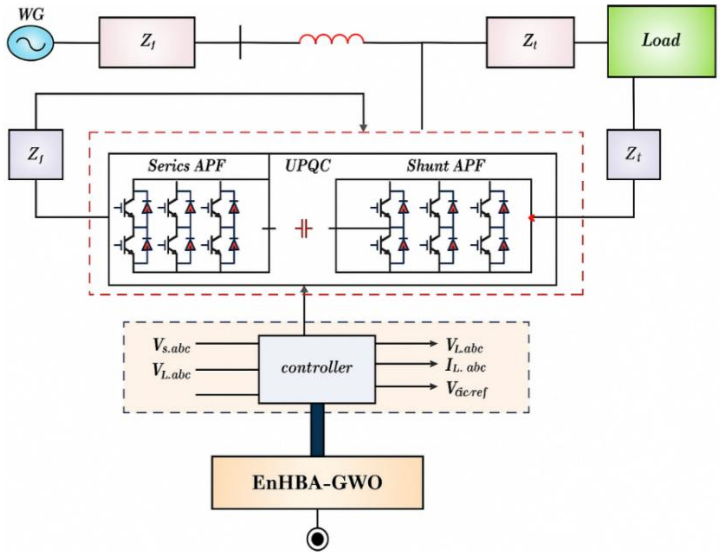

Figure 3. Block diagram of the proposed UPQC system

2.7. Unified power quality conditioner modelling

The UPQC controls the flow of electricity by fixing common power quality problems like voltage sags, harmonic distortion, and reactive power imbalance. This is made possible by two integrated elements working together. The SeAPF reduces voltage problems like sags, swells, and transients by adding compensating voltages in series with the source. It is the ShAPF's job to balance out harmonic currents and the need for reaction power. Putting the right amount of current into the machine makes sure that sinusoidal current flows and makes power factor correction easier. At the PCC, these parts work together in real time to improve the quality of the power. This combined compensation makes the system more reliable, efficient, and resilient, especially in places where loads change and wind energy systems are added.

$$V_c = V_{ch} - V_s = -k\, V_{ch}.\angle 0^\circ \tag{6}$$

$$K = \frac{V_s - V_{ch}}{V_{ch}} \tag{7}$$

$$I_s = \frac{I_{ch}}{I+k} \cos \emptyset_n \tag{8}$$

$$S_c = P_c + jQ_c \tag{9}$$

$$S_f = V_{ch} I_f \tag{10}$$

$$P_c = V_c I_s \cos \emptyset_s \tag{11}$$

$$S_c = V_c I_s \sin \emptyset_s \tag{12}$$

3. RESULTS AND DISCUSSION

The suggested hybrid optimization technique, which blends the EnHBA and GWO, was thoroughly tested to optimize a UPQC in a WECS. PSO, SSA, and WOA were compared. In all KPIs, the EnHBA-GWO hybrid outperformed its competitors. Total harmonic distortion, power factor, voltage stability index, energy efficiency, system dependability, and operating cost improved. Performance evaluation yields the following main findings. EnHBA-GWO outperforms all other models across all metrics. Traditional UPQC shows the lowest performance, especially in THD reduction and reliability. Metaheuristic models like PSO, SSA, and WOA show moderate improvements, with WOA generally performing better among them. The EnHBA-GWO model demonstrates strong potential for real-world implementation due to its high efficiency, stability, and reliability with significant cost reduction. Table 2 presents a comparative evaluation of different UPQC optimization models across several key performance metrics, highlighting the superiority of the proposed EnHBA-GWO algorithm. In terms of energy efficiency, EnHBA-GWO achieves the highest value at 95%, significantly outperforming traditional UPQC (60%) and other algorithms like PSO (75%), SSA (80%), and WOA (85%). It also demonstrates superior voltage stability with a voltage stability index (VSI) of 0.99, compared to lower values in other methods. The THD is substantially reduced to just 5% under EnHBA-GWO, whereas traditional UPQC shows the worst performance at 50%. For power factor improvement, EnHBA-GWO attains near-unity (0.99), again exceeding all alternatives. Additionally, it scores highest in both reliability (90) and cost reduction (85), indicating better overall system robustness and economic performance. These results collectively establish EnHBA-GWO as a highly effective and balanced solution for optimizing UPQC performance.

