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Optimal Placement of UPQC for the Enhancement of Power Quality with a Novel Hybrid Meta-Heuristic Optimisation Approach

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This research paper presents Flexible Alternating Current Transmission System (FACTS) devices, specifically Unified Power Quality Conditioner (UPQC), are implemented to significantly enhance power system stability. Various meta-heuristic optimisation algorithms are applied to position the Unified Power Quality Conditioner (UPQC) within power systems. However, the optimisation algorithms failed to demonstrate increased reliability and the feedback signal. This work presents a technique for improving Power Quality, utilizing a hybrid approach that integrates Improved Grey Wolf Optimisation (IGWO) with the Opposition Based Learning (OBL). The developed hybrid optimisation technique identifies the optimal positioning of the UPQC device, emphasizing the cost associated with the UPQC, the Voltage Stability Index (VSI), and Total power losses. The implemented technique is executed within the IEEE 33 and IEEE 57 test bus system. The performance of the hybrid optimisation technique is compared to existing techniques, including Cuckoo Search Optimisation (CSO), Grey Wolf Optimisation (GWO), Improved Grey Wolf Optimisation (IGWO.

Keywords: Unified Power Quality Conditioner (UPQC), Hybrid Optimisation algorithm, optimal placement problem, Total Power Loss, Power Quality, Voltage Stability Index(VSI).

1. Introduction

The increasing demand for electrical energy, combined with the placement of FACTS Devices, has led to significant challenges in power system operations. Among these challenges are voltage stability, Total power losses, and maintaining an acceptable power quality level[1]. To address these issues, researchers and engineers have turned to advanced optimisation techniques to design and deploy devices such as the Unified Power Quality Conditioner (UPQC)[2]. The UPQC is versatile power quality device capable improving overall voltage stability. However, identifying the optimal placement and sizing of the UPQC in a power system is critical to ensuring its effectiveness and economic feasibility[3]. This requires the use of sophisticated optimisation algorithms that consider multiple objectives, including the cost of the UPQC, Voltage Stability Index (VSI), and Total power losses [4,5].

According to recent research, the Unified Power Quality Conditioner (UPQC) can achieve multiple objectives simultaneously. Many academics have examined UPQC as a power quality solution for electrical distribution networks [5,6].However, due to the high costs, UPQC location in the distribution system should be carefully considered and optimised. In an effective scenario, UPQC placement optimisation requires minimising Total power losses and enhancing voltage profiles [7].UPQCs are cost-effective to install, operate, and maintain, despite their benefits. The network placement and size of a UPQC also affect its effectiveness. Proper placement of UPQC can improve voltage stability, reduce Total power losses, and lower investment costs[8].

The optimal placement of the UPQC in a power system involves multiple objectives includes cost minimization, voltage stability index and Total power loss reduction[9,10]. The cost of the UPQC includes capital investment, installation, and maintenance expenses. Minimizing these costs is crucial to ensure the economic feasibility of the device. The VSI is a measure of the voltage stability of a power system[11]. Enhancing the VSI is essential for maintaining a stable and reliable power supply, particularly in networks with high penetration of renewable energy sources[12]. Minimizing Total power losses is a key objective in power system optimization[13,14]. Reduced Total power losses lead to improved system efficiency and lower operational costs.These objectives are often conflicting, necessitating the use of advanced multi-objective optimisation techniques to achieve a balanced solution[15].The Grey Wolf Optimizer (GWO) is a nature-inspired optimisation algorithm that mimics the social hierarchy and hunting behaviour of grey wolves. GWO has gained popularity for its simplicity, flexibility, and effectiveness in solving complex optimisation problems. However, the standard GWO has certain limitations, such as slow convergence and a tendency to get trapped in local optima[16].

The Improved Grey Wolf Optimizer (IGWO) addresses these limitations by introducing enhancements to the original algorithm. These enhancements may include dynamic adjustment of control parameters, adaptive weight factors, and hybridization with other optimisation techniques[17]. IGWO improves the balance between exploration and exploitation, enabling it to navigate the search space more effectively and find global optima.Opposition-Based Learning (OBL) is an optimisation concept that accelerates the convergence of optimisation algorithms by simultaneously evaluating candidate solutions and their opposite counterparts.

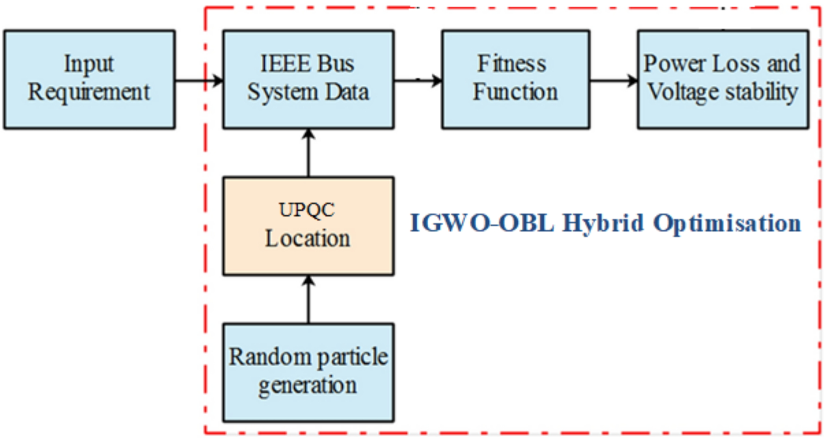

Figure No 1: Block Diagram of Overall System

The opposite of a solution is defined based on its position relative to the search space boundaries. By considering both the current solution and its opposite, OBL increases the likelihood of identifying better solutions and escaping local optima[17]. OBL is particularly useful in hybrid optimisation frameworks, where it complements the strengths of other algorithms. For example, combining OBL with IGWO enhances the exploration capabilities of the hybrid algorithm while maintaining a strong focus on exploitation.

The hybrid IGWO-OBL optimisation framework leverages the strengths of both IGWO and OBL to achieve superior performance in multi-objective optimisation problems. The integration of OBL into IGWO introduces diversity into the population, enhances global search capabilities, and accelerates convergence[18]. The initial population of candidate solutions is generated randomly within the search space. Opposite solutions are calculated for each candidate and the better solutions between the original and opposite populations are selected for the next iteration. The IGWO algorithm updates the positions of the wolves (solutions) based on the social hierarchy and adaptive control parameters. The hunting mechanism of the wolves is guided by the alpha, beta, and delta leaders[19]. The fitness of each solution is evaluated based on the multi-objective criteria, including UPQC cost, VSI, and Total power losses. The algorithm iterates until the stopping criterion, such as a maximum number of iterations or a convergence threshold, is met.The hybrid IGWO-OBL optimisation framework is applied to determine the optimal placement and sizing of the UPQC in a power system as shown in figure 1.

