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COMBINED ALLOCATION OF DISTRIBUTED GENERATION AND UNIFIED POWER QUALITY CONDITIONER IN DISTRIBUTION NETWORK

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Abstract : The high penetration of distributed generation (DGs) can lead to negative impacts on the distribution system, such as increased power losses and voltage violations. A promising solution to address these challenges is the strategic deployment of unified power quality conditioner (UPQC). This paper investigates the combined allocation of DGs and UPQC in distribution networks using practical load models to mitigate power losses and voltage violations. The study formulates an objective for cost minimization, encompassing both the investment and operational costs of DGs and UPQC. For the first time, the Crayfish Optimization Algorithm (COA) is applied to optimize this problem. The proposed approach is validated on the IEEE 33 bus radial distribution system. The findings underscore the importance of DG installation, showing potential cost savings of up to 32.791% compared to scenarios without such installations. Moreover, compared to conventional deployments, a coordinated approach achieves a cost reduction of 39.635% through optimized DG and UPQC placement.

IndexTerms - **Unified power quality conditioner, optimization, Distributed generation**.

I. INTRODUCTION

The integration of photovoltaic (PV) based distributed generation (DG) units in distribution networks has been growing due to environmental concerns [1] [2]. However, the introduction of nonlinear loads into these networks introduces harmonics, which degrade power quality (PQ). Allocating Unified Power Quality Conditioners (UPQC) is a strategy to improve PQ by offering reactive power adjustment. Additionally, UPQC helps enhance network energy efficiency and bus voltages [3]. Therefore, Efficiently allocating Distributed Generation (DG) and Unified Power Quality Conditioner (UPQC) is essential for improving power system performance. Studies have demonstrated that UPQC is capable of efficiently reducing voltage and current distortions resulting from the integration of distributed generation [4]. Additionally, the installation of an Improved UPQC (I-UPQC) in Radial Distribution Systems (RDS) has been found to notably decrease power loss, under-voltage problems, and reactive power demands, thereby enhancing system efficiency [5]. Furthermore, by utilising advanced optimisation algorithms such as the Grey Wolf Optimisation (GWO) method, it is possible to improve the voltage profiles and minimise line losses in radial distribution systems by optimising the real power injections at unity power factor as Distributed Generation (DG). This highlights the significance of efficient allocation strategies for both DG and Unified Power Quality Conditioner (UPQC) in power systems [6]. In [7], the Black Widow Optimization Algorithm (BWOA) was employed to optimally allocate distributed generation (DG) with the goal of minimizing overall real power loss in distribution systems. In [8], the Differential Evolution (DE) algorithm was used to solve the optimal allocation of Unified Power Quality Conditioner (UPQC) aiming to minimize power losses and reduce investment costs. In [9], the Salp Swarm-Crow Search (SSCS) Algorithm was adopted for the optimal allocation of UPQC, focusing on cost minimization. In [10], an improved Adaptive Cuckoo Algorithm (ACA) was introduced for the optimal allocation of DGs, aiming to minimize generation costs, network loss costs, and DG environmental costs. In [11], a combined approach using Crow Search Algorithm (CSA) and Lion Algorithm (LA) was introduced for the optimal allocation of UPQC in power systems, aiming to minimize power losses, UPQC costs, and voltage deviations. In [12], the Ant Lion Optimization (ALO) was employed for the optimal allocation of DGs, focusing on enhancing techno-economic and environmental benefits. To the best of the authors' knowledge, there are no existing reports on coordinated allocation of DGs and UPQC considering operational, environmental, and economic costs. This study introduces the COA algorithm to tackle the allocation issues of DGs and UPQC with voltage-dependent load models. The effectiveness of this approach is demonstrated through multiple test cases conducted on the IEEE 33-bus distribution system.

The current paper makes the following primary contributions:

- Introducing a planning model for integrating DGs and UPQC into distribution networks.
- Addressing operational, environmental, and economic challenges through an integrated planning approach for DGs and UPQC.
- Analyzing the influence of practical loads on the allocation of UPQC and DGs.

The paper is structured as follows: Section 1 presents the mathematical formulation of the research objectives. Section 2 outlines the introduced COA method. Section 3 summarizes the findings and discussions, while Section 4 concludes the paper.