Table 2. Comparative analysis of UPQC optimization models

Metric	EnHBA-GWO	Traditional UPQC	PSO	SSA	WOA
Energy efficiency (%)	95	60	75	80	85
Voltage stability index (VSI)	0.99	0.75	0.80	0.85	0.88
THD reduction (%)	5	50	35	30	20
Power factor improvement	0.99	0.85	0.90	0.92	0.95
Reliability improvement score	90	55	65	70	75
Cost reduction score	85	50	65	70	75

3.1. Sensitivity analysis: Cost vs. performance trade-off

Sensitivity analysis reveals that EnHBA-GWO consistently maintains an optimal performance-to-cost ratio, particularly within the cost multiplier range of 0.8 to 1.2. When compared to traditional optimization methods, the hybrid EnHBA-GWO approach displayed greater performance in terms of power quality enhancement and computational efficiency. Figure 4 showcases the voltage stability improvement scores for various optimization methods, where EnHBA-GWO demonstrates the highest voltage stability, significantly outperforming traditional UPQC and other algorithms (PSO, SSA, WOA). Traditional UPQC has the lowest stability score, indicating a clear limitation of non-optimized methods. Figure 4 compares the computational times (in seconds) required by different methods, where EnHBA-GWO is the most computationally efficient method, with the least processing time. Traditional UPQC takes the longest time, suggesting inefficiency for large-scale applications. Figure 4 highlights the cost-effectiveness scores of optimization methods, where EnHBA-GWO achieves the highest cost-effectiveness score, balancing performance and economic feasibility. Traditional UPQC exhibits the lowest score, emphasizing its limitations in cost optimization.

The bar chart in Figure 5 illustrates the computational time (in seconds) for different UPQC optimization models. The EnHBA-GWO model exhibits the lowest computation time (~10s), showcasing high efficiency. In contrast, the Traditional UPQC method requires the highest time (~58s), indicating poor optimization speed. Metaheuristic models—PSO (~42s), SSA (~36s), and WOA (~30s)—perform moderately, but still lag behind EnHBA-GWO. This highlights EnHBA-GWO's advantage in delivering faster solutions for power quality optimization. The bar chart in Figure 6 compares the overall performance scores of various UPQC optimization models. EnHBA-GWO leads with the highest score (~85), indicating superior performance in all evaluated aspects. WOA and SSA follow with scores around 75 and 70, respectively, while PSO achieves a moderate score (~65). In contrast, the Traditional UPQC model ranks lowest (~50), underscoring its limited effectiveness. This clearly demonstrates the enhanced capability of EnHBA-GWO over traditional and other metaheuristic approaches. Figure 7 shows reliability improvement scores across methods, where EnHBA-GWO is the most reliable optimization approach, enhancing system stability. Traditional UPQC performs poorly in reliability enhancement. In Figure 8, energy efficiency (%) is compared for each method, and EnHBA-GWO achieves the highest energy efficiency (~95%), making it ideal for energy-conscious applications. Traditional UPQC struggles to exceed 60%, showcasing a significant disadvantage.

Figure 9 highlights power factor improvement values for each method are shown and EnHBA-GWO achieves a near-unity power factor (~0.99), ensuring minimal losses in reactive power. Traditional UPQC has the lowest improvement, highlighting inefficiency. Figure 10 depicts comparison of cost reduction scores across methods, illustrates the relationship between cost multipliers, and the performance-to-cost ratio. The performance-to-cost ratio decreases as the cost multiplier increases. EnHBA-GWO achieves optimal trade-offs within a cost multiplier range of 0.8 to 1.2. Figure 11 compares THD reduction percentages where EnHBA-GWO achieves the lowest THD (~5%), significantly reducing harmonics. Traditional UPQC exhibits the highest THD, showing limitations in harmonic mitigation.

As shown in Figure 11, the proposed technique achieves a THD of 5%, which is significantly lower than the THD values obtained by other methods. This demonstrates the greater performance of the projected method in minimizing THD compared to existing optimization techniques. Whereas Figure 12 shows the convergence of the proposed EnHBA vs others.