The optimisation problem is formulated with the objectives of minimizing UPQC cost, enhancing VSI, and reducing Total power losses. Constraints, such as voltage limits and power flow equations, are incorporated into the problem[20]. The power system is modelled using standard test systems, such as IEEE bus systems, to simulate various scenarios and evaluate the performance of the UPQC.The hybrid IGWO-OBL algorithm is implemented to solve the optimisation problem. The algorithm searches for the optimal location and size of the UPQC that satisfies the objectives and constraints[21].

UPQC implementation is critical for improving power quality and voltage stability in modern power systems. The optimum placement and sizing of the UPQC determines its economic and technical feasibility. For this complex multi-objective optimisation issue, the hybrid IGWO-OBL optimisation framework is effective. The hybrid method improves convergence, robustness, and solution quality by combining IGWO with OBL. This approach improves UPQC efficiency and power system efficiency and reliability. In recent years, hybrid optimisation techniques have gained popularity for complicated engineering issues. The Improved Grey Wolf Optimiser (IGWO) and Opposition-Based Learning (OBL) optimisation perform in multi-objective optimization[22].

The hybrid IGWO-OBL optimisation framework offers several benefits for identifying the optimal placement of the UPQC. The integration of OBL accelerates convergence and enhances the likelihood of finding global optimal. The hybrid algorithm is robust to variations in system conditions and parameters. The framework effectively handles multiple conflicting objectives, providing a balanced solution that meets the requirements of cost, VSI, and Total power losses.

2. PROBLEM STATEMENT

The increasing demand for electricity, combined with the rising complexity of contemporary power networks, poses considerable challenges to system stability, power quality, and operational efficiency. Conventional approaches to voltage regulation and power quality management may be inadequate, especially as power systems integrate renewable energy sources and distributed generation. The Unified Power Quality Conditioner (UPQC) is a critical device engineered to tackle these challenges. It offers both series and shunt compensation to mitigate issues such as voltage stability index and reducing Total power losses and to enhance overall power quality. The optimal deployment of a UPQC in a power system presents a complex challenge that necessitates thorough analysis of system parameters and operational constraints. The placement and sizing of the UPQC are essential considerations that influence its effectiveness. An optimal design can result in considerable enhancements in voltage stability, reductions in total power loss, and minimised costs. Furthermore, considering the intricate and frequently opposing goals (such as reducing Total power losses, ensuring acceptable voltage levels, and managing costs), it is crucial to employ suitable optimisation methods to determine the optimal placement and sizing of the UPQC.This paper investigates the optimal placement and sizing of UPQCs within power systems. The focus is on enhancing voltage stability, decreasing Total power losses, and reducing installation costs, all within a single-objective optimisation framework. This paper further expands the analysis to encompass a multi-objective optimisation framework, taking into account the financial viability of the UPQC solution, which aims to balance cost and performance effectively.

3. PROPOSED METHODOLOGY FOR THE OPTIMAL PLACEMENT OF UPQC IN POWER SYSTEMS

The strategic positioning of Unified Power Quality Conditioners (UPQCs) within electrical networks is essential for enhancing the overall stability, efficiency, and power quality of the system. The UPQC is engineered to improving the voltage stability index (VSI) and minimising total power losses. Determining optimal locations and sizes for these devices presents a complex challenge due to the need to optimise multiple objectives, including the reduction of total power loss, enhancement of voltage stability, and minimisation of installation costs. This methodology outlines a framework for the optimal placement and sizing of UPQCs within a power system, employing a blend of single-objective and multi-objective optimisation techniques. The objective is to enhance voltage stability, decrease total power losses, minimise the installation costs of the UPQC, and attain an optimal financial fitness trade-off within a multi-objective framework.

4. PROBLEM FORMULATION FOR OPTIMAL PLACEMENT OF UPQC

The Unified Power Quality Conditioner (UPQC) is a crucial device for improving the performance and reliability of power systems. Its optimal placement and sizing involve complex multi-objective optimisation to balance system stability, total power losses, costs, and financial fitness. This problem formulation outlines the objectives, constraints, and methodology for addressing this optimisation challenge, focusing on the application of various optimisation techniques and comparing results with hybrid optimisation methods. Power quality and voltage stability are critical challenges in modern power systems due to increasing load demand, integration of renewable energy sources, and system contingencies. The UPQC addresses these challenges by mitigating total power loss, stabilizing voltage profiles. However, determining the optimal location, size, and operational parameters of the UPQC is a multi-faceted problem, influenced by system constraints and performance objectives.

The optimisation problem is formulated to achieve the following objectives:

- Minimization of Total power losses Reducing Total power losses in the system.
- Enhancement of Voltage Stability Index (VSI) Improving the voltage stability of the system.
- Minimization of UPQC cost Reducing the overall installation and operational costs associated with the UPQC.
- Evaluate financial fitness under multi-objective optimisation scenarios

The objective function is mathematically expressed as a multi-objective function, considering appropriate weights for each factor. Constraints such as bus voltage limits, line capacity, and the operational constraints of UPQC are included. By comparing the results of traditional optimisation methods with hybrid techniques such as Improved Grey Wolf Optimizer (IGWO) combined with Opposition-Based Learning (OBL), the study highlights the effectiveness of hybrid approaches.

The optimisation problem involves single and multi-objective scenarios.

4.1 SINGLE OBJECTIVE OPTIMISATION

Single-objective function is to minimise a specific factor (e.g., power loss) while ensuring that constraints on other system parameters, such as voltage stability and installation costs, are upheld. This analysis will focus on the performance of UPQC in enhancing the voltage stability index (VSI) and reducing total power losses, while also taking into account the costs associated with UPQC installation.

Voltage Stability Index (VSI) Improvement

Enhance system robustness under varying load conditions by minimizing the voltage deviation. The Voltage Stability Index (VSI) quantifies how stable a bus in a power system is with respect to voltage collapse. It helps identify buses prone to instability and is a critical metric in voltage stability analysis.