1. Problem Formulation

The purpose of the current issue is to identify a resolution that minimises the total annual cost. This cost covers the expenses related to the acquisition of DER and UPQC-O, as well as the expenses related to their management and operation, the cost of grid electricity, and the cost of emissions.

1.1 Objective Function

The objective function (OF) of the proposed approach is to minimize the total economic cost. This includes both the investment and operation costs of the system, as defined in the following expression: (1).

$$min.O\,F = inv_{cost} + oper_{cost} \quad (1)$$

The first term in equation (1) represents the investment cost (inv_{cost}) of both PV-based DG and UPQC.

$$INV_{COST} = AC^{PV}\sum_{i\in\Omega_{PV}}\left(C_{PV}^{inv}P_{PV,i}^{rated}\right) + AC^{UPQC}\sum_{ij\in\Omega_{UPQC}}\left(C_{UPQC}^{inv}Q_{UPQC,ij}^{rated}\right) \quad (2)$$

Where

$$AC^{x} = \frac{dr(1+dr)^{lf\,x}}{(1+dr)^{lf\,x-1}};\, x\in\{PV, UPQC\}$$

AC stands for annual cost, the metric used to convert the total cost into a yearly cost. In this context, lf represents the asset lifetime period, and dr denotes the discount rate. The first and second terms in equation (2) represent the annual costs for PV (C_{PV}^{inv}) and UPQC (C_{UPQC}^{inv}) respectively.

Where the second term in equation (1) is the operating costs ($oper_{cost}$), which is stated in (3).

$$OPER_{COST} = \sum_{t=1}^{T}\begin{pmatrix}\sum_{ij\in\Omega_{UPQC}} C_{UPQC}^{OM,t}Q_{UPQC,ij}^{t}\\ +\sum_{i\in\Omega_{PV}} C_{PV}^{OM,t}P_{PV,i}^{t}\\ +C_{ens}^{t}P_{ens}^{t} + C_{emis}P_{sub}^{t} + C_{loss}^{t}P_{loss}^{t}\end{pmatrix}N_{days} \quad (3)$$

The first and second terms in Equation (3) reflect the expenses for the operation and maintenance (O&M) of UPQC equipment and PV-based DGs, respectively. The third term represents the cost of energy not served, while the fourth term accounts for the cost of energy loss. Lastly, the fifth term indicates the cost of emissions. To convert the daily costs into annual costs, these terms must be multiplied by the total number of days in a year, denoted by N_{days}.

1.2 System operation constraints

The proposed model must satisfy the following constraints (4)-(11). Equations (4) and (5) define the maximum installation limits for UPQC and PV-based DG. Equations (6) and (7) describe the formulations for active and reactive power flow. Equation (8) imposes constraints on bus voltage, while Equation (9) governs branch current capacity. Equations (10) and (11) represent active and reactive power for load models characterized by constant power, constant impedance, and constant current. These formulations are detailed below:

$$0 \le Q_{UPQC,ij}^{rated} \le Q_{UPQC,ij}^{max} \quad (4)$$

$$0 \le P_{PV,i}^{rated} \le P_{PV,i}^{max} \quad (5)$$

$$P_i^t = V_i^t\sum_{i\in\Omega_{bus}} V_j^t\left(G_{ij}\cos\theta_{ij}^t + B_{ij}\sin\theta_{ij}^t\right) \quad (6)$$

$$Q_i^t = V_i^t\sum_{i\in\Omega_{bus}} V_j^t\left(G_{ij}\sin\theta_{ij}^t - B_{ij}\cos\theta_{ij}^t\right) \quad (7)$$

$$V_i^{min} \le V_{i,s}^t \le V_i^{max} \quad (8)$$

$$0 \le I_{l,s}^t \le I_l^{rated} \quad (9)$$

$$P_{L,i} = P_{L,i}^{act}\left[Z_L^p\left(\frac{V_i}{V_{act}}\right)^2 + I_L^p\left(\frac{V_i}{V_{act}}\right) + P_L^p\right] \quad (10)$$

$$Q_{L,i} = Q_L^{act}\left[Z_L^q\left(\frac{V_i}{V^{act}}\right)^2 + I_m^q\left(\frac{V_i}{V^{act}}\right) + P_L^q\right] \quad (11)$$

