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A Novel Pelican Bird Optimization Algorithm based Optimal Allocation of Combined DGs and EVCSs for Improving Voltage Stability of RDS

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Abstract

Objectives: The main objective of the proposed investigation is to enhance the voltage stability of Radial Distribution System (RDS). It is achieved by proper allocation between combined Electric Vehicle Charging Stations (EVCSs) and Distributed Generators (DGs) in RDS. Here, three objective functions such as Real Power loss, Average Voltage Devotion Index (AVDI) and Voltage Stability Index (VSI) are considered. **Methods:** The multi-objective optimization problem is implemented using a novel and an effective Pelican Optimization Algorithm (POA) to attain the best compromised solutions. POA is a nature inspired parameter less optimization tool and it is well suited for solution of complex, non-linear voltage stability problem. It determines the most excellent site and size of the EVCSs and DG units. The control parameter of POA considered are population size as 40, the number of variables as 8 and the maximum number of iterations as 100. MATLAB 14.0 platform is utilized for the projected problem. **Findings:** The bench mark test system of IEEE-33 node system is considered to authenticate the presentation of planned POA methodology. The outcomes such as minimized power loss and AVDI, improved voltage at each bus and VSI are presented. The percentage of loss reduction 39.30% is enhanced, when compared with the base case approach and 5.42 % more improved than the other existing methods like TLBO and HHO approaches. Similarly, the VSI 24.96 % is improved, when compared with the base case method and 1.58 % better than the other obtainable methods. **Novelty:** The POA is a newly urbanized and well-designed optimization algorithm. It efficiently reaches the global optimal solutions with less time duration. The comparative study with the existing algorithm of TLBO and HHO is considered to prove the performance of Projected POA approach.

Keywords: Radial distribution system; Distributed Generators; Electric Vehicles; Charging Stations; Voltage stability; Network loss reduction; Pelican Optimization Algorithm

1 Introduction

In the electric power distribution sector, network loss reduction and voltage stability improvement is a significant optimization problem for delivering quality power with cheaper cost to the costumers. Due to increasing overload of the customer, voltage fluctuation, real and reactive power loss in the network and voltage deviation is increased in RDS. Presently, the EVCSs, DGs, capacitor banks and various FACTS devices are utilized to maximize the voltage stability and performance of the RDS [1,2].

Generally, researchers have applied various intelligent soft computing techniques like GA, PSO, DE, ABC, etc. for optimal allocation and sizing of compensating devices. Sometimes, these existing techniques produce premature and local optimal solution due its own limitations. The control parameters of GA, PSO, DE, etc. like mutation, crossover, and selection operations among individuals produce the lower convergence but the proposed POA approach may offer better convergence behavior in some cases due to its emphasis on collaboration and communication among the agents, which can lead to faster exploitation of promising solutions. The more flexibility along with Exploration and Exploitation Balance of the POA, easily determines the optimal solution of RDS with minimal computation time.

In recent studies, researchers have explored different classical and soft computing methods for optimal allocation of EVCSs and other components to improve the performance of RDS. The TLBO algorithm [3] has been suggested for identifying the best position of EVCSs to reduce network loss, AVDI and VSI. The passive filters have been proposed to control the effects of AHDI and network losses by appropriate installation of EVCSs. A mathematical approach has been implemented for determining the optimal locations and capacities of solar energy-assisted charging stations for an urban area [4]. A hybrid approach of BFO-PSO technique [5] has been used in the selection of charging station location considering network losses, AVDI and VSI in RDS.

The PSO [6] has been suggested to determine the site and also sizing of EVCS. Here, an unbalanced load has been considered to check the recital of PSO approach. The JAYA algorithm [7] has been used to implement the optimal charging station allocation and analyze the JAYA efficiency for different test cases with varying load conditions. The bald eagle search algorithm [8] has addressed the multi objective problem of DG/DSTATCOM with EVCSs in RDS. The algorithm has displayed the solutions with and without installation DSTATCOM in RDS.