The Voltage Stability Index for bus i is defined as,

$$VSI_i = \frac{|V_i|^4}{4(P_i^2+Q_i^2)(R_{ij}^2+X_{ij}^2)} \quad (1)$$

Where $|V_i|^4$:voltage magnitude at bus i.$\left(P_i^2 + Q_i^2\right)$Square of Apparent Power Flow represents the squared apparent power demand at bus i, where P_i Real power injected or consumed at bus iii. Q_i Reactive power injected or consumed at bus i.$\left(R_{ij}^2 + X_{ij}^2\right)$ impedance of the Line , R_{ij}^2 is the resistance, and X_{ij}^2 is the reactance of the line connecting bus i to its adjacent bus j. The term $R_{ij}^2 + X_{ij}^2$ is the squared magnitude of the line impedance.

The VSI enhancement objective is expressed as

$$F_{VSI} = \max\left(1 - \frac{VSI_i}{VSI_{max}}, 0\right) \quad (2)$$

Where VSI_{max} is the desired maximum VSI threshold.

Total Power Loss Minimization

In a power system, real power losses occur due to the resistance R_k of the transmission and distribution lines. These losses can be mathematically represented as a function of power flow variables and line characteristics. The power loss minimisation is expressed as

$$F_{loss} = \sum_{k=1}^{N_{lines}} R_k \left(\frac{P_k^2+Q_k^2}{|V_K|^2}\right) \quad (3)$$

Where $N_{lines}$is Number of lines in the system.$R_k$describes resistance of line k.$P_k$and $Q_k$represents active and reactive power flows through line k.$|V_K|$describes voltage magnitude at the sending end of line k.

UPQC Installation Cost Minimization

The cost of a Unified Power Quality Conditioner (UPQC) depends on its fixed installation cost and the variable cost based on its size (apparent power capacity). It can be expressed mathematically as:

$$F_{cost} = C_{fixed} + C_{var} \cdot S_{UPQC} \quad (4)$$

Where C_{fixed}Fixed cost of installing UPQC.C_{var} Variable cost per unit size.S_{UPQC}Apparent power rating of UPQC

Single objective function

The objective function is considering appropriate weights for each factor. Constraints such as bus voltage limits, line capacity, and the operational constraints of UPQC are included. The overall objective function is a $w_1F_{loss} + w_2F_{VSI} + w_3F_{cost}$ combination of multiple performance metrics to evaluate and optimize the placement and sizing of UPQC in a power system. Each term and weight in the equation is defined as follows:

$$F_{total} = w_1F_{loss} + w_2F_{VSI} + w_3F_{cost} \quad (5)$$

Where F_{loss} describs Power loss objective represents the total power losses in the system .F_{VSI} describes voltage stability Index objective represents the voltage stability of the system. F_{cost} describes cost objective represents the cost associated with the solution, such as the cost of placing of UPQC.

$w_1, w_2, w_3$are the weighting factors that balance the importance of each objective in the overall optimisation process. $w_1$weight for minimizing total power losses. w_2 weight for enhancing voltage stability. w_3 weight for minimizing cost.

4.2 MULTI-OBJECTIVE OPTIMISATION

The objective is to optimize the placement and sizing of UPQC to improve power quality and system performance which include

Minimisation of Total power losses

$$\boldsymbol{f_1 = P_{loss} = \sum_{i=1}^{N} g_{ij}(V_i^2 + V_j^2 - 2V_iV_j \cos\theta_{ij})} \quad (6)$$

Where $\boldsymbol{g_{ij}}$ is the conductance of the line between buses i and j and $\boldsymbol{\theta_{ij}}$ is the phase angle difference

Improvement of Voltage Stability Index(VSI)

Enhance system robustness under varying load conditions

$$\boldsymbol{f_2 = \sum_{i=1}^{N} \left(\frac{4V_i(V_{nom} - V_i}{V_{nom}^2}\right)} \quad (7)$$

Where $\boldsymbol{V_i}$ is the voltage magnitude at bus i, $\boldsymbol{V_{nom}}$ is the nominal voltage and N is the number of buses

Minimization of UPQC Installation Cost (C)

The cost of installation and operation of UPQC

$$\boldsymbol{f_3 = a + b.S_{UPQC} + c.S_{UPQC}} \quad (8)$$

Where $\boldsymbol{S_{UPQC}}$ =Apparent power rating of UPQC

a,b,c installation and operational cost coefficients.

The multi-objective optimisation combines the above objectives into a weighted fitness function:

Weighted sum fitness function

$$\boldsymbol{f(x) = w_1f_1 + w_2f_2 + w_3f_3} \quad (9)$$

Where $\boldsymbol{w_1}$, $\boldsymbol{w_2}$and , $\boldsymbol{w_3}$ are the assigned weights with relative importance.

$\boldsymbol{f_1}$, $\boldsymbol{f_2}$ and $\boldsymbol{f_3}$ are the Total power loss minimization , voltage stability index improvement and UPQC cost minimization respectively.

4.3 CONSTRAINTS

Active and reactive power of the line can be represented in relation to bus voltage magnitude and phase angle, leading to the formulation of power balance equations.

Voltage Constraints

Voltage limits ensure that the voltage magnitudes at all buses in a power system remain within a permissible range for safe and efficient operation.

$$\boldsymbol{V_{min} \leq |V_i| \leq V_{max} \forall\, i \in N_{buses}} \quad (10)$$

$\boldsymbol{V_{min}}$, $\boldsymbol{V_{max}}$ are the permissible voltage limits and $|\boldsymbol{V_i}|$ voltage magnitude at bus i.

Power Flow Constraints

Power flow equations describe the balance between power generation, consumption, and losses in an electrical power system. These equations ensure that power is conserved at each bus in the network.

$$\boldsymbol{P_i - P_{gen,i} + P_{loss,i} = 0} \text{ and } \boldsymbol{Q_i - Q_{gen,i} + Q_{\ loss,i} = 0} \quad (11)$$

Where $\boldsymbol{P_{gen,i}}$ and $\boldsymbol{Q_{gen,i}}$ are generated active and reactive power at bus i.

Operational Limits of UPQC

The Unified Power Quality Conditioner (UPQC) serves as a multifunctional device designed to enhance power quality by managing both voltage and current within power systems. Operational limits are established for the UPQC to guarantee its proper and safe functioning.