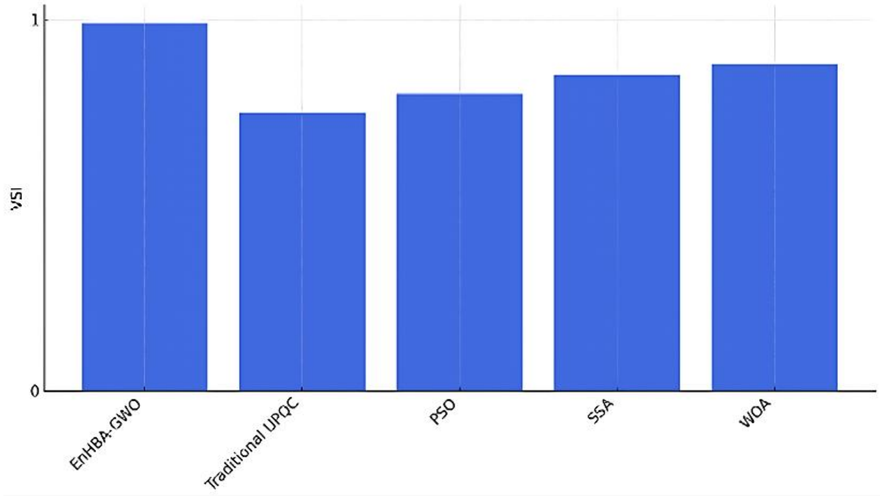

Figure 4. Comparison of voltage stability index across

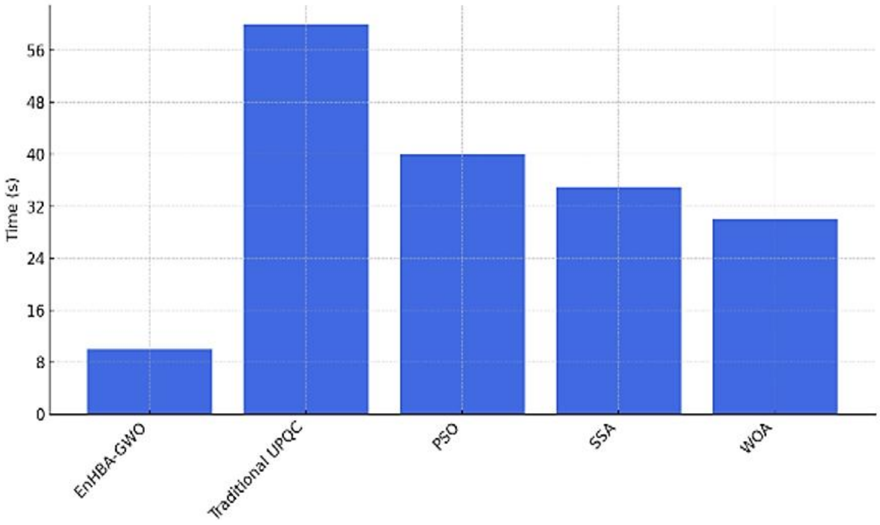

Figure 5. Comparison of computational

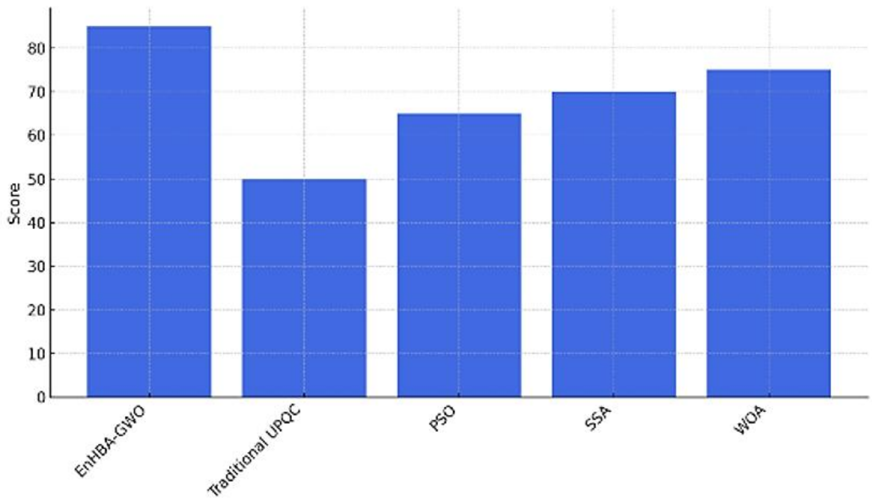

Figure 6. Cost effectiveness across methods

