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Allocation of real power generation based on computing over all generation cost: an approach of Salp Swarm Algorithm

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Abstract: Economic Load Dispatch (ELD) is utilized in finding the optimal combination of the real power generation that minimizes total generation cost, yet satisfying all equality and inequality constraints. It plays a significant role in planning and operating power systems with several generating stations. For simplicity, the cost function of each generating unit has been approximated by a single quadratic function. ELD is a subproblem of unit commitment and a nonlinear optimization problem. Many soft computing optimization methods have been developed in the recent past to solve ELD problems. In this paper, the most recently developed population-based optimization called the Salp Swarm Algorithm (SSA) has been utilized to solve the ELD problem. The results for the ELD problem have been verified by applying it to a standard 6-generator system with and without due consideration of transmission losses. The finally obtained results using the SSA are compared to that with the Particle Swarm Optimization (PSO) algorithm. It has been observed that the obtained results using the SSA are quite encouraging.

Key words: economic load dispatch, heuristic algorithms, optimization, Particle Swarm Algorithm, Salp Swarm Algorithm

Nomenclature

P is the active power, Q is the reactive power, C is energy cost production, a, b, c represent the fuel coefficients, n is the total number of generators in the power system, P_D, P_L stand for the power demand and power losses, respectively, d_k^1 is the position of the leader in the k-th dimension for the SSA algorithm, FS_k is the target food source in the k-th dimension, r_1, r_2, r_3 represent the random numbers, ul_k, ll_k represent the upper limit and lower limit of the k-th dimension, N is the total number of iteration of the optimization algorithm, $\boldsymbol{x}_i$, $\boldsymbol{v}_i$ stand for the vectors of velocity and positions of the i-th particle for the PSO algorithm, w, c_1, c_2 represent the weight of inertia and learning factors for the PSO algorithm.

1. Introduction

With the advancement of technologies and tremendous increment in population during some past decades, the electricity demand has been increased exponentially. But due to socio-economic factors and environmental considerations, there have been certain limitations in setting up new power generating units at the load centers. Also, the size of local power plants depends upon the local demand. As this is not practically feasible, so interconnection of several power grids is essential and most probably the only way to fulfill this ever-growing demand for electricity.

Economic Load Dispatch (ELD) is extremely crucial for any power system to determine the values of active (P) and reactive (Q) powers required by all the buses of the power system along with their complex voltage values ($|V|$, δ) before actually operating the power system. This helps in planning the number of transmission lines required to meet the worst possible demand of that power system [1–3]. Although this can be handled by several population-based metaheuristic algorithms, they are suitable only for maximizing the economic pact of the concerned system without taking other desirable features into account. But as modern power systems deal with quite complex networks along with more guaranteed reliability of the power supply, therefore, the key to handle the ELD problem of such a system is to maximize the benevolence of the economy for varieties of operating constraints, because such systems are so unpredictable about operating equilibria. This has to be done by taking due care of the reduction in fuel cost along with total power loss in the transmission system of the network [4, 5]. Several such algorithms have been suggested for overcoming this difficulty like the Chaotic Biogeography Based Optimization (CBBO) [6], a self-adaptive differential evolutionary algorithm with the amalgamation of multiple mutation strategies (ADE-MMS) [7], the Grey Wolf Optimization (GWO) with certain amelioration [8], the hybrid Genetic Algorithm (GA) with Interior-Point Algorithm (IPA) and the Sequential Quadratic Programming (SQP) method as described in [9], based on NoFree Lunch (NFL) theorem, an Artificial Cooperative Search (ACS) algorithm was suggested in [10], the hybrid Grey Wolf Optimization (GWO) method with an valve loading effect in [11], etc.