Genetic Algorithm with forward/backward sweep methodology [9] has been proposed to locate and scale the EVCSs in a distribution grid. Here, the distributed PV/BESSs were prevalent. The DG with EVCSs was continuously allocated by GA method. It has provided local premature solutions with higher program outcome duration. A hybrid GA-PSO [10] has been used in an IEEE-69 node test system to improve the voltage profile by proper allocation of both PV constrained DGs and plug-in EVCSs.

In this paper, an attempt has been made to enhance the voltage stability and reduce the network losses of RDS by determining optimal locations of DGs and EVCSs in RDS. A novel and an effective Pelican Optimization Algorithm is proposed to obtain the optimal solutions. The proposed problem is considered as a multi-objective optimization problem and it has considered the network power loss, AVDI and VSI. The competence of the method is tested on the standard IEEE-33 node test systems. The proposed algorithm efficiently identifies the site along with sizing of the DGs and EVCSs with different cases and the obtained results are compared with other soft computing approaches.

2 Methodology

2.1 Problem formulation

Objective Function

The DGs and EVCSs have been implemented for compromised best solution for the projected problem in RDS. The major purpose of the proposed problem is to reduce the network losses, AVDI, improve the voltage at each bus and VSI. It is achieved by installing the DGs and EVCSs at an appropriate place to obtain the required value in proposed RDS [11–14]. The POA methodology is applied to attain a suitable place and essential value of DGs and EVCSs. The DGs and EVCSs inject or absorb the real and reactive power to enhance the stability of RDS.

The projected MOF is represented in a single objective function by adding the penalty factors (w_1, w_2 and w_3). The mathematical formulation of the proposed problem is defined as follows:

$$F(k) = min\left\{ w_1 f_1(k) + w_2 f_2(k) + w_3 \left(\frac{1}{f_{3(k)}} \right) \right\} \tag{1}$$

Where

$$f_1(k) = min\sum_{i=1}^{br} R_i * I_i^2 \tag{2}$$

$$f_2(k) = \frac{1}{b}\sum_{k=1}^{b}|1 - V_k|^2 \tag{3}$$

$$f_3(k) = \left\lfloor |V_k|^4 - 4(P_k x_{jx} + Q_k r_{jk})^2 - 4\left(P_k r_{jk} + x_{jk}\right)|V_k|^2 \right\rfloor \tag{4}$$

Constraints of RDS

The proposed objective functions satisfy the standard operating equality and inequality constraints of distribution networks, DG units and EVCSs. The constraints are mathematically reported in the following equations:

- Power balance constraints of Real and Reactive power

$$\sum_{k=1}^{NG} PG_k - P_L = P_d \tag{5}$$

$$\sum_{k=1}^{NG} QG_k - Q_L = Q_d \tag{6}$$

- Generator limits of DG units

$$PG_k^{min} \leq PG_k \leq PG_k^{max} \tag{7}$$

- Voltage Limits of Each bus

$$0.95 \leq V_k \leq 1.05,\, k = 1,2,3,.....,n \tag{8}$$

- Charging Point limit constraints

$$nCP_{min} \leq nCP \leq nCP_{max} \tag{9}$$

- EV Charging Station limit constraints

$$nCS_{min} \leq nCS \leq nCS_{max} \tag{10}$$

2.2 Proposed Pelican Optimization Algorithm (POA)

The POA is a population-based nature inspired optimization method developed by Pavel Trojovský and Mohammad Dehghani in the year of 2022[15–17]. POA is based on natural life cycle of pelican birds searching the food sources and hunting behavior in the water surface. The two searching operators of POA like progress towards food and surfing on the water outside are efficiently searching the optimal solution for constrained problems. The ability of this algorithm has been checked by 23 different mathematical functions and best compromised solutions have been obtained. The mathematical modeling of initialization function, creating the population, current positions, updating of search agents, and representation of searching agents are clearly described in the following sections.