Size Constraints

S_{UPQC} as a constraint guarantees that the installed UPQC adheres to its maximum permissible dimensions and stays within the limits of the power system and device specifications. The size constraint is defined as follows:

$$\boldsymbol{0 \leq S_{UPQC} \leq S_{max}} \quad (12)$$

$\boldsymbol{S_{UPQC}}$ is the apparent power of the UPQC, representing the total power.The maximum allowable apparent power for the UPQC is denoted as $\boldsymbol{S_{max}}$.

Maximum and Minimum Reactive Power Injection and Absorption

The UPQC is capable of injecting or absorbing reactive power to regulate voltage levels and enhance the power factor within the system.

$$\boldsymbol{Q_{min} \leq Q_{UPQC} < Q_{max}} \quad (13)$$

Where $\boldsymbol{Q_{UPQC}}$ refers to the reactive power that the UPQC is capable of injecting or absorbing within the system.$\boldsymbol{Q_{min}}$ denoted as the minimum reactive power limit .$\boldsymbol{Q_{max}}$ is defined as the maximum reactive power limit.

Placement constraints

The placement of the Unified Power Quality Conditioner (UPQC) is essential in power system optimisation to enhance the overall performance of the system. Due to the requirement that the UPQC be installed at designated buses or lines, it is necessary to establish location constraints along with the corresponding decision variables. The specified constraints will direct the IGWO-OBL hybrid optimisation algorithm in identifying the optimal placement and sizing of the UPQC, while maintaining system stability and enhancing performance.

Location constraints

UPQC can only be placed at specific buses and identify the bus or line for UPQC placement

$$\boldsymbol{x_{location}} \in \{\mathbf{1}, \mathbf{2}, \dots \dots, \boldsymbol{N}\} \tag{14}$$

Where N is the total number of buses in the system.$\boldsymbol{x_{location}}$ represents the bus number at which the UPQC is to be installed.The selection of the bus $\boldsymbol{x_{location}}$will depend on factors like the voltage profile, Total power losses, and the need for reactive power compensation at that bus.

Size Constraints:

For determining the size and rating of the UPQC, Size Decision Variable $\boldsymbol{x_{size}}$ .The size of the UPQC is represented by the apparent power rating $\boldsymbol{S_{UPQC}}$,, which must satisfy the size constraint

$$\boldsymbol{x_{size}} = \boldsymbol{S_{UPQC}} \tag{15}$$

Optimisation Approach

In an optimisation problem, it’s essential to represent candidate solutions in a form that is suitable for computational analysis. In this case, each candidate solution must specify the location, size, and reactive power compensation associated with the UPQC.

$$\boldsymbol{x} = [\boldsymbol{x_{location}}, \boldsymbol{S_{UPQC}}, \boldsymbol{Q_{UPQC}}] \tag{16}$$

Where $\boldsymbol{x_{location}}$ is the bus number at which the UPQC is placed.$\boldsymbol{S_{UPQC}}$ is the apparent power rating of the UPQC.$\boldsymbol{Q_{UPQC}}$ is the reactive power compensation or injection absorbed or injected by the UPQC.

5. OPTIMISATION METHOD

The Test systems are analysed with IGWO-OBL Optimisation Method accordingly.

IGWO-OBL Hybrid Optimisation

The IGWO-OBL hybrid algorithm integrates the enhancements of IGWO with the exploratory benefits of OBL. The hybridization improves the exploration and exploitation phases, thereby increasing the overall efficiency of the search process. The IGWO-OBL hybrid optimisation algorithm is mathematically defined as follows:

During this Initialization phase stage, N wolves are randomly distributed across the search space within the range $[\boldsymbol{I_j}, \boldsymbol{u_j}]$ as defined by Equation (17).

$$\boldsymbol{X_{ij}} = \boldsymbol{I_j} + \boldsymbol{rand}[\mathbf{0},\mathbf{1}] \times (\boldsymbol{u_j} - \boldsymbol{I_j}), \boldsymbol{i} \in [\mathbf{1}, \boldsymbol{N}], \boldsymbol{j} \in [\mathbf{1}, \boldsymbol{D}]. \quad (17)$$

The position of the $\boldsymbol{i^{th}}$ wolf during the $\boldsymbol{i^{th}}$ iteration can be represented by a vector of real numbers $\boldsymbol{X_i(t)} = [\boldsymbol{x_{i1}}, \boldsymbol{x_{i2}}, \ldots .\, \boldsymbol{x_{iD}}]$, where D denotes the dimensionality of the problem. The entire wolf population is documented within the Pop matrix, consisting of N rows and D columns. The fitness function, $\boldsymbol{f(X_i(t))}$, computes the fitness value of $\boldsymbol{X_i(t)}$.

During Phase of movement the Individual hunting, in conjunction with group hunting, represents an intriguing aspect of the social behaviour exhibited by grey wolves. This behaviour serves as a motivation for researchers to develop the GWO. The Dimension Learning-Based Hunting (DLH) search method represents an additional mobility strategy incorporated within the IGWO framework. Each individual wolf in DLH is recognized by its neighbours as a potential candidate for the new position of $\boldsymbol{X_i(t)}$. Equation (18) determines the dimension of the new location of the wolf, $\boldsymbol{X_i(t)}$, where this specific wolf is influenced by its various neighbours and randomly selects a wolf from the population. The DLH search method subsequently yields an additional candidate for the new position of the wolf $\boldsymbol{X_i(t)}$, referred to as $\boldsymbol{X_{i-DLH}(t+1)}$, alongside $\boldsymbol{X_{i-GWO}(t+1)}$. Equation (18) calculates the radius $\boldsymbol{R_i(t)}$ by utilizing the Euclidean distance between the current position of $\boldsymbol{X_i(t)}$ and the candidate's position $\boldsymbol{X_{i-GWO}(t+1)}$.

$$\boldsymbol{R_i(t)} = \|\boldsymbol{X_i(t)} - \boldsymbol{X_{i-GWO}(t+1)}\| \quad (18)$$

The neighbors of $\boldsymbol{X_i(t)}$, denoted as $\boldsymbol{N_i(t)}$, are constructed using Equation (19) based on a radius Ri (t), where $\boldsymbol{D_i}$ signifies the Euclidean distance between $\boldsymbol{X_i(t)}$ and $\boldsymbol{X_j(t)}$.