II .Solution Algorithm: Crayfish Optimization Algorithm (COA)

The Crayfish Optimization Algorithm (COA) [13] is inspired by crayfish behaviors such as foraging, vacationing, and competiti on. It simulates crayfish using their claws and feet for handling food and defense. The foraging and competition stages correspond to the exploitation phase, while the summer vacation stage corresponds to the exploration phase. In COA, a crayfish colony represents potential solutions, with their positions determined by environmental temperature. During foraging, the optimal solution is akin to the best food position, modeled using sine and cosine formulas to reflect crayfish eating habits. COA is explained through five distinct stages.

Stage 1: Initialization:

The Crayfish Optimization Algorithm (COA) begins by randomly generating a set of candidate solutions (Cf) within the defined search space. These candidates are determined by the population size (N) and dimensionality (dim), as described in Eq. (12).

$$Cf = \begin{bmatrix} Cf_{1,1} & \cdots & Cf_{1,dim} \\ \vdots & \ddots & \vdots \\ Cf_{N,1} & \cdots & Cf_{N,dim} \end{bmatrix} (12)$$

Here, C_f represents the initial positions of the population, (N) denotes the number of individuals in the population, and (dim) signifies the dimensionality of the search space. $Cf_{i,j}$ refers to the position of the i-th individual in the j-th dimension, as calculated in Eq. (13).

$$Cf_{i,j} = lb_{i,j} + (ub_{i,j} + lb_{i,j}) \times rand \ (13)$$

Here, ub_{ij} and lb_{ij} denotes the upper and lower limits of the i-th individual in the j-th dimension, respectively, while ($rand$) denotes a random number.

Stage 2: Impact of temperature on crayfish consumption

Temperature changes significantly influence crayfish behavior, prompting them to transition between different stages. According to Eq. (14), when the temperature exceeds 30°C, crayfish move to cooler areas for the summer. At optimal temperatures, they engage in foraging, with their feeding amount being temperature-dependent. The ideal feeding range for crayfish is between 15°C and 30°C, with 25°C being optimal. As a result, their feeding behavior approximates a normal distribution, particularly strong between 20°C and 30°C. The COA thus defines a temperature range from 20°C to 35°C. The mathematical model for crayfish intake is detailed in Eq. (15).

$$Temp = rand \times 15 + 20 \ (14)$$

$$p = W \times \left(\frac{1}{\sqrt{2\times\pi}\times\sigma} \times exp\left(-\frac{(Temp-\mu)^2}{\sigma^2}\right)\right) \quad (15)$$

Here, μ denotes the optimal temperature for crayfish, while σ and W are parameters used to adjust the amount of food consumed by crayfish at different temperatures.

Stage 3: Exploration Phase of Summer Resort

If the temperature go beyond 30°C, it becomes so high for the crayfish, prompting them to seek refuge in a cave. The cave, denoted as (Cf_{shade}), is described as follows:

$$Cf_{shade} = \frac{Cf_G + Cf_L}{2} \ (16)$$

Here, Cf_G correspond to the optimal position achieved through cumulative iterations, while (Cf_L) indicates the optimal position within the current population.

The phenomenon of crayfish engaging in fights over territory within caves is seen as a stochastic occurrence. If the value of a random variable ($rand$) is below 0.5, it signifies the lack of competing crayfish, which permits the crayfish to enter the cave straight for the summer. The procedure is mimicked in the following manner:

$$Cf_{i,j}^{it+1} = Cf_{i,j}^{it} + S \times (Cf_{shade} - Cf_{i,j}^{it}) \ (17)$$

Within this particular framework, it denotes the present count of iterations. Moreover, S is a curve that exhibits a declining trend, as demonstrated by the following equation:

$$S = 2 - \left(\frac{it}{IT_{max}}\right) (18)$$

Here, IT_{max} denotes the upper limit for the number of iterations. During the summer resort phase, crayfish strive to reach the cave, which represents the most favorable outcome. During this phase, crayfish exhibit a behavior of approaching the cave, so efficiently putting people in closer proximity to the optimal solution. This process improves the COA's capacity to exploit, leading to faster convergence of algorithms.