In this paper, a novel bio-inspired method of the Salp Swarm Algorithm (SSA) for solving the problem of ELD for finding optimal real power generation is presented. The authors of [12] have devised the method of the SSA and multi-objective SSA. They have stated its efficiency in finding optimal solutions to many challenging and computationally expensive design problems of engineering like a marine propeller and airfoil design. It was demonstrated that the ability to solve problems of the real-world having very difficult and quite unknown search spaces is one of the best merits of this method. The same was also applied, tested, and confirmed by other novel works of several authors like the application of the Maximum Power Point Tracker (MPPT) problem in a PV-based solar plant [13], a feature selection logistic regression problem using an improved SSA with PSO [14], in solar PV cell models for parameter identificationand classification [15], feature selection with global optimization using the Chaotic SSA [16], the Efficient Binary SSA for feature selection with a crossover scheme [17], predicting activities of the chemical compound based on swarming behavior of the SSA [18], etc. Keeping all these benefits, versatilities, flexibilities and other merits ofthe SSA, we have implemented this method for finding the solution of the ELD problem. Moreover, many research manuscripts in international literature prove the good performance of this algorithm in relation to other heuristic algorithms [19–21].

The main aim of the paper is to develop the effective optimization procedure using the SSA algorithm. The own optimization procedure was developed in the MATLAB environment. The developed version of the SSA algorithm has been applied to solve the ELD problem. The procedure has been tested and a good convergence has been achieved. The novelty of this work can be summarized as below:

- A novel SSA algorithm is proposed, which results in accurate solutions.
- The SSA algorithm has been applied to solve the ELD problem by using it to a 6-generator system with and without consideration of transmission losses.
- The main objective of ELD is to minimize the total cost function by considering both equality and inequality constraints.
- The results obtained with the SSA algorithm are analyzed and compared with the PSO algorithm.

The paper is presented as: Section 1 – the summarized overview of the problem, a brief literature review, the scope of work, and the organization of the paper. Following this, Section 2 highlights the considered economic dispatch problem.The grid conditions that constrain the economic dispatch are also presented. Along with this, resource considerations affecting economic dispatch are discussed in brief as well. In addition to all the above-mentioned aspects, equality and inequality constraints are also discussed in the same section. After this, Section 3 highlights the method of optimization presented in this paper, i.e., the SSA optimization. Next, Section 4 presents MATLAB programming which is used to solve the problem with and without losses. Also, case study data and results are presented in this section. Lastly, Section 5 presents the conclusions drawn from the given investigations.

2. Problem formulation

The objective function, most commonly used in the ELD problem formulation, is minimizing the total operating cost of the fuel consumed in the production of electric power within a given time interval. The cost functions of each generating unit are assumed as functions of real power generation only and are represented as the sum of the quadratic cost model at each generator. The objective of ELD to minimize the total cost function, can be shown mathematically as:

$$C = \sum_{i=1}^{n} F_i \left(P_i\right), \tag{1}$$

$$C_i \left(P_{Gi}\right) = c_i + b_i P_{Gi} + a_i P_{Gi}^2, \tag{2}$$

$$C_T = \sum_{i=1}^{m} C_i \left(P_{Gi}\right), \tag{3}$$

where: C is the net cost of the production, P_i is the active power generated by the generator unit, i, n is the total number of generators available in the power system, a_i, b_i, c_i are the fuel coefficients of the cost function.

The equality constraint is the real power balance constraint. The real power generated must be equal to demand and losses:

$$\sum_{i=1}^{m} P_{Gi} = P_D + P_L, \tag{4}$$

where: P_D is the power demand, P_L is the power losses.

Power losses can be calculated by using the equation:

$$P_L = \sum_{k=1}^{N_l} g_k \left[V_a^2 + V_b^2 - 2V_a V_b \cos\left(\delta_a - \delta_b\right)\right], \tag{5}$$

where: N_l represents the number of transmission lines, g_k is the conductance at the branch k, and voltages at the buses a and b are represented by V_a and V_b, respectively. The angle difference between the buses a and b are expressed as $\delta_a - \delta_b$.

The inequality constraints for real power generation is given as:

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}. \tag{6}$$

There are several methods available for finding the solution of the economic load dispatch problems. The most common of them are: (a) the Lambda-iteration method, (b) the interior-point method, (c) the gradient method, (d) the dynamic programming method, (e) Newton's method, (f) linear or non-linear programming methods, and (g) metaheuristic optimization methods.

Optimization is definedas the process of finding the best solution to a given problem under given circumstances. At present, metaheuristic algorithms are employed to solve a huge number of multi-objective optimization and constrained optimization problems. These algorithms are characterized by good efficiency and good performance [22, 23]. The optimization techniques used in this paper are also metaheuristic techniques. These are the PSO and the SSA.