Initialization of Populations

The lower and upper boundaries of POA randomly generate the initial population by the following equation with help of random number.

$$x_{i,j} = l_j + rand.\left(u_j - l_j\right), i = 1,2,3,\ldots..,N, j = 1,2,3,\ldots.,m, \tag{11}$$

The randomly generated populations are reprinted in the matrix form. The size of the matrix $N \times m$is represented in the below equation:

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} X_{1,1} & \cdots & X_{1,j} & \cdots & X_{1,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ X_{i,1} & \cdots & X_{i,j} & \cdots & X_{i,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ X_{N,1} & \cdots & X_{N,j} & \cdots & X_{N,m} \end{bmatrix}_{N\times m} \tag{12}$$

The above initial populations are used to determine the objective functions of the projected work and are represented in the vector form as shown in Equation (13):

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \tag{13}$$

The POA approach is represented in the two phases based on the hunting behavior of pelicans. The hunting behavior is simulated using two phases:

(i) Moving towards prey (exploration phase).

(ii) Winging on the water surface (exploitation phase).

Phase 1: Moving towards Prey

The movement of pelican towards the prey is mathematically represented by the following equations:

$$X_{i,j}^{p_1} = \begin{cases} X_{i,j}, + rand\,.\,(P_j - I\,.\,X_{i,j}). & F_p < F_i; \\ X_{i,j}, + rand\,.\,(X_{i,j} - P_j), & else, \end{cases} \tag{14}$$

The position of the POA is updated using the below equation:

$$X_i = \begin{cases} X_i^{P_1}, & F_i^{P_1} < F_i; \\ X_i, & else, \end{cases} \tag{15}$$

Phase 2: Winging on the Water Surface

This behavior of pelicans during hunting in the water surface is mathematically defined as follows:

$$X_{i,j}^{P_2} = X_{i,j} + R\,.\,(1 - \frac{t}{T}).\,(2\,.\,rand - 1).X_{i,j}, \tag{16}$$

The position of the phase 2 is updated using the following equation:

$$X_i = \begin{cases} X_i^{P_2}, & F_i^{P_2} < F_i; \\ X_i, & else, \end{cases} \tag{17}$$

2.3 Implementation of proposed POA methodology for Multi-objective Voltage stability problem

The following steps are applied to achieve proper placement and optimal value of EVCSs and DGs to enhance the voltage profile and reduce the network loss using POA approach.

1. Read the line data, bus data, load data and features of EVs and CSs of the proposed 33 node test systems.
2. Run the distribution power flow for base case study and calculate the base case power loss, AVDI, VSI and voltage at each bus using the exact loss formula for the base case.
3. Determine the number of DG units and EVCSs, number of charging points (CPs) and rating of the charging points that are to be used in the RDS.
4. Initialize the parameters of the POA such as Population, dimension, maximum no of iteration, lower and higher limits of control parameters.

5. Set iteration=1.
6. Compute the fitness value of each population (i.e. optimal location and value of DGs and EVCSs, power loss in a network) in exploration and exploitation phase of POA.
7. Evaluate the multi-objective functions for each exploration and exploitation phase.
8. Update the position of exploration and exploitation phase and then memory for the most excellent fitness values in an array.
9. Compute the present position of exploration and exploitation phase.
10. Check that all constraints are satisfied: if yes, move to the next step, else go to step 6.
11. Check if the number of iteration processes is equal to a maximum number of iterations: if yes, go to next step otherwise go to step 5.
12. Project the global best results of multi objective problem such as enhanced voltage profile, minimized power loss, AVDI, improved VSI and STOP the program.

3 Results and Discussion

The proposed POA approach is tested on a standard IEEE test 33 node system and the ability of the POA is verified. The line data and bus data of the test system are adapted from the reference [11]. The simulations are carried out using MATLAB 14.0 platform which is implemented on the computer having i5 Intel Core, 4210U processor, up to 2.5 GHz and 8 GB of RAM memory. This paper considers EVCSs and DGs for solution of multi-objective optimization problem. The data of the EVCSs are taken from the reference [18]. It includes EV power rating, No. of CPs and Rating of CS (kW) respectively. The one-line diagram of 33-node RDS is shown in Figure 1.