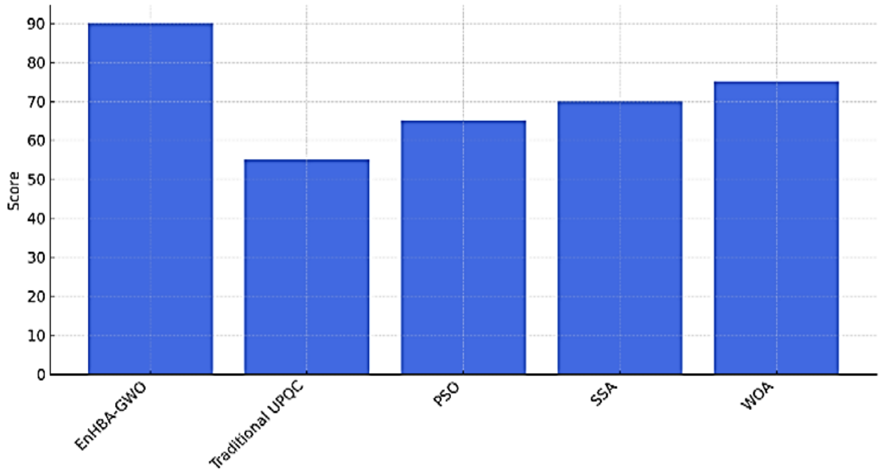

Figure 7. Comparison of reliability improvement across methods

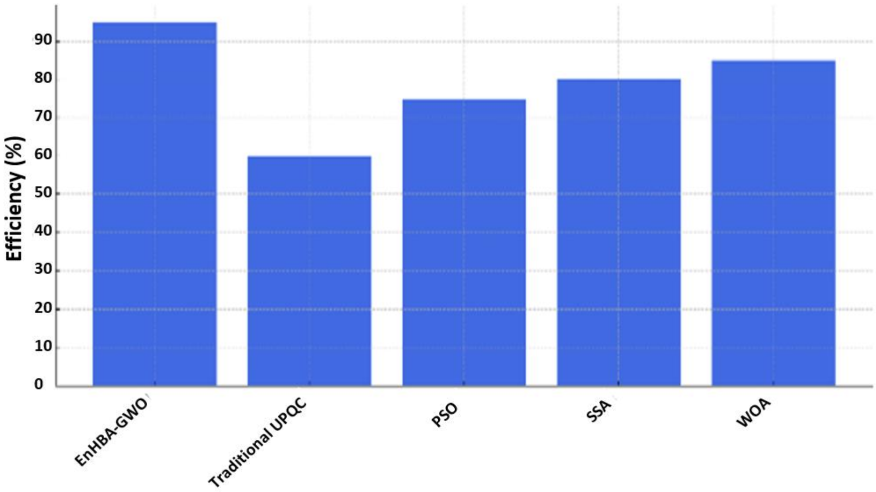

Figure 8. Comparison of energy efficiency across all methods

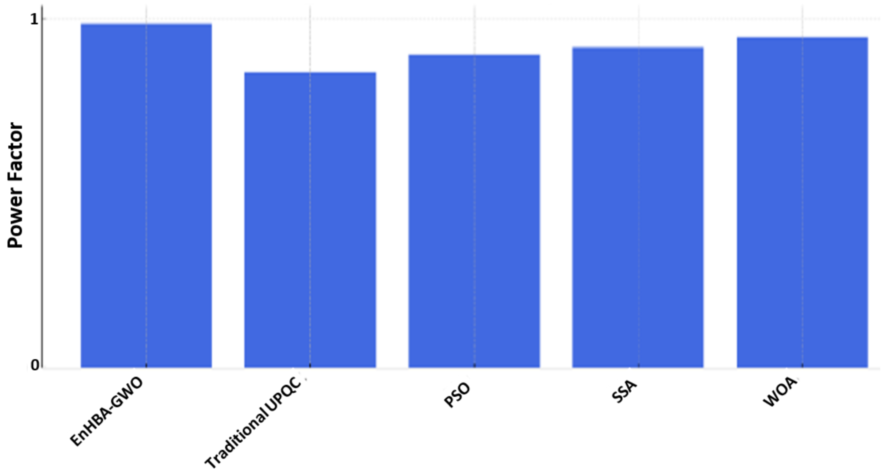