Stage 4: Exploitation Phase of Competition

If the temperature rises beyond 30 degrees and the *rand* value is below 0.5, it suggests that the cave is attracting organisms other than crayfish. Equation (35-19) depicts the crayfish engaging in competition to gain dominance over the cave.

$Cf_{i,j}^{it+1} = Cf_{i,j}^{it} - Cf_{z,j}^{it} + Cf_{shade}$ (19)

Here, Cf_{ij} correspond to a randomly chosen individual crayfish.

$z = round\left(rand \times (N-1)\right) + 1$ (20)

Crayfish engage in intraspecific competition, with each individual crayfish (Cf_i) adjusting its location in response to the position of another crayfish (Cf_z). This positional change expands the search range of the COA, hence enhancing the algorithm's capacity for exploration.

Stage5: Exploitation Phase of Foraging

Temperatures equal to or lower than 30°C are considered appropriate for crayfish feeding. During this period, crayfish exhibit vigorous locomotion as they approach the source of food. After discovering the food, crayfish evaluate the dimensions of the food item. They utilise their claws to dismantle sizable food items and thereafter ingest them by rotating among its second and third locomotor limbs.

$Cf_{food} = Cf_G$ (21)

The dimension of food Q is denoted as:

$Q = k \times rand \times \left(\frac{fitness_i}{fitness_{food}}\right)$ (22)

Here, the variable k represents the food factor, which denotes the maximum size of food and has a constant value of 3. The variable " $fitness_i$ " denotes the fitness value of the crayfish at index i, whereas " $fitness_{food}$ " reflects the fitness value associated with the position of the food. The crayfish evaluates the size of food by considering the dimensions of the largest food item. If Q is greater than (k+1)/2, it indicates that the meal portion size is excessive. Presently, the crayfish is utilising its primary claw attachment to shred its prey. The following equation is used to mimic this process:

$Cf_{food} = exp\left(-\frac{1}{Q}\right) \times Cf_{food}$ (23)

The equation that describes the foraging behaviour of crayfish, considering the relationship between the food obtained by crayfish and their food intake, can be expressed as follows:

$Cf_{i,j}^{it+1} = Cf_{i,j}^{it} + Cf_{food} \times p \times \left(cos(2 \times \pi \times rand) - sin(2 \times \pi \times rand)\right)$ (24)

If Q is greater than or equal to (k+1)/2, the crayfish can directly approach the meal and consume it without any more steps. The present situation can be succinctly explained by the subsequent equation:

$Cf_{i,j}^{it+1} = \left(Cf_{i,j}^{it} - Cf_{food}\right) \times p + p \times rand \times Cf_{i,j}^{it}$ (25)

Crayfish employ diverse feeding tactics depending on the dimension of their food (Q), with the food (Cr_{food}) representing the most favourable option. Crayfish will actively approach food that is of an appropriate size (Q) for ingestion. If the value of Q is excessively great, it signifies a substantial disparity among the crayfish and the best possible outcome. Consequently, endeavours are undertaken to decrease the occurrence of (Cr_{food}) by placing it in proximity to the food item. During the foraging stage, the COA algorithm strives to attain the most favourable solution, hence improving its ability to utilise resources and exhibiting robust convergence capabilities. The procedure of COA is illustrated in Table 1.

Table 1: Proposed Algorithm 1 Pseudo-Code of COA

III. Results and Discussions

Fig. 1 portrays single lime diagram of the IEEE 33-bus distribution system [14] was used to validate the accuracy of the proposed methodology. The load profile data and PV generation output data were sourced from [15]. Cost parameters for UPQC and PV-based DG were derived from [3] and [16]. The price for unserved electricity is set at $2,000 per megawatt-hour (MWh) [17], while the emission cost is assumed to be $100 per ton of CO2 equivalent (tCO2e), with an emission rate of 0.4 tCO2e per MWh [17]. The total harmonic distortion (THD) is assumed to be 20%. The optimization process employed a maximum population size of 30 and 100 iterations. The proposed COA optimization for the optimal allocation of DGs and UPQC units was implemented in a MATLAB environment.

