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Full Length Research Paper

Optimal location of facts devices for solving multi-objective optimal power flow (OPF) using improved shuffled leaping frog algorithm

K. Ravi[1]* and M. Rajaram[2]

[1]School of Electrical Engineering, VIT University, Vellore, India.
[2]Anna University of Technology, Tirunelveli, Tamilnadu, India.

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Renewable energy is the demand of the future and wind energy plays a very pivotal role in it but the main disadvantage with wind energy is that its efficiency is very low and the main reason for this is the demand for reactive power. If the power network is not able to satisfy the wind farm reactive power requirement, the overall energy losses in the distribution networks would be increased. Hence minimization of losses is proposed by using reactive power compensation with flexible alternating current transmission system (FACTS) devices used for compensation. This paper proposes an algorithm based on the shuffle frog leaping algorithm (SLFA) to solve the multi-objective OPF problem. Furthermore, this paper presents an improved shuffle frog leaping algorithm (ISLFA) which profits from a mutation in order to reduce the processing time and improve the quality of solutions, particularly to avoid being trapped in local optima. The IEEE 30-bus test system is presented to illustrate the application of the proposed problem.

Key words: Static synchronous compensator, flexible alternating current transmission system, improved shuffled leaping frog algorithm.

INTRODUCTION

Nowadays, wind farms contributing to the energy production is continuously growing because of their economical and environmental protection attraction. However, large wind farms have higher reactive power demand that may not be easily satisfied. Therefore, connecting the wind farms to the power network becomes a more challenging task and their impacts are likely to be more widespread. (Thomas and Welsh, 1996) shows that the ability of a power network to meet wind farms reactive power requirement is a major factor determining the amount of power that can be integrated into the system. Moreover, the operational wind farms may bring voltage stability problem since the main factor causing voltage instability is the deficiency of reactive power in the system (Kundur, 1994).

Therefore, it is necessary to provide reactive power locally, and as close as possible to the demand levels. In order to meet the wind farm reactive power requirement, capacitors or static Var compensator (SVC) are employed to compensate reactive power commonly. They are used to carry out energy loss reduction, voltage regulation, and system security improvement. Economic benefits of the capacitor compensation depends mainly on where and how many capacities of the capacitor are installed, as well as proper control schemes of the capacitors at different wind turbines power output levels in the wind farms. Optimal capacitor compensation has been investigated since the 60’s. Considerable variety of methods has been brought on to solving this problem. In the early, the conventional analytical methods in conjunction with some heuristics were very commonly employed to relax this problem. Later, the capacitor sizes were considered as discrete variables and employed dynamic programming to solve the problem in Duran

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*Corresponding author. E-mail: ravikeee@yahoo.co.in.

(1983). Regarding capacitor size as continuous variables, a gradient search based iterative procedure was proposed to deal with fixed and switched type capacitor installation problem in Grainger et al. (1984) In the 90's, combinatorial optimization algorithms were introduced as a means of solving the capacitor placement problem: simulated annealing was proposed in Chiang et al. (1990), genetic algorithms in Sundhararajan and Pahwa, (1994), and Tabu search algorithms in Huang et al. (1996).

Moreover, the operational wind farms may bring voltage stability problem since the main factor causing voltage instability is the deficiency of reactive power in the system. Therefore, it is necessary to provide reactive power locally, and as close as possible to the demand levels. Flexible ac transmission systems (FACTS) have been developed to improve the performance of weak ac systems and enhance transmission capabilities over long ac lines. FACTS controllers can be used in all the three states of the power system, namely: steady state, transient and post transient steady state. FACTS devices can regulate the active and reactive power as well as voltage-magnitude (Baghaee et al., 2008; Shahgholian et al., 2010). Dynamic application of FACTS controllers includes transient stability improvement, oscillation damping (dynamic stability) and voltage stability enhancement. Facts controller can control shunt impedance, series impedance, voltage, current and phase angle (Sankar and Ramareddy, 2008). FACTS devices types and categories are presented in (Sze et al., 2003): series controllers such as thyristor controlled series capacitor (TCSC) (Jovicic et al., 2005) and static synchronous series compensator (SSSC) (El-Zonkoly, 2006), shunt controllers such as SVC (Amin, 1999), static synchronous compensator (STATCOM) (Shahgholian et al., 2008) and STATCOM with energy-storage system (Kuiava et al., 2009), combined series-shunt controllers such as unified power flow controller (UPFC) (Collins et al., 2006) and combined series-series controllers such as interline power controller (IPFC) (Mishra et al., 2002). A good number of papers are available on modeling, simulation, operation and control fundamental of the FACTS devices. Simulation of FACTS controllers is mainly done in the following two ways: (a) detailed calculations in 3 phase systems and (b) steady state and stability analyses (Povh, 2004). Shunts FACTS devices are used for controlling transmission voltage, power flow, reducing reactive loss, and damping of power system oscillations for high power transfer levels. STATCOM is a kind of dynamic reactive power compensator, which has been developed in recent days.