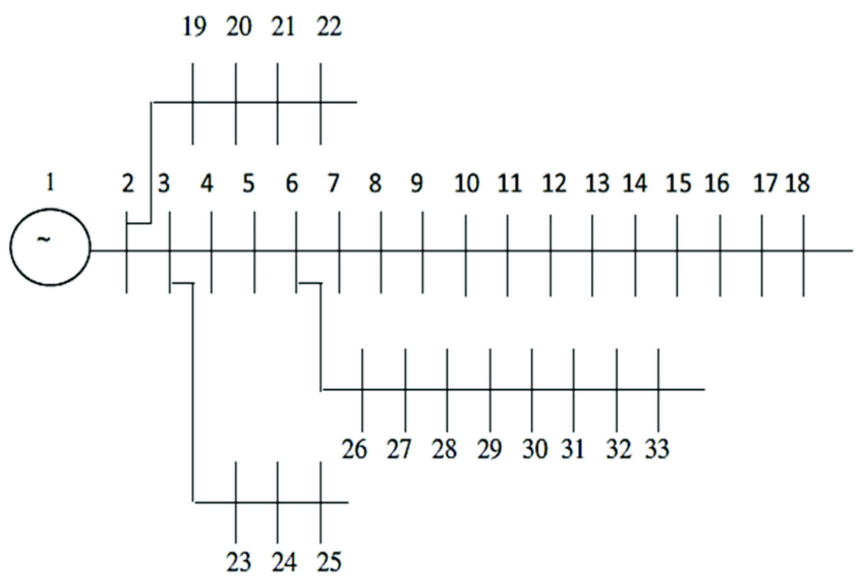

Fig 1. One-line diagram of IEEE-33-node RDS

The effectiveness and reliability of predictable POA are tested on standard IEEE-33 node test system using MATLAB platform. The system and load data of the 33-node network are adapted from [18]. The voltage rating is 12.66 KV with an absolute real and reactive power load of 3715 KW and 2300 KVAr are considered in this test system. The common control parameters of POA are obtained by trial-and-error method, including population size = 40, Maximum iterations = 100, total variables = 8.

The following test cases are considered to test the performance of the POA approach:

- Base case distribution load flow analysis
- Optimal allocation of EVCSs using POA in RDS
- Optimal allocation of both DGs and EV-CSs using POA with minimum number of CPs at minimum power rating all CSs.

Table 1. omparison of Voltage profile of 33 node test system with different cases

Bus No.	Base Case Voltage (p.u)	Only EVCSs Voltage (p.u)	DGs with EVCSs Voltage (p.u)
1	1.0000	1.0000	1
2	0.9970	0.9953	0.9975
3	0.9829	0.9780	0.99194
4	0.9754	0.9704	0.98954
5	0.9680	0.9630	0.98745
6	0.9495	0.9444	0.98062
7	0.9460	0.9408	0.97833
8	0.9323	0.9271	0.97494
9	0.9260	0.9207	0.97471
10	0.9201	0.9148	0.975
11	0.9192	0.9139	0.97528
12	0.9177	0.9124	0.97595
13	0.9115	0.9062	0.97835
14	0.9092	0.9038	0.97622
15	0.9078	0.9024	0.97489
16	0.9064	0.9010	0.9736
17	0.9043	0.8989	0.9717
18	0.9037	0.8983	0.97113
19	0.9965	0.9937	0.99597
20	0.9929	0.9807	0.99239
21	0.9922	0.9800	0.99169
22	0.9916	0.9793	0.99105
23	0.9793	0.9715	0.9899
24	0.9726	0.9648	0.98631
25	0.9693	0.9614	0.98602
26	0.9475	0.9424	0.98033
27	0.9450	0.9399	0.98005
28	0.9335	0.9283	0.97727
29	0.9253	0.9201	0.97565
30	0.9217	0.9165	0.97619
31	0.9176	0.9123	0.97226
32	0.9167	0.9114	0.9714
33	0.9164	0.9111	0.97113
	Base Case Power Losses (KW)	**210.9897**	
	Base Case AVDI (p.u)	**0.0040541**	
	Base Case Minimum VSI (p.u)	**0.667174**	
	Base Case Vmin (p.u)	**0.9038**	

Initially, Distribution load flow analysis approach is applied and the base case voltage of each bus, VSI, minimum VSI, Voltage deviation index, minimum voltage and power loss of the proposed network are determined. It is considered as Case 1 and the obtained simulation results are given in Table 1 and VSI is shown in Figure 2.