3. Optimization technique

3.1. The Salp Swarm Algorithm

The SSA is based on the behavior of salps, that are physically very similar to jelly-fish [12]. Most of the behaviors of salps are still under investigation by the researchers due to their extreme living environment under deep oceans. But the most amazing fact of forming a swarm of the salp chain for better locomotion utilizing rapid coordinated foraging and changes is of utmost importance from the optimization algorithm point of view.

Being a recently devised technique, the mathematical modelling of the SSA is quite simple yet very effective. Based on the concept of the leader and followers, the modelling of the SSA is derived. The first member of the salp chain is considered as a leader and position update with each iteration is determined by the position of the leader. The position of the leader for an k-th dimensional search space is decided by the following equation.

$$d_k^l = \begin{cases} FS_k + r_1\left[r_2\left(ul_k - ll_k\right) + ll_k\right] & \text{for } r_3 \geq 0 \\ FS_k - r_1\left[r_2\left(ul_k - ll_k\right) + ll_k\right] & \text{for } r_3 < 0 \end{cases}, \tag{7}$$

where: d_k^1 is the position of the leader in the k-th dimension, FS_k is the target food source in the k-th dimension, r_1, r_2, and r_3 are the random numbers, ul_k is the upper limit of the k-th dimension, ll_k is the lower limit of the k-th dimension.

r_1, being the most important parameter as it balances the exploration and exploitation part of the SSA, is defined by the following equation:

$$r_1 = 2e^{\left(\frac{\Delta n}{N}\right)}, \tag{8}$$

where N is the total number of iterations to be performed and Δn is the current iteration number.

The other two random numbers r_2 and r_3 are included in the range of 0 to1. They decide whether the position update in the k-th dimension is towards positive infinity or negative infinity and they determine the step size of each iteration. Similarly, the position update of the follower salps in the salp chain, using Newton's second law of motion, is given by the following equation:

$$d_k^f = \frac{1}{2}\alpha\tau^2 + \mu_0\tau, \qquad f \geq 2, \tag{9}$$

where: d_k^f is the position of the f-th follower salp in the k-th dimension, τ is the time required for completion of that iteration, $\alpha = \dfrac{u_{\text{final}}}{u_0}$, where $u = \dfrac{d - d_0}{\tau}$, u_0 is the initial velocity.

If u_0 is considered as 0 and the discrepancy between iterations is equal to 1 as time in optimization is mostly the time required in the iteration, Equation (8) will become:

$$d_k^f = \frac{1}{2}\left(d_k^f - d_k^{f-1}\right), \qquad f \geq 2. \tag{10}$$

Therefore, with help of Equations (6) and (9), this algorithm ofthe SSA can be simulated.

To test the validity of the above mathematical modelling, this algorithm is simulated on a chain of 20 salps that are randomly placed in the search space with fixed or moving food sources. When inspected, the behaviour of the salps over nine consecutive iterations shown sufficient evidence regarding swarm formation and locomotion following the above-proposed equations right after the first iteration. It is also seen that as the leader salp changes its position around the food source, the other salps follow it gradually over time.

For making this algorithm suitable for optimization of a real-world problem, a little adjustment is required. For a single objective function, there is only one global optimum and that point can be assumed as the food source for the leading salp and salp chain to find. But the main problem is that this point is unknown in this case. The optimization procedure was elaborated in the MATLAB environment.The pseudo-code for solving the problem is given below.

Initialization of salp population d_i
while (terminating condition has not arrived)
    %% calculating the fitness of each salp
G = best salp
    Update r_1 using Equation (7)
for (d_i)
if (i == 0)
update the position of leading salp by Equation (6)
else
update the position of follower salps by Equation (9)
end
end
based on ul_k and ll_k, amend salps
end
return G

The pseudo-code can be explained as all the salps are randomly placed in the search space with an upper limit (ul_k) and lower limit (ll_k). Then, the fitness of each salp is determined. The salp with the best fitness is assumed as the position of the unknown food source (G) that is to be chased by the salp chain. The value of the first random number r_1 is calculated with the help of Equation (7). After that, the positions of each salp in the chain are updated using Equations (6) (for leader) and (9) (for followers). If somehow, any position of a single salp falls outside the specified limits, it is brought back to the boundary. This sequence is repeated, except for the initialization, until a satisfactory result is achieved. It is to be kept in mind that the position of the food source (G) will change during the optimization process as the chain would, most probably, explore and exploit the search space around it.