The optimization of location of FACTS devices depends on the amount of local load, the location of the devices, their types, their sizes, improvement stability, the line loading and system initial operating conditions (Gerbex et al., 2003; Sidhartha and Patel, 2009; Panda and Patel, 2007). There are several methods for finding optimal locations of FACTS devices in both vertically integrated and unbundled power systems. In Cai et al. (2004) an algorithm for find the best location for the FACTS devices in multi-machine power systems using genetic algorithm is proposed. In Gerbex et al. (2001) three criteria are considered for FACTS optimal allocations: available transfer capability criterion, steady state stability criterion and economic criterion.

An alternative model that can optimize the placement of FACT devices based on multiple time periods with losses considered proposed in Yu and Lusan (2004). In Sharma et al. (2007) the optimal location of a shunt FACTS device is investigate for an actual line model of a transmission line having series compensation at the center to get the highest possible benefit. Consequently, evolutionary algorithms because of their independency from the type of objective functions and constraints have been used by many researchers in recent years (Niknam et al., 2005a, b; Niknam et al., 2010). One of the new evolutionary algorithms with a great potential for optimization applications is the SFLA. In fact, this algorithm can solve complex optimization problems, which are nonlinear, non-differentiable and multi-modal but it may trap in local optima. To overcome this problem, in this paper a new SFLA algorithm is proposed to improve the local exploration of the algorithm in the entire search space. The main idea behind the new frog leaping rule is to extend the direction and the length of each frog's jump by emulating the frog's perceptions. The modification expands the local search space and improves the performance of the SFLA.

Swarm optimization techniques are derived from Darwin's evolutionary theory of 'survival of the fittest'. In this paper we have developed an improved compared PSO, BFO and other optimization techniques for finding the optimal location of FACTS devices with multiple objective functions. MATLAB2008a is used for modeling and running the simulation.

PROBLEM FORMULATION

The objective of this paper is to minimize the fuel cost, losses and maximize the system load ability by optimal location of FACTS devices using optimal power flow. Hence, the multi-objective function can be proposed as:

$$f_1(x,u)=\sum_{m=1}^{N_G} Fl_m=\sum_{m=1}^{N_G}[a_m+b_m P_{Gm}+c_m P_{Gm}^2 \tag{1}$$

$$f_2(x,u)=\lambda_1\times(\sum_{m=1}^{N_L} Vl_m+\sum_{j=1}^{N_E} Bol_n+c) \tag{2}$$

$$f_3(x,u)=P_L+\lambda_V(V_{Gm}-V_{Gm}^{\lim})^2+\lambda_{Qm}\sum Q_{Gm}^{g\lim})^2 \tag{3}$$

Subject to

$$P_{Gm}+P_{ms}-P_{Dm} -\sum_{n=1}^{N_B} V_m V_n \mathrm{Y}_{mn}\cos(\theta_{mn}+\delta_m-\delta_n)=0;\forall m\in N_B \tag{4}$$

$$Q_{Gm}+Q_{ms}-Q_{Dm} -\sum_{n=1}^{N_B} V_m V_n \mathrm{Y}_{mn}\sin(\theta_{mn}+\delta_m-\delta_n)=0;\forall m\in N_B \tag{5}$$