In case 2, the EVCSs and DGs are considered with the total load demand of 6640 KW. The proposed POA optimizes the best location of EVCS and DGs with minimum number of CPs. The obtained optimal location of DGs and EVCSs are 13, 25, 30 and 2, 19, 25 respectively. The obtained optimal size of DGs and EVCSs are 872 KW, 1500 KW, 1204 KW, and 975 KW, 975 KW, 975 KW respectively the voltage and VSI at each bus for base case, considering EVCSs and both DGs and EVCSs are compared and numerically reported in Table 2.

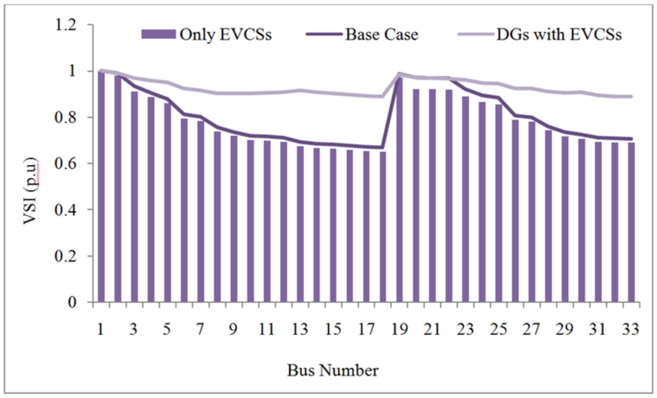

Fig 2. Comparison of VSI of 33 node RDS

Table 2. Simulation results for IEEE-33 node RDS by proposed POA approach

Parameters	**Value**
Optimal Loaction of DG units	13, 25,30
Optimal sizing of DG units (KW)	872, 1500, 1204
Optimal Loaction of EVCSs	2, 19, 25
Optimal sizing of EVCSs (KW)	975, 975, 975
Real Power Loss (KW)	82.93
Reactive Power Loss (KVAr)	56.88
Real power loss index (p.u)	0.39303
Voltage profile index (p.u)	0.00041976
Average Voltage Deviation Index (p.u)	0.00041976
Voltage Stability Index (p.u)	0.88941
Minimum Voltage (p.u)	0.97113

Table 3. Comparison of Simulation results proposed with existing Methods

Case	**Methods**	**Locations of DGs and EV Charging Stations**	**Size of DGs and EV Charging Stations (KW)**	**Power losses (KW)**	**AVDI (p.u)**	**VSI (p.u)**	**Vmin (p.u)**
Case 1 (Base Case)	-	-	-	210.9897	0.0040541	0.667174	0.9038
Case 2	**POA (proposed)**	**13, 25, 30 and 2, 19, 25**	**872, 1500, 1204, and 975, 975, 975**	**82.93**	**0.00041976**	**0.88941**	**0.97113**
	TLBO [11]	13, 24, 30 and 2, 19, 25	834.61, 1500, 1139.39 and 975, 975, 975	94.3847	0.0047	0.8799	0.9685
	HHO [11]	13, 24, 30 and 2, 19, 25	837.01, 1500, 1137 and 975, 975, 975	94.3844	0.0047	0.8799	0.9685
Objective function using POA (Proposed)					**0.30912**		

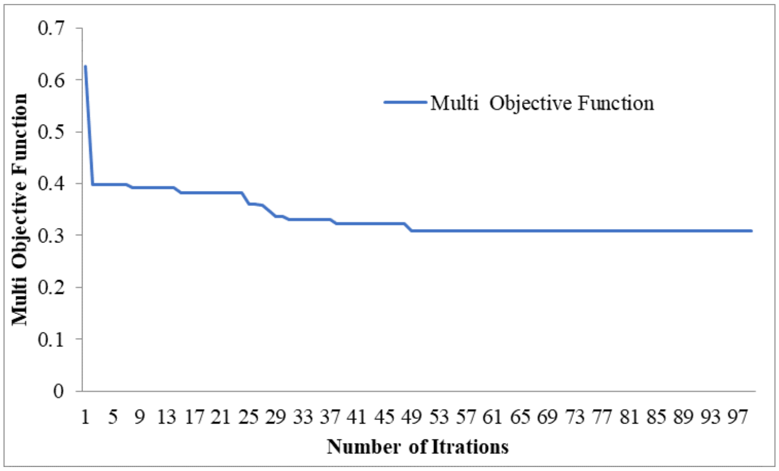

Fig 3. Convergence characteristics of DGs and EVCSs placement for IEEE-33 node test system