$$\boldsymbol{N_i(t)} = (\boldsymbol{X_j(t)} | \boldsymbol{D_i}(\boldsymbol{X_i(t)}, \boldsymbol{X_j(t)} \le \boldsymbol{R_i(t)}, \boldsymbol{X_j(t)} \in \boldsymbol{Pop} \quad (19)$$

Following the establishment of the neighbourhood of $\boldsymbol{X_i(t)}$, Equation (20) is employed to calculate the $\boldsymbol{d^{th}}$ dimension of $\boldsymbol{X_{i-DLH}(t+1)}$. This is achieved by integrating the $\boldsymbol{d^{th}}$ dimensions of a randomly selected neighbour $\boldsymbol{X_{n,d}(t)}$ from $\boldsymbol{N_i(t)}$ and a randomly chosen wolf $\boldsymbol{X_{r,d}(t)}$ from the $\boldsymbol{Pop}$.

$$\boldsymbol{X_{i-DLH}(t+1)} = \boldsymbol{X_{i,d}(t)} + \boldsymbol{rand} \times (\boldsymbol{X_{n,d}(t)} - \boldsymbol{X_{r,d}(t)}) \quad (20)$$

In the selecting and updating phase, the optimal candidate is determined by evaluating the fitness values of two candidates, $\boldsymbol{X_{i-GWO}(t+1)}$ and $\boldsymbol{X_{i-DLH}(t+1)}$, in accordance with the specified equation.

$$\boldsymbol{X_i(t+1)} = \begin{Bmatrix} \boldsymbol{X_{i-GWO}(t+1)}, \boldsymbol{if\ f(X_{i-GWO} < f(X_{i-DLH})} \\ \boldsymbol{X_{i-DLH}(t+1)\ otherwise} \end{Bmatrix} \quad (21)$$

To update the new location of $\boldsymbol{X_i(t+1)}$, if the fitness value of the nominated candidate is less than that of $\boldsymbol{X_i(t)}$, then $\boldsymbol{X_i(t)}$will be updated to this candidate. Otherwise, $\boldsymbol{X_i(t)}$remains unchanged in the $\boldsymbol{Pop}$. Upon completion of this process for all individuals, the iteration counter is incremented by one. The search may then be repeated multiple times until the maximum number of iterations is reached.

The DLH search technique employs dimension learning to enhance the equilibrium between local and global search, all while preserving diversity. The IGWO-OBL hybrid optimisation consists of three steps: initializing, movement, and fitness evaluation and updating.

Initialization

Initialize the population of wolves $\boldsymbol{X_i(t)}$ randomly within the solution space. Generate the opposition solution $\boldsymbol{X_i'(t)}$ for each wolf utilizing the OBL technique.

$$\boldsymbol{X_i'(t) = X_{min} + X_{max} - X_i(t)} \tag{22}$$

Incorporate the opposite solutions $\boldsymbol{X_i'(t)}$ into the population. The current population comprises both original and opposing solutions.

Fitness Evaluation

Evaluate the fitness of both $\boldsymbol{X_i(t)}$ and $\boldsymbol{X_i'(t)}$ solution. Select the better solution between $\boldsymbol{X_i(t)}$ and $\boldsymbol{X_i'(t)}$ as the current best solution.

Update Positions using IGWO

Revise the locations of the wolves by applying the equations from the Improved Grey Wolf Optimisation (IGWO) methodology. To update the position of each wolf, utilize the following general formula, which is derived from the Grey Wolf Optimisation (GWO) method.

$$\boldsymbol{X_i(t+1) = X_i(t) + A(t).D_\alpha} \tag{23}$$

Where

$\boldsymbol{D_\alpha}$ is the distance from the alpha wolf's position ,calculated as

$$\boldsymbol{D_\alpha = |C_1.X_\alpha - X_i(t)|} \tag{24}$$

A(t) represents a coefficient that is dynamically adjusted to regulate the balance between exploration and exploitation during each iteration. As an illustration, the computation can be expressed as follows:

$$\boldsymbol{A(t) - 2.rand(0,1) - 1} \tag{25}$$

which is linearly decaying in iterations

$\boldsymbol{C_1, C_2, C_3}$ are random vectors within the range of [0, 2], directing the wolves towards optimal solutions. Generate the opposition of the updated solution $\boldsymbol{X_i'(t+1)}$ and determine both.

Execute the position update and OBL process for multiple iterations until a predefined stopping criterion is satisfied (e.g., reaching the maximum number of iterations or achieving convergence to an acceptable fitness level). Upon meeting the stopping criterion, the optimal solution identified throughout the iterations should be returned. The Flowchart of the proposed system is shown in figure 2.

6. ALGORITHM OF IGWO-OBL HYBRID OPTIMISATION

The Improved Grey Wolf Optimizer (IGWO) integrated with Opposition-Based Learning

(OBL) is a hybrid optimisation approach that enhances the standard GWO by improving its exploration and exploitation capabilities. The incorporation of OBL helps in accelerating convergence and avoiding local optima by considering both the current solution and its opposite. The steps for the IGWO-OBL hybrid optimisation algorithm for the optimal placement and sizing of UPQC are described below which includes initialization, Iterative Optimisation Process and Termination Criteria.

Initialization parameters include 'N' candidate selection number of wolves, Decision variables include $x_{location}, S_{UPQC}$ and Q_{UPQC} .The maximum number of iteration i.e, Max Iter. The control parameter α that linearly decreases from 2 to 0.The opposite solution describes Computation of opposite candidates for enhanced search space exploration

Step 1: Randomly generate the initial population of wolves $\boldsymbol{X_i(t)} = [\boldsymbol{x_{i1}}, \boldsymbol{x_{i2}}, \ldots \boldsymbol{x_{iD}}]$,where each wolf $\boldsymbol{x_{i1}} = [\boldsymbol{x_{location}}, \boldsymbol{S_{UPQC}}, \boldsymbol{Q_{UPQC}}]$.

Step 2: Evaluate the fitness of each wolf based on the objective function $\boldsymbol{f(x) = w_1 f_1 + w_2 f_2 + w_3 f_3}$.Where $\boldsymbol{w_1}, \boldsymbol{w_2}$and , $\boldsymbol{w_3}$ are the assigned weights with relative importance.$\boldsymbol{f_1}$, $\boldsymbol{f_2}$ and $\boldsymbol{f_3}$ are the Total power loss minimization, voltage stability index improvement and UPQC cost minimization respectively

Step 3: Determine the top three wolves α Best solution,β Second-best solution and δ Third-best solution.