$$\sum_{m=1}^{N_G} P_{Gm} + P_D - P_L = 0 \tag{6}$$

$$\sum_{m=1}^{N_G} Q_{Gm} + Q_D - Q_L = 0 \tag{7}$$

$$P_{Gm}^{\max}\le P_{Gm}\le P_{Gm}^{\min},\forall_m\in N_G \tag{8}$$

$$Q_{Gm}^{\max}\le Q_{Gm}\le Q_{Gm}^{\min},\forall_m\in N_G \tag{9}$$

$$V_{Gm}^{\max}\le V_{Gm}\le V_{Gm}^{\min},\forall_m\in N_B \tag{10}$$

$$\left|S_m\right|\le S_m^{\max},\forall_m\in N_L \tag{11}$$

$$X_{Sm}^{\max}\le X_{Sm}\le X_{Sm}^{\min},\forall_m\in N_{TCSC} \tag{12}$$

$$Q_{Sm}^{\max}\le Q_{Sm}\le Q_{Sm}^{\min},\forall_m\in N_{SVC} \tag{13}$$

Where *F* is known as the objective vector, *f*1 and *f*2 are the two objective functions to be optimized, x is the vector of dependent variables, and u is the vector of control variables. The first objective is to minimize the total generation fuel cost ($ /h), which is represented in Equation (1) where a a_m, b_m and c_m are fuel cost coefficients, P_{Gm} the active power output generated by the mth generator, *N*G is the total number of generators in the power network, and *Flm* is the fuel cost for each generator.

The second objective is to enhance the system loadability within security margin. The FACTS devices are placed in the network in order to increase the system loadability, and at the same time to prevent overloads and voltage violations. The objective function is based on indexes quantifying the system load ability and the security state in terms of voltage levels and branch loading, which is expressed in Equation (2) where *V l* and Bol_m represent voltage levels and branch loading, respectively. N_B and N_L are the total numbers of load buses and transmission lines, respectively; *c* is a positive constant; and *λl* is a load parameter of the system, which aims to find the maximum amount of power that the network is able to supply within system security margin.

MODELING OF FACTS DEVICES

The mathematical models of the FACTS devices are developed mainly to perform the steady-state research. Therefore the TCSC is modeled to modify the reactance of the transmission directly. The SVC is modeled using the power injection method (Chung and Li, 2000). Furthermore, for the TCSC, mathematical model is integrated into the model of the transmission line as shown in Figure 1(a). The TCSC can serve as the capacitive or inductive compensation respectively by modifying the reactance of the transmission line. In this simulation, the reactance of the transmission line is adjusted by TCSC directly. The rated value of TCSC is a function of the reactance of the transmission line where the TCSC is located:

$$X_u=X_{line}+X_{TCSC},X_{TCSC}=rtcsc.X_{line} \tag{14}$$

Where X_{Line} is the reactance of the transmission line and rtcsc is the coefficient which represents the compensation degree of TCSC. To avoid overcompensation, the working range of the TCSC is between -0.7X_{Line} and 0.2 X_{Line} (Jovcic and Pillai, 2005).

$$rtcsc_{min} = -0.7,\ rtcsc_{max} = 0.2 \tag{15}$$

For an SVC connected at a bus bar i of a line section represented by the quadruple (yi0, yik, yk0) as shown in Figure 1(b). The contribution of the SVC to the new admittance matrix relates to the element shunt. It results in the admittance matrix

$$Y_{new}^{line}=\begin{pmatrix} Y_{ik}+Y_{i0}+Y_{SVC} & -Y_{ik} \\ -Y_{ik} & Y_{ik}+Y_{k0} \end{pmatrix} \tag{16}$$

$$Y_{SVC}=j\frac{1}{X_L X_C}\left[X_L-\frac{X_c}{\pi}2\pi-\alpha+\sin 2\alpha\right] \tag{17}$$

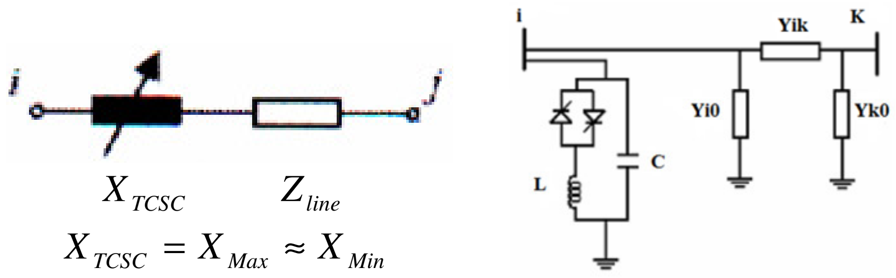
The SVC is given as the following expression:

$$X_{SVC}\alpha=j\frac{\pi X_L}{2\pi-\alpha+\sin 2\alpha-\pi\dfrac{X_L}{X_C}} \tag{18}$$