Some of the valuable remarks about a single-objective SSA are listed below:

- The best solution obtained so far would be saved and assigned as a food source variable (G), so it will never get lost even after the deterioration of the complete salp chain;
- The leader salp will always explore and exploit the search space around it because its position will be updated with respect to the food source (G) which is the best fit for that iteration;
- Follower salps move towards the leader gradually, updating their position with respect to each other;
- Stagnation at local optima is avoided by the slow movement of followers;
- As the random number (r_1) decreases continuously during optimization, the SSA first explores then exploits the search space.

– Only one parameter (r_1) is the most dominant and controlling the whole action of optimization. This makes the SSA simple to understand and easy to implement.

3.2. The Particle Swarm Algorithm

According to the authors, the Particle Swarm Optimization algorithm is nowadays the most popular and often used method of optimization, along with genetic algorithms. The classical PSO method is very often modified, in order to achieve better convergence [24, 26]. Modifications are most widely used in the case of an optimizationprocess with a few to dozens or so decision variables, and an aim function in the allowed space includes a few local extremes.

The PSO method belongs to herd algorithms, its numerical model was derived from observations of groups of animals in their natural environment. This method was presented in 1995 by R. Eberhart and J. Kennedy [26]. The mathematical model of this method used the mechanisms of schools of fish and flocks of birds. During solving the task of optimization, the group of individuals in the swarm shifts within an allowed space of the investigated task and looks for the global extreme. A single particle is described in this method by its location $\boldsymbol{x}$ and velocity $\boldsymbol{v}$. In the PSO method, virtual individuals cooperate with one another. Each individual gathers information about the location of the leader of the swarm – meaning a particle in the swarm with the best fitting, because such a particle has the highest value of an objective function. In the algorithm, the velocity of this i-particle in the k-th iteration is set as follows:

$$\boldsymbol{v}_k^i = w\boldsymbol{v}_{k-1}^i + c_1 r_1 \left(\boldsymbol{x}_L^i - \boldsymbol{x}_{k-1}^i\right) + c_2 r_2 \left(\boldsymbol{x}_G - \boldsymbol{x}_{k-1}^i\right), \tag{11}$$

where: w_1 is the weight of inertia, $\boldsymbol{v}_{k-1}^i$, $\boldsymbol{x}_{k-1}^i$ are the vectors of velocity and the position of the i-th particle at the $k-1$ iteration, respectively, c_1, c_2 are the learning factors, r_1, r_2 are the random numbers, usually from the range of 0 to 1.

Finally, the particle position is calculated as:

$$\boldsymbol{x}_k^i = \boldsymbol{x}_{k-1}^i + \left(\frac{\boldsymbol{v}_k^i}{\Delta t}\right), \tag{12}$$

where Δt is the time steep length. In the recently published manuscript concerning the application of the PSO, the parameter Δt is very often neglected in the mathematical model because of the assumption [27] that the length of the step equals the unit time.

4. Results and discussions

The different cases considered in ELD are PSO with and without loss and a comparison betweenthe SSA and thePSO algorithm.

The results of the optimization calculation taking into account the cost coefficient is presented in Table 1. Next, a 6-generator system with loss coefficients given in Table 2 is considered. The output is considered here in two forms, one is with loss and the other is without loss.

The parameters of applied optimization procedures, i.e. the PSO and the SSA are listed in Table 3.

Table 1. Cost coefficients of 6-generator data

Units	a	b	c	$P_{\min}$	$P_{\max}$
1	0.15240	38.53973	756.79886	10	125
2	0.10587	46.15916	451.32513	10	150
3	0.02803	40.39655	1 049.9977	35	225
4	0.03546	38.30553	1 243.5311	35	210
5	0.02111	36.32782	1 658.5596	130	325
6	0.01799	38.27041	1 356.6592	125	315