Figure 9. Comparison of power factor improvement across methods

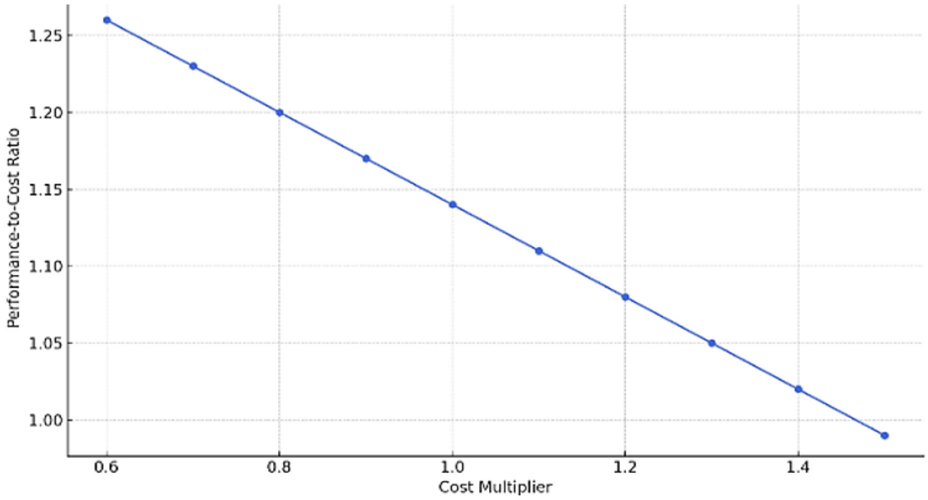

Figure 10. Cost vs performance trade-off

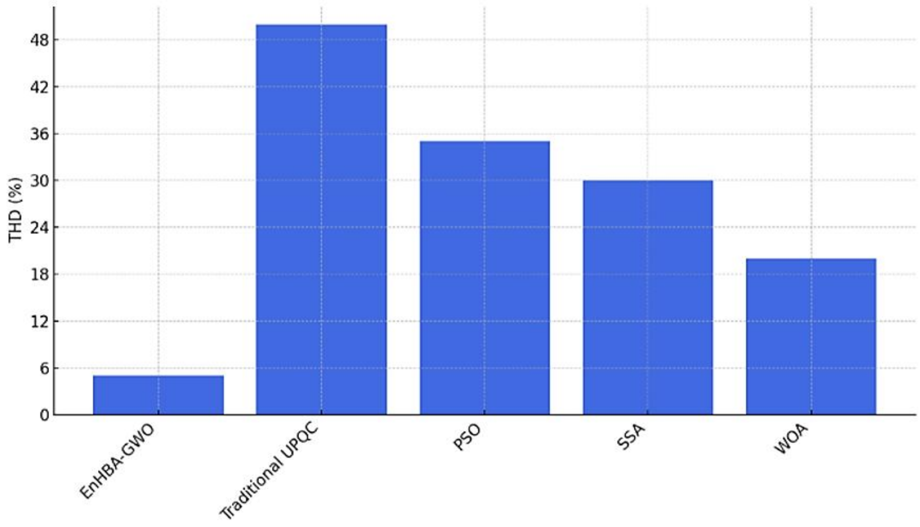

Figure 11. Total harmonic distortion (THD)