Table 2. Cases studied

Cases	PV	UPQC
Case 1	×	×
Case 2	✓	×
Case 3	✓	✓

✓: means not considered, ×: means considered

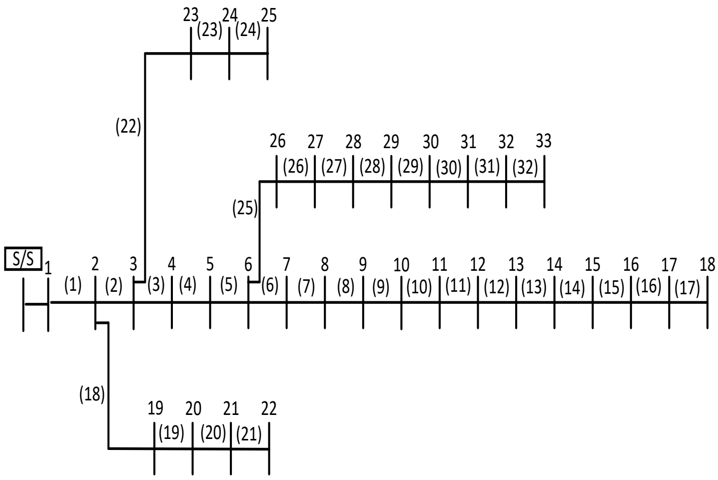

Figure 1. single-line diagram of the 33-bus distribution system

a. Cases studied:

Three distinct studies evaluating the effectiveness of the proposed methodology were conducted, as detailed in Table 3. These studies encompass three different scenarios, with Case 1 being the most prevalent among them.

b. Discussions on numerical results:

Table 3. Simulation Results under different cases

Parameters	Case 1	Case 2	Case 3
Investment cost (k$)	0.000	338.548	451.057
O & M cost (k $)	0.000	16.927	22.553
Energy loss cost (k $)	4801.424	2808.891	2257.357
Reliability cost (k $)	527.571	522.705	521.260
Emission cost (k $)	1055.142	603.630	601.545
Total cost (k $)	6384.137	4290.702	3853.772
Savings in total cost (k $)	------	2093.435	2530.365
Total cost reduction (%)	------	32.791	39.635

The most significant components are detailed in Table 3, including the installation costs, operation and maintenance (O&M) expenses of PV-based distributed generation (DG) units and unified power quality conditioners (UPQC), energy loss costs (ELC), cost of energy not served (ENS), and carbon emission costs across different scenarios. Although the investment cost of DGs increased by $338.548k, case 2 revealed savings of approximately $2093.435k, which is 32.791% higher than case 1. This underscores the value of allocating PV-based DGs in distribution networks. Similarly, case 3 resulted in savings of about $2530.365k, a 39.635% increase compared to case 1, despite the investment cost rising to $451.057k. This highlights the significance of integrating both PV-based DGs and UPQC devices into distribution systems.
Table 4 lists the optimal locations and sizes for UPQC and PV-based DG, s across various scenarios. The table indicates that the total capacities of PV-based DG units decreased with the incorporation of UPQC, as demonstrated in case 3. This emphasizes the importance of the combined allocation of UPQC and DG units.

Table 4. Optimal location and sizes of DER and UPQC-O

Cases	PV/ UPQC	(location, size in kW/kVAR)
Case 2	PV	(13, 650), (24, 800), (30, 800)
Case 3	PV	(12, 650), (21, 800), (25, 800)
	UPQC	(29, 320), (30, 830)

c. Evaluation of proposed COA and other metaheuristic approaches

An evaluation has been undertaken to assess the performance of different metaheuristic algorithms, including DE [8], SCSS [9], ACA [10], and the proposed COA, due to the intricate nature of case 3. Fig. 2 illustrates the convergence patterns of various algorithms. Table 5 displays the minimum, average, and standard deviation values attained by these metaheuristic methods. The suggested COA has successfully reached a minimum value of $3853.77k, indicating its superior performance compared to DE [8], SCSS [9], and ACA [10], which reached values of $4202.76k, $4189.98k, and $3991.25k, respectively. The COA technique efficiently balances between diversification and intensification, resulting in solutions that are closer to the global optimum. Additionally, it keeps a record of previous best solutions.