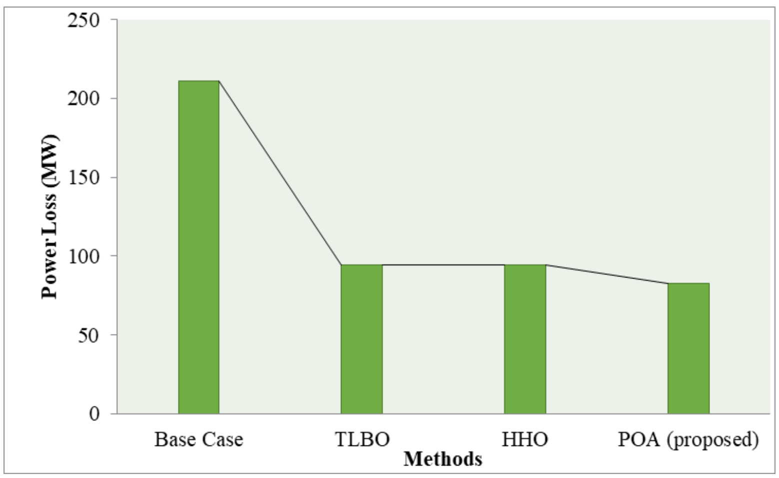

Fig 4. Comparison of Power loss of proposed method with Existing methods

The outcomes of the proposed approach such as optimal location and sizing of DGs and EVCSs, power loss, AVDI, VSI and Vmin are numerically tabulated in Table 2. Here, power loss is 69.49 % reduced as compared with the base case (case 1). A convergence characteristic of DGs and EVCSs placement for IEEE-33 node test system is shown in Figure 3. The simulation results are compared with TLBO and HHO techniques and are given in Table 3 and graphically compared and shown in Figure 4. The comparison shows that the proposed POA is a powerful and promising technique for solution of complex non-linear optimization problems.

4 Conclusion

An effective Pelican bird optimization algorithm has been successfully applied to determine the best placement and required value of DGs and EVCSs for enhancing the stability of RDS. The proposed POA has two different search phases such as moving towards prey (exploration phase) and winging on the water surface (exploitation phase). The more Flexibility with Exploration and Exploitation Balance of the POA easily determines the optimal solutions for RDS with minimum computational time. The case study with 33-node system has been considered to analyze the performance of POA. The simulation results of Power loss, AVDI and VSI are numerically and graphically displayed. The Voltage stability index 24.96 % is enhanced, when compared with the base case method which 1.58 % is better than the other obtainable methods of TLBO and HHO approach. The comparison shows that POA is a successful and an effective optimization tool for solution of complex engineering optimization problems.

Appendix A: Notations

Parameters	Notations
$F(k)$	Multi-objective function
$f_1(k)$	Power loss objective function
$f_2(k)$	Average voltage deviation index function
$f_3(k$	Voltage stability index function
w_1, w_2 and w_3.	Waiting factor of Multi-objective function
R_i	Resistance of ith transmission line
I_i^2	Square of current through ith transmission line
V_k	Voltage at kth bus
x_{jk}	Reactance of bus J and K
Q_k	Reactive power at kth bus
PG_k	Real Power generation of kth DG unit
P_L	Real Power Loss
P_d	Real Power Demand
QG_k	Reactive Power generation of kth DG unit
Q_L	Reactive Power Loss
Q_d	Reactive Power Demand
PG_k^{min}	Minimum Real Power generation of kth DG unit
PG_k^{max}	Maximum Real Power generation of kth DG unit
CP_{min}	Minimum chargibg Points
CP	Charging Points
nCP_{max}	Maximum charging Points
nCS_{min}	Minimum number of Charging stations
nCS	Number of Charging stations
nCS_{max}	Maximum number of Charging stations

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