STATCOM is a shunt compensation device which can be used for improving the voltage profile. Figure 2 show the STATCOM model. It is a shunt controller and it injects current to the transmission line. System voltage is greater than generator voltage, it absorbs the reactive power and if smaller then it generates the reactive power. It can be used on both voltage sourced and current sourced convertor. It can be designed to be an active filter to absorb system harmonics. Different FACTS devices and their different location have varying advantages. STATCOM modeling was done as per suggestions in Shahgholian et al. (2008). STATCOM is always located on a load bus. The bus on which STATCOM is being placed is converted from PV bus to PQ bus. Thus STATCOM is considered as a synchronous generator whose real power output is 0 and its voltage is set to 1 p.u.

SLFA ALGORITHM

The OPF problem is a non-linear optimization problem. By



$$X_{TCSC} = X_{Max} \approx X_{Min}$$

Figure 1. Block diagram of the (a) TCSC (b) SVC.

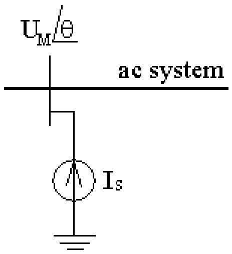


Figure 2. Static synchronous compensator (STATCOM) Model.

Table 1. ISLFA Algorithm parameters.

Variable	Value
Number of frogs	15
Number of memeplex	15
Iteration $_{max1}$	80
Iteration$_{max2}$	100
Iteration of mutation	10

considering the increased emission non-linearity degree and local optima numbers of this problem, it is necessary to solve it with a very accurate algorithm to prevent it from being trapped in local optima and to converge it to globally optimum results in proper time. SFLA mimics the metaphor of natural biological evolution that is based on populations of frogs in nature searching for food (Eusuff and Lansey, 2003). The SFLA is a decreased based stochastic search algorithm which is started with an initial frog population whose characteristics represent the decision variables of the optimization problem. An initial population of F frogs is created randomly. For K-dimensional problems (K variables), a frog i is represented as $X_i = (x_{i1,}x_{i2,........}x_{ik})$. Initially, the objective function is calculated for each frog, and afterwards frogs are sorted in a descending manner according to their fitness. In SFLA, the total population is divided into groups (memeplexes) that search independently.

In this process, the first frog goes to the first memeplex, the second frog goes to the second memeplex, frog m goes to the qth memeplex, and frogmþ1 goes to the first memeplex, and so on. In each memeplex, the frogs with the best and the worst fitness are recognized as Xb and Xw, respectively. Also, the frog with the best fitness in all memeplexes is recognized as Xg. Then, the following process is applied to improve only the frog with the worst fitness (not all frogs) in each iterate. Correspondingly, the location of the frog with the worst fitness is regulated as follows:
Change in the location,

$$V_i = rand(.) \times (X_b - X_w) + rand(.) \times (X_g - X_w) \quad (19)$$

$$X_{w(new)} = X_w + V_i \quad -V_{\max} \le V_i \le V_{\max} \quad (20)$$

Where *rand*(.) is a random number between 0 and 1, and V_{max} is the maximum permitted change in a frog's location. If this process generates a better solution, it replaces the worst frog. Otherwise, the calculations in Equations (17) and (18) are repeated for specific iterations (Itermax1). In addition, to provide the opportunity for random generation of improved information, random virtual frogs are generated and substituted in the population if the local search cannot find better solutions respectively in each iterate. After a number of iterations (Itermax1), all groups are combined and share their ideas with themselves through a shuffling process. The local search and the shuffling processes continue until the defined convergence criteria are satisfied. The aim of the entire process is to determine global optimal solutions. Besides the privileges of SFLA, it also has some problems, such as the possibility of being trapped in the local optima or premature convergence to local optima. Therefore, for solving the complicated optimization problem it is necessary to enhance the SFLA algorithm's search ability by mutation or hybrid this algorithm by other optimization problems. In this paper a new proposed ISLFA has been introduced in order to support the SLFA drawbacks.