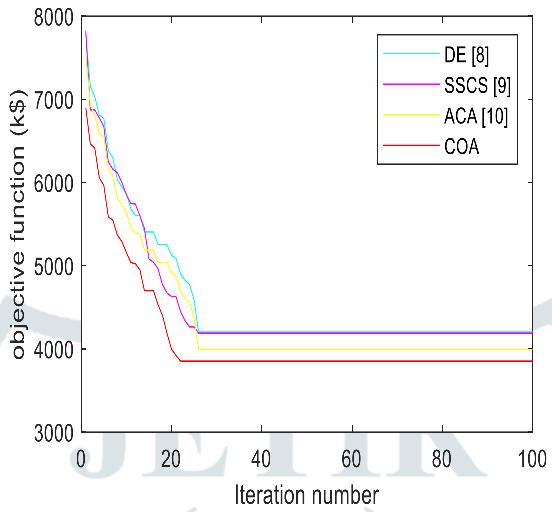

Figure 2. Convergence pattern of different algorithms

Table 5. Relative study of different metaheuristic approaches

Metaheuristic approach	Minimum value (k$)	Mean value (k$)	Standard deviation (k$)
DE [8]	4202.76	4594.50	791.43
SSCS [9]	4189.98	4532.85	762.41
ACA [10]	3991.25	4381.33	788.09
Proposed COA	3853.77	4133.56	656.46

IV. Conclusion

This paper presents the Crayfish Optimization Algorithm (COA) technique as a solution for the integrated planning model of Distributed Generators (DGs) and Unified Power Quality Conditioners (UPQC). The simulations illustrate that the suggested planning model and COA solver efficiently generate the desired and are operationally viable. The integration of Unified Power Quality Conditioners (UPQC) and Distributed Generators (DGs) has the potential to yield significant advantages in terms of minimizing energy loss, lowering energy consumption, mitigating dependability costs, and curbing carbon emissions in the network. The COA solution frequently surpasses other reported algorithms in achieving superior results. The study highlights the importance of DG installations, demonstrating possible cost reductions of up to 32.791% compared to scenarios where such installations are absent. In addition, a synchronized strategy results in a significant decrease in costs of 39.635% by strategically positioning DGs and UPQC, as opposed to traditional implementations. The integration of distributed generation (DGs) and unified power quality conditioner (UPQC) devices not only increases the financial advantages of distribution networks but also enhances their reliability, adaptability, and environmental efficiency.

Nomenclature

Indices	
$i/j, s$	Index for bus/node, scenario
T,t	Index for Total time duration, time
Sets	
$\Omega_{bus}/\Omega_{UPQC}$	Set of buses/ set of buses mounted with UPQC

Ω_{PV}	set of buses mounted with PV generation
Parameters	
N_{pv}/N_L	Total number of installed PV and loads
$Ndays$	Number of days in a year
$Q_{UPQC}^{rated}, P_{PV}^{rated}$	Rated capacity of UPQC and PV based DG
$C_{UPQC}^{inv}, C_{PV}^{inv}$	Investment cost of UPQC and PV based DG
$C_{UPQC}^{OM,t}, C_{PV}^{OM,t}$	Cost of operation and maintenance of UPQC and PV based DG
$C_{emis}, C_{loss}, C_{ens}$	Cost of emission, energy not served and losses
$P_{PV,i}^{max}, Q_{UPQC,ij}^{max}$	Maximum rating capacity of PV and UPQC
V_i^{max}, V_i^{min}	Maximum/minimum bus voltage magnitude
I_l^{rated}	Rated current in the line l
Variables	
$P_{sub}^t, P_{ens}^t, P_{loss}^t$	power from substation , energy not served and Power loss at t^{th} hour
$Q_{UPQC,i}^t/P_{PV,i}^t$	Reactive power from UPQC, active power from wind and PV based DG at t^{th} hour
$P_i^t Q_i^t$	Active/ reactive power at i^{th} bus at t^{th} hour
V_i^t	Voltage magnitude at i^{th} bus at t^{th} hour
I_l^t	current through branch l at t^{th} hour

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