Step 4: Compute the opposite population $\boldsymbol{X_{opposite}}$ using opposition-based learning$\boldsymbol{x_{opposite,i} = LB + UB - x_i}$,where $\boldsymbol{LB}$ and $\boldsymbol{UB}$ are the lower and upper bounds of the decision variables. Evaluate $\boldsymbol{X_{opposite}}$ and replace less fit wolves in $\boldsymbol{X}$ with fitter wolves from $\boldsymbol{X_{opposite}}$.

Step 5: Update the positions of wolves, each wolf updates its position based on its distance to α, β, and δ. Compute the attraction coefficients $\boldsymbol{A = 2a.r - a}$, $\boldsymbol{C = 2.r}$ where $\boldsymbol{a}$ linearly decreases from 2 to 0 over iterations. r is a random number in [0,1].

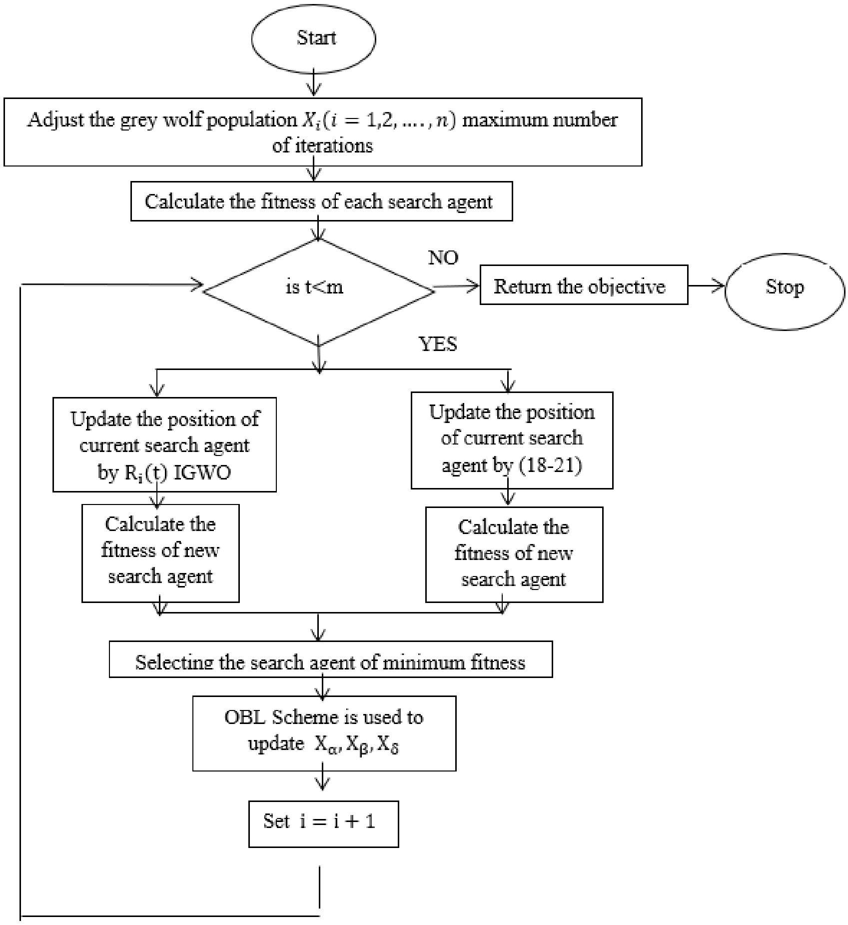

Figure No 2: Flow chart of IGWO-OBL Hybrid Optimisation

Step 6: update the position of each wolf using the following equations. Distance to the best wolves $\boldsymbol{D_\alpha}=|\boldsymbol{C_1.X_\alpha - X}|$, $\boldsymbol{D_\beta}=|\boldsymbol{C_2.X_\beta - X}|$ $\boldsymbol{and}$ $\boldsymbol{D_\delta}=|\boldsymbol{C_2.X_\delta - X}|$.New positions $\boldsymbol{X_1 = X_\alpha - A_1.D_\alpha}$, $\boldsymbol{X_2 = X_\beta - A_2.D_\beta}$, $\boldsymbol{X_3 = X_\delta - A_3.D_\delta}$ and $\boldsymbol{X_{new}}$

Step 7: Introduce opposition-based learning, Calculate the opposite positions $\boldsymbol{X_{opposite,new}}$ for the updated wolves. Evaluate $\boldsymbol{X_{opposite,new}}$ and compare their fitness with $\boldsymbol{X_{new}}$.Replace $\boldsymbol{X_{new}}$ with $\boldsymbol{X_{opposite,new}}$ if the opposite solution has a better fitness.

Step 8: Constraints handling, Ensure that the updated solutions satisfy all constraints Location Constraint includes$[\boldsymbol{x_{location}, S_{UPQC}, Q_{UPQC}}]$, Size Constraint includes $\boldsymbol{0 \leq S_{UPQC} \leq S_{max}}$ and Reactive Power Constraint includes $\boldsymbol{Q_{min} \leq Q_{UPQC} < Q_{max}}$.Use a penalty function to handle solutions that violate constraints.

Step 9: Update α, β, and δ.After evaluating the fitness of all solutions (including the opposite ones), update the top three wolves α describes as best solution,β describes second-best solution and δ describes third-best solution.

Step 10: Repeat the iterative process until one of the following conditions is met. The maximum number of iterations $\max iter$ is reached. The improvement in the fitness value falls below a pre-defined threshold.

7. RESULTS AND DISCUSSION

The proposed IGWO-OBL hybrid optimisation was tested on IEEE 30_bus and IEEE 57_bus through single objective optimisation , multi-objective optimisation.The results were compared with existing accepted approaches . According to the study, the suggested approach produced superior voltage stability index, increased efficiency and reliability, and notable drops in P_{loss} and Reduced overall $UPQC_{cost}$.

CASE I: Evaluating Performance on the IEEE-30 Bus System

The proposed IGWO-OBL method is tested in IEEE 30_bus through single objective optimisation , multi-objective optimisation .The results of the suggested technique definitely outperform the results of the reaming method which can be observe by seeing Table 1.