Improved shuffle frog leaping algorithm (ISFLA)

The original SFLA may be trapped in local optima due to its drawback in finding the worst frog position. In this paper, two new modifications are employed to overcome the aforementioned deficiencies. In each memeplex, the position of the frog with the worst fitness is adjusted as follows:

$$\Delta X_{improved1} = rand(.)\cdot(X_{best} - T_F \cdot X_M) \quad (21)$$

$$X_{worst}^{new} = X_{worst}^{old} + \Delta X_{improved1} \quad (22)$$

Where, X_M is the mean value of individuals in each memeplex. TF is

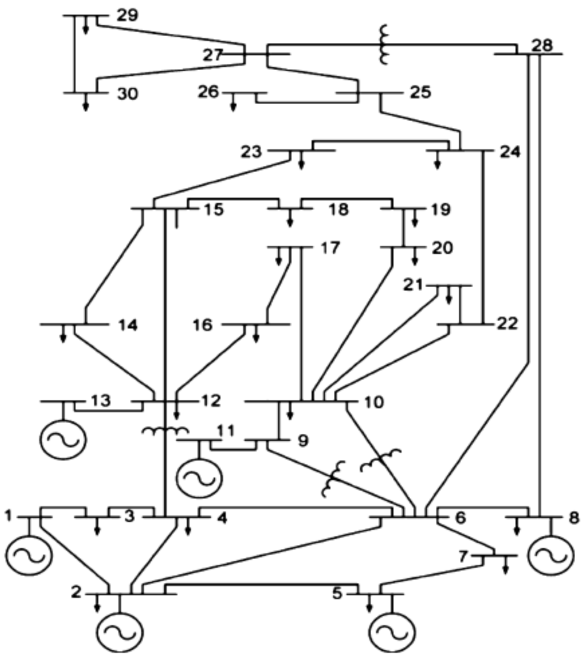


Figure 3. Single line diagram of IEEE 30 bus system.

a heuristically determined constant factor and is chosen randomly from values 1 or 2 ($T_{F=}$ round [1 + rand (0, 1)]). To improve the diversity of the search space vector, a frog Xj is selected from the population of the frogs such that Xj ≠ Xi. Subsequently, Table 1 shows the parameters used for solving ISLFA algorithm.

The position is determined using the following equation.

$$\begin{aligned} &if, f(X_n) \geq f(X_m) \\ &\Delta X_{improved2} = rand(.)\cdot(X_n - X_m) \\ &else \\ &\Delta X_{improved2} = rand(.)\cdot(X_n - X_m) \\ &end \end{aligned} \tag{23}$$

The new improved individual is generated as follows:

$$X_m^{new} = X_m^{old} + \Delta X_{improved\,2} \tag{24}$$

If the performance of the generated frogs in Equation (19) or (20) is better than the worst frog, it replaces the worst frog. Otherwise a new solution is generated by a Chaotic Local Search (CLS), as follows.

At first, the best solution in each memeplex is considered as an initial solution (X^0_{cls}) for CLS, where X^0_{cls} is scaled into [0, 1] according the following equation:

$$\begin{aligned} &X^0_{cls} = [X^1_{cls,0}, X^2_{cls,0}, ...X^n_{cls,0}]_{1\times n} \\ &C_{xo} = [cx^1_0, cx^2_0, ...cx^n_o] \\ &\alpha^j_0 = \frac{x^j_{cls,0} - x_{j,\min}}{x_{j,\max} - x_{j,\min}}, j = 1,2,.......,n \end{aligned} \tag{25}$$

Then, the chaos population for CLS is generated as:

$$\begin{aligned} &X^i_{cls} = \left[x^1_{cls,i}, x^2_{cls,i}, ...x^n_{cls,i}\right]_{1\times n}, i = 1,2,.......N_{chos} \\ &x^j_{cls,i} = cx^j_{i-1} \times (x_{j,\max} - x_{j,\min}) + x_{j,\min}, j = 1,2,.....,n \end{aligned} \tag{26}$$

Where, cx^j_i indicates the jth chaotic variable and Nchoas is the number of individuals for CLS. Then, the best solution among them is replaced with the worst solution.