Table 2. Loss coefficients (B_{ij}) of 6-generator data

B_{ij}	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$	$j = 6$
$i = 1$	0.000140	0.000017	0.000015	0.000019	0.000026	0.000022
$i = 2$	0.000017	0.000060	0.000013	0.000016	0.000015	0.000020
$i = 3$	0.000015	0.000013	0.000065	0.000017	0.000024	0.000019
$i = 4$	0.000019	0.000015	0.000017	0.000071	0.000030	0.000025
$i = 5$	0.000026	0.000016	0.000024	0.000030	0.000069	0.000032
$i = 6$	0.000022	0.000020	0.000019	0.000025	0.000032	0.000085

Table 3. Values of thePSO and SSA parameters

Type of algorithm	Parameters	Values
PSO	Swarm size	20
PSO	Maximum number of iterations	100
PSO	$c_1 = c_2$	2
PSO	w_1	1
SSA	Search agents	20
SSA	Maximum number of iterations	100

4.1. Without loss

In this case, the loss coefficients are neglected and ELD is carried out without losses. The optimization process was run fifteen times on the same computer for the SSA and the PSO algorithm.The best obtained result from ten runs of the optimization procedure is shown in Table 4. Additionally, the best, worst, mean values [23] of the objective function during computer simulations and standard deviations were listed. It can be noticed, that a better value of the standard deviation was obtained for the SSA.This proves better repeatability of the optimal result. Also, better values for the best and mean objective functions were attained by the SSA.

Table 4. Control variables of 6-generator system underthe conditionof no loss using PSO and SSA optimization procedures

Variables	Optimized values with PSO	Optimized values with SSA
P_1 [MW]	10.5	28.759
P_2 [MW]	11.1	10
P_3 [MW]	140.73	123.24
P_4 [MW]	55.01	126.901
P_5 [MW]	283.65	260
P_6 [MW]	299.01	251.1
P_L [MW]	–	–
P_D [MW]	800	800
Fuel cost (Rs/h)	**40 972.89**	**40 676**
Fuel cost ($\$/h$)	**556.96**	**552.93**
Best	40 972.89	40 676
Worst	41 018	40 693
Mean	40 982.89	40 683.65
Standard deviation	9.622862	5.543239
Computation time in hours per run	0.47	0.44

Figure 1 presents a comparison of the convergence curves for the best optimization process selected from fifteen runs of the optimization procedure. Based on the obtained results in the case

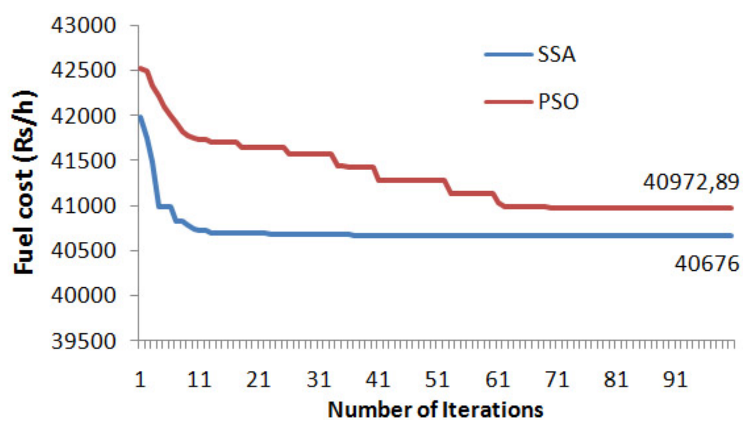

Fig. 1. Convergence characteristics without loss for SSA and PSO algorithms

of the SSA, it can be observed that at the beginning of the optimization calculation a significant improvement in the value of the objective function was attained. The solution close to optimal one was obtained after 15 iterations of the SSA algorithm. In the case of the PSO procedure, the convergence process is definitelyworst than for the developed SSA procedure. For the PSO procedure the results close to optimal one was obtained after 61 iterations. It shows that the SSA converges quickly compared to PSO. In both the cases, the number of iterations given in Table 3 was assumed to be 100 and the time of computation calculated for each iterationup to the end of the 100-th iteration has been considered even after the convergence was achieved.