Table No 1: Numerical values for IEEE 30 bus single objective optimisation

Algorithm	Location 1	Location 2	VSI Improvement (p.u)	Total Power loss (MW)	Execution time
GWO	Bus no: 7, 22, 14	Bus no: 3, 19, 26	0.6	39.6481	5 Sec
IGWO	Bus no: 11, 28, 5	Bus no: 15, 10, 27	0.8	42.1967	3.5 Sec
CSO	Bus no: 2, 30, 17	Bus no: 25, 9, 21	0.7	38.6231	3.2 Sec
IGWO-OBL Hybrid method	Bus no: 3, 20, 4	Bus no: 8, 29, 11	1.0	37.4975	3 sec

In IEEE 30_bus test system IGWO-OBL hybrid method is compared with tradional method like GWO,IGWO and CSO at different bus locations. The IGWO-OBL hybrid method achieves the highest VSI improvement (1 p.u), showing the best voltage stability performance. IGWO-OBL hybrid method again outperforms others with the lower total power loss (37.4975 MW) for better VSI improvement and faster execution. The IGWO-OBL hybrid method is the fastest algorithm (3 seconds) compared to IGWO,GWO and CSO.

IGWO-OBL hybrid method achieves the highest VSI improvement (1 p.u), highlighting its superior performance for voltage stability. IGWO-OBL total power loss (47.2077MW), showcasing its effectiveness in minimizing losses . IGWO-OBL hybrid method offers the highest cost reduction ($15000, 21.05%).

Table No 2: Numerical values for IEEE 30 bus For multi-objective optimisation

Algorithm	Location	VSI Improvement (p.u)	Total Power loss (MW)	Cost Reduction ($)	Execution time
GWO	Bus no: 4, 18, 29	0.7	57.3012	18083.45 (4.80%)	3 Sec
IGWO	Bus no: 12, 6, 23	0.8	49.8745	16925.78 (5.66%)	2.96 Sec
CSO	Bus no: 30, 8, 16	0.5	55.1234	15160.32 (20.21%)	3.2 Sec
IGWO-OBL Hybrid method	Bus no: 1, 10, 3	1.0	47.2077	15000 (21.05%)	2.49 sec

IGWO-OBL hybrid method is the fastest algorithm (2.49 seconds). IGWO-OBL Hybrid Method excels in VSI improvement, cost reduction, lower total power loss and high execution speed. The results of the proposed technique clearly exceed those of the reaming method, as evidenced by the data presented in Table 2.Within the framework of the IEEE 30-bus system, a fitness value of $3 \times \mathbf{10^4}$achieved after 100 iterations utilising the IGWO-OBL hybrid algorithm signifies that the optimisation process has effectively minimised critical objectives, including total power loss reduction, voltage stability, and cost minimisation is shown in figure 3.

The IGWO-OBL hybrid algorithm integrates the capabilities of the Improved Grey Wolf Optimisation (IGWO) and Opposition-Based Learning (OBL), facilitating efficient exploration of the solution space while achieving swift convergence.The Opposition-Based Learning (OBL) mechanism enhances convergence by producing opposite solutions to diversify the population, thereby facilitating a more rapid attainment of the optimal solution.Upon completion of 100 iterations, the fitness value of $3 \times \mathbf{10^4}$indicates that the algorithm has identified an optimal or near-optimal configuration for the IEEE 30-bus system, effectively balancing the trade-offs among total power loss, voltage stability, and cost reduction. The convergence curve demonstrates an initial rapid decrease, succeeded by a stabilisation phase, which indicates the effective exploration and fine-tuning mechanisms inherent in the IGWO-OBL hybrid algorithm.

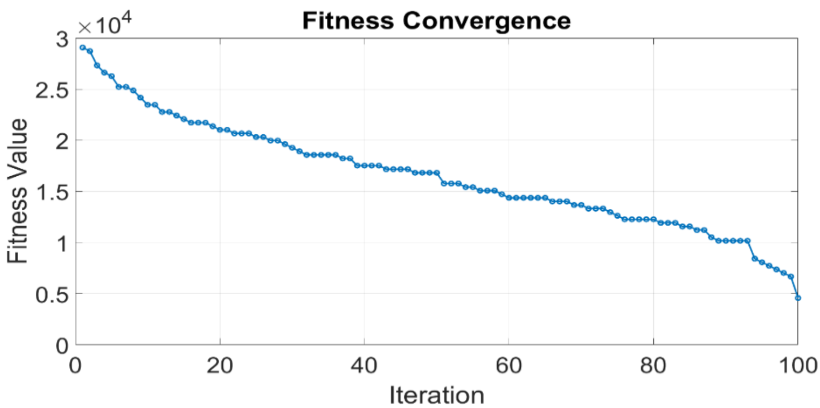

Figure No 3: Convergence graph for IEEE 30 bus at multi-objective function

CASE II: Evaluating Performance on the IEEE-57 Bus System

The proposed IGWO-OBL method is tested in IEEE 57_bus through single objective optimisation , multi-objective optimisation . The results of the proposed technique clearly exceed those of the reaming method, as evidenced by the data presented in Table 3.IGWO-OBL Hybrid Method achieves the best VSI improvement (1.0 p.u). IGWO-OBL method, despite its superior VSI improvement, has the total power loss (0.0620 MW). IGWO-OBL Hybrid Method is the fastest (3.1 seconds) time to execute compared to IGWO, GWO and CSO.

Table No 3: Numerical values for IEEE 57 bus single objective optimisation

Algorithm	Location 1	Location 2	VSI Improvement (p.u)	Total Power loss (MW)	Execution time
GWO	Bus no: 15, 42, 8	Bus no: 21, 46, 11	0.34	0.1284	3.3 Sec
IGWO	Bus no: 25, 37, 3	Bus no: 5, 39, 29	0.85	1.4752	3.8 Sec
CSO	Bus no: 29, 54, 12	Bus no: 22, 4, 19	0.78	0.3467	3.5 Sec
IGWO-OBL Hybrid method	Bus no: 40, 54, 9	Bus no: 9, 36, 14	1.0	0.0620	3.1 sec

IGWO-OBL Hybrid Method achieves the best VSI improvement (1.0 p.u), indicating exceptional voltage stability enhancement.IGWO-OBL Hybrid Method has lowered total power loss (0.0620 MW), indicating it prioritizes voltage stability over minimizing total power loss .