SIMULATION AND RESULTS

In order to illustrate the efficiency and robustness of the proposed ISLFA algorithm, this algorithm is performed on 30-bus IEEE test system which has 41 transmission lines and the system demand is 283.4 MW in all simulations. The one line diagram of IEEE 30-bus test system is shown in Figure 3.

Reactive power flow across circuits is determined by the difference in the voltage magnitudes between the terminating buses; if this difference is high then the reactive power flow across circuits is increased and causes an increase in power loss.

Also one of the important aims of OPF is to keep all voltages at values between 0.95 and 1.05 p.u around the nominal point of operation, thus ensuring that the system is sufficiently far away from the point of the collapse. Therefore, Voltage magnitude limits of all buses are set to 0.95 to 1.05 p.u. in this paper. The proposed work was implemented in MATLAB 8.6 computing environment with Pentium IV, 2.66 GHz computer with 512 MB RAM. MATPOWER and PSAT (Milano, 2005) is a package of MATLAB m-files for solving power flow and optimal power flow problems. It is intended as a simulation tool for researchers and educators which will be easy to use and modify. In this paper we have changed MATPOWER by adding ISLFA codes in order to implement the multi-objective OPF problem with FACTS devices in power systems.

Detailed PSAT modeling has been developed and implemented various FACTS devices and simulated the results. PSAT is an open source software .we can solve OPF and CPF with FACTS devices.

Table 2 shows the comparisons between the multiple FACTS devices on single bus. From the table, STATCOM gave minimum loss compared to other devices in wind farm with SCIG, similarly in Table 3 present the comparisons between the multiple FACTS devices on multiple buses.

Table 4 shows comparison of minimization of fuel cost and loss obtained by proposed algorithm with other algorithm such as SGA (Bouktir et al., 2008), EGA (Bakistzis et al., 2002), ACO (Slimani and Bouktir, 2007), FGA (Saini et al., 2006), TS (Abido, 2003), and EP (Ongsakul and Tantimaporn, 2006).

Table 2. Comparision of FACTS devices on single bus connection.

Type of Generator	Type of FACTS	P_{loss}	Q_{loss}
SCIG	STATCOM	0.0966	0.08513.
SCIG	SSC	0.15356	0.35996
SCIG	TCSC	0.16822	0.49315

Table 3. Comparision of FACTS devices on multiple bus connection.

Type of generator	Type of facts	P_{loss}	Q_{loss}
SCIG	STATCOM	0.07653	-0.03972.
SCIG	SSC	0.15113	0.34191
SCIG	TCSC	0.15113	0.34191

Table 4.Comparision of fuel cost and losses by proposed algorithm and other algorithm on different FACTS devices.

Name of different algorithms	FACTS devices used	Generation cost ($/hr)	Real power loss (MW)
Standard GA (SGA) (Bouktir et al., 2008)	STATCOM, SVC	803.699	9.517
Enhanced GA (EGA) (Bakistzis et al., 2002)	STATCOM, SVC	802.06	9.390
Ant colony optimization (ACO) (Slimani and Bouktir, 2007)	STATCOM, SVC	802.578	9.8520
Fuzzy based GA (FGA) (Saini et al., 2006)	STATCOM, SVC	802.003	9.494
Ta bu search (TS) (Abido, 2003)	STATCOM, series capacitor	802.292	------
Evolutionary program (EP) (Ongsakul and Tantimaporn, 2006)	STATCOM, series capacitor	802.620	-------
Improved shuffled frog leaping algorithm (ISFLP)	STATCOM	800.1585	8.398

Conclusion

The paper has presented a novel method for optimal location of FACTS devices in a power system using ISFLA .Many types of FACTS devices have been implemented and analysed in this paper. From the four FACTS devices STATCOM, gave the minimum loss and fuel cost because of its most optimum result as shown in Tables 2 - 4. It can be seen from the simulation results, with ISFLA, it was possible for utility to place FACTS devices in a transmission system and wind farm such that the optimal reactive power planning can be achieved and the system real power loss can be minimized. It has been verified that is suitable for finding optimal placement of FACTS devices in large-scale power systems and the result of the reactive power planning for the power systems can be improved using this novel biologically inspired algorithm.

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