The standard deviation is used to analyse a set of data: the bigger the standard deviation, the more our data is spread out. The smaller the standard deviation, the less variation in our data set. Table 4 shows that the standard deviation for PSO is 9.622862, and for the SSA is 5.543239, that indicates that the standard deviation is lower for the SSA compared to PSO, which means that final solution spreading is less in the SSA. In other words, the SSA provides the solution near to the optimal value for all runs, which shows the effectiveness of the SSA. Similarly, the same thing happened in the case of Table 5.

Table 5. Control variables of 6-generator system with loss using PSO and SSA optimization procedures

Variables	**Optimized values with PSO**	**Optimized values with SSA**
P_1 [MW]	21.1556	32.683
P_2 [MW]	19.5081	14.455
P_3 [MW]	131.0177	141.34
P_4 [MW]	161.5091	135.84
P_5 [MW]	268.0939	257.83
P_6 [MW]	225.4203	243.19
P_L [MW]	26.7047	25.338
P_D [MW]	800	800
Fuel cost (Rs/h)	**42 024.28**	**41 896**
Fuel cost ($\$/h$)	**571.25**	**569.14**
Best	42 024.28	41 896
Worst	42 043	41 908
Mean	42 033.08	41 899.9
Standard deviation	6.086687	4.158125
Computation time in hours per run	0.556	0.482

4.2. With loss

In this section, loss coefficients of the above stated six generator systems are also considered. Also in this case the results from fifteen runs of the optimization procedures were compared.

Both optimization procedures were analyzed. The best result for the SSA and PSO procedures are shown in Table 5. The convergencecurves of the optimization process for the SSA and PSO algorithm are presented in Figure 2.

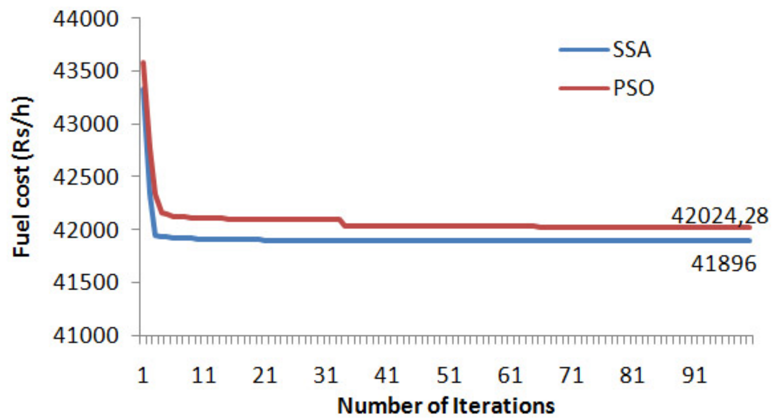

Fig. 2. Convergence characteristics with loss for SSA and PSO algorithms

In the case of taking losses into consideration, it can be observed that very good convergence of the optimization process was achieved. The solution close to optimal one was obtained after 6 iterations of the SSA, and about 30 iterations of the PSO algorithm. Also, the better quality of the optimization procedure was obtained for the SSA.

In the case of this task, a better value of the standard deviation for the SSA was also obtained. It was observed that taking losses into account the total computation time during the PSO procedure was extended by about 16%. Whereas, in the case of the SSA, the total calculation time was increased by about 8%.

From the above simulation results, it can be noticed that for the same system and same demand, the fuel cost for the system considering loss coefficients is high compared to the system neglecting losses. Therefore, it can be concluded that a system with losses requires more fuel costs to meet the standard load flow equations.

5. Conclusions

In this novel work, acompletely new approach for solving the ELD problem using the SSA is proposed. The feasibility and efficacy of the proposed techniquein solving the ELD problems giving due consideration to the generator constraints, are presented.The optimization software was elaborated in the MATLAB environment. Economic load dispatch is conducted and it is observed that the total generation is being economically dispatched to meet the required demand. Also, the convergence curves for each problem were investigated. The computational results obtained from this reveal thatin most generatorswith the same power system the method of theSSA gave quite improved results compared to that obtained from the PSO algorithm.

The obtained results for the SSA are encouraging. Based on the presented simulation results, one can observe much better performance and efficiency of the elaborated SSA procedure in relation to the classical PSO procedure. In the case of the optimization task without loses, the effectiveness of the SSA procedure was definitely better in comparison to the PSO procedure. The SSA procedure allows for a quadruple reduction in computation time compared to PSO in the case of the task without losses.

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