IGWO-OBL Hybrid Method delivers the highest cost reduction ($47000, 4.08%), making it the most economical choice.IGWO-OBL Hybrid Method is the fastest algorithm (2.9 seconds).IGWO-OBL Hybrid Method Excels in VSI improvement, cost savings, and execution speed and minimizing total power loss, prioritizing voltage stability over loss mitigation compared to IGWO,GWO and CSO. The results of the proposed technique clearly exceed those of the reaming method, as evidenced by the data presented in Table 4.

Table No 4: Numerical values for IEEE 57 For bus multi-objective optimisation

Algorithm	Location	VSI IMPROVEMENT (p.u)	Total Power loss (MW)	Cost Reduction($)	Execution time
GWO	Bus no: 46, 11, 33	0.45	9.5384	48529 (0.962%)	3.8 Sec
IGWO	Bus no: 5, 39, 51	0.62	11.2456	49003 (0.00612%)	4 Sec
CSO	Bus no: 10, 21, 30	0.05	8.9991	48175 (1.68%)	3.5 Sec

IGWO-OBL Hybrid method	Bus no: 20, 10, 2	1.0	8.1272	47000 (4.08%)	2.9 sec

In the analysis of the IEEE 57-bus system, the IGWO-OBL hybrid algorithm attains a fitness value of $6 \times \mathbf{10^4}$following 100 iterations, demonstrating successful optimisation. The fitness function represents a combination of multiple objectives, including the minimisation of Total power losses, enhancement of voltage stability, and reduction of operational costs is shown in figure 4.The Improved Grey Wolf Optimiser (IGWO) refines the conventional Grey Wolf Optimiser (GWO) through the implementation of adaptive search mechanisms, thereby enhancing the balance between exploration and exploitation. This facilitates the prevention of premature convergence and enhances the algorithm's capacity to identify the global optimum.

The Opposition-Based Learning (OBL) technique enhances the convergence process by producing solutions that are the inverse of existing ones, thereby promoting a more diverse exploration and improved search coverage.Upon completion of 100 iterations, the fitness value reaches a stable point at 6×10^4, indicating that the algorithm has effectively identified a near-optimal solution.

The convergence curve is expected to display an initial sharp decline as the algorithm investigates the solution space, subsequently transitioning into a plateau phase during the fine-tuning of the solution.

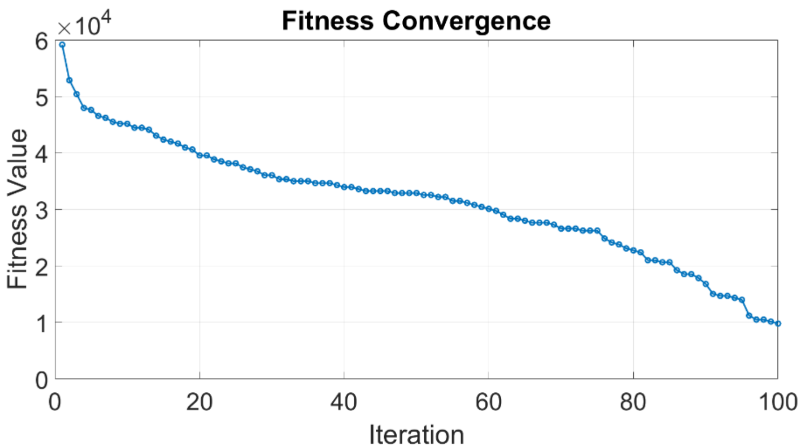

Figure No 4: Convergence graph for IEEE 57 bus at multi-objective function

In conclusion, the 6×10^4fitness value obtained after 100 iterations demonstrates the algorithm's effectiveness in optimising the performance of the IEEE 57-bus system. It successfully balances Total power loss, stability, and costs, while ensuring efficient convergence through the IGWO-OBL hybrid method.

The voltage levels of voltage source inverter, $P_{loss,}$ $UPQC_{cost}$ and Final Fitness for various optimisation techniques and proposed optimisation algorithm of IEEE 30 bus and IEEE 57 bus radial test system performance is illustrated in Table No 1,2,3 and 4 . The proposed optimisation algorithm shows better performance at voltage levels of voltage source inverter, $P_{loss,}$ $UPQC_{\ cost}$ and Final Fitness under single objective problem and multi objective problem.

8. CONCLUSION

This paper presents an enhancement of the PQ model, which is based on a IGWO-OBL hybrid optimisation for optimal sizing and location of UPQC in power distribution systems. The optimal solution was developed using the Improved Grey Wolf Optimizer in the framework of opposition-based learning model, resulting in the technique being designated as IGWO-OBL hybrid optimisation. The IGWO-OBL hybrid algorithm effectively identifies the optimal position of the UPQC device by evaluating Total Power losses, UPQC costs, and VSI parameters. The performance of the developed technique was analysed in IEEE 30 and IEEE 57 bus systems, and the results are compared with other conventional techniques such as GWO, IGWO, CSO, and the IGWO-OBL hybrid optimisation. The results were obtained accordingly. The performance of the developed model was verified effectively. To enhance performance and ensure stability in power systems while addressing power quality issues, the optimal sizing and positioning of the Unified Power Quality Conditioner (UPQC) within the power system was implemented using the developed methodology.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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AUTHOR CONTRIBUTIONS

Conceptualization, L.Vamsi Narasimha Rao; Methodology, L.Vamsi Narasimha Rao; Validation, L.Vamsi Narasimha Rao, P.S.Prakash, and M.Veera kumari; Formal analysis L.Vamsi Narasimha Rao, P.S.Prakash, and M.Veera kumari; Investigation, L.Vamsi Narasimha Rao, P.S.Prakash, and M.Veera kumari; Resources, L.Vamsi Narasimha Rao, P.S.Prakash, and M.Veera kumari; Data curation, L.Vamsi Narasimha Rao, P.S.Prakash, and M.Veera kumari; Writing—original draft preparation, L.Vamsi Narasimha Rao; Writing—Review and Editing, L.Vamsi Narasimha Rao, P.S.Prakash, and M.Veera kumari; Visualization; L.Vamsi Narasimha Rao, P.S.Prakash, and M.Veera kumari; Supervision; P.S.Prakash, and M.Veera kumari

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