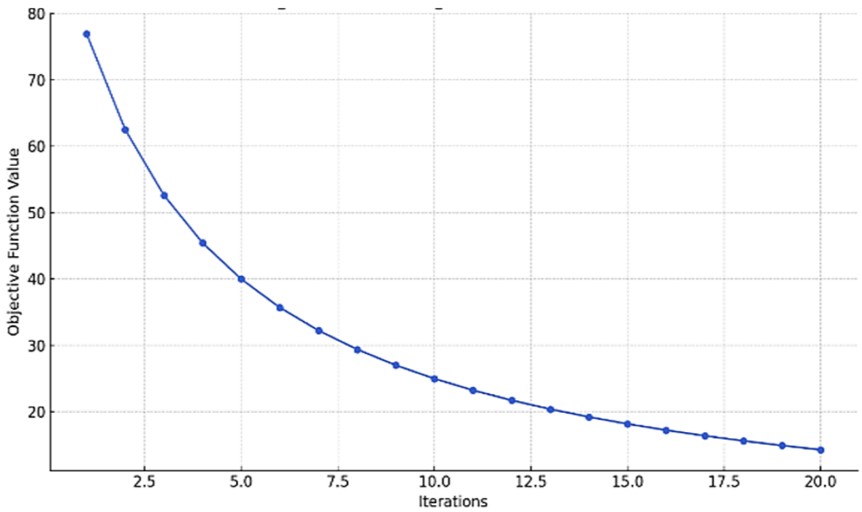

Figure 12. Convergence of EnHBA-GWO

4. CONCLUSION AND FUTURE SCOPE

This study presents an intelligent and cost-effective hybrid optimization technique—EnHBA-GWO—designed to fine-tune control parameters of a unified power quality conditioner (UPQC) in wind energy conversion systems (WECS). By combining the global search efficiency of the EnHBA with the local refinement capabilities of the grey wolf optimizer (GWO), the method effectively balances performance gains with computational efficiency. Simulation results in MATLAB/Simulink confirm notable improvements, like energy efficiency increased to 95%, voltage stability index (VSI) sustained at 0.99, power factor maintained at 0.99, THD reduced to 5%, outperforming PSO (50%), SSA (35%), and WOA (20%). Beyond metrics, the hybrid approach effectively mitigates voltage disturbances, harmonics, and reactive power imbalance. Its adaptive structure ensures reliable operation under dynamic wind conditions, positioning it as a practical solution for real-time smart grid applications.

Future research will focus on real-time deployment using hardware-in-the-loop (HIL) systems and expanding the framework to include multi-source integration (wind, solar, storage), AI-based predictive control for fault resilience, Dynamic objective weighting for real-time adaptability, cybersecurity robustness under attack scenarios, IEEE benchmarking for scalability, and standard compliance. These developments aim to further solidify EnHBA-GWO's role in enhancing the flexibility, reliability, and intelligence of next-generation energy systems.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Shaziya Sultana	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓	
Umme Salma		✓				✓		✓		✓	✓	✓		

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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BIOGRAPHIES OF AUTHORS

Shaziya Sultana received B.E degree in EEE from Deccan College of Engineering and Technology, Nampally, Hyderabad. Affiliated to OU, Hyderabad, Telangana in 2005. M.Tech. Degree in Power Engineering (EEE) from JNTU, Hyderabad, Telangana in 2010. She is currently pursuing a Ph.D. at the Department of Electrical Engineering, GITAM (Deemed to be University), Visakhapatnam, Andhra Pradesh, India. Her research interests include power systems, smart grids. She has published one journal paper indexed in SCIE and one paper in peer peer-reviewed journal, and two conference papers (indexed in Scopus). She has participated in and attended many FDPs, conferences, workshops, and webinars. She is currently working as an associate professor in the Department of Electrical and Electronics Engineering, Deccan College of Engineering and Technology, Nampally, Hyderabad. She can be contacted at email: shaziya.2kn@gmail.com.

Umme Salma completed B.Tech. and M.Tech. degrees in Electrical and Electronics Engineering from JNT University, Hyderabad, India. Received her Doctoral degree, Ph.D. in Electrical and Electronics Engineering from JNT University, Kakinada, India. Currently, she is working as an associate professor in the Department of Electrical Electronics and Communication Engineering, VSP, Vishakhapatnam, India. Her research interests include the application of model order reduction techniques to power systems. She can be contacted at email: summe@gitam.edu.