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Optimal Power Flow of DC-Grid Based on Improved PSO Algorithm

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Abstract – Voltage sourced converter (VSC) based direct-current (DC) grid has the ability to control power flow flexibly and securely, thus it has become one of the most valid approaches in aspect of large-scale renewable power generation, oceanic island power supply and new urban grid construction. To solve the optimal power flow (OPF) problem in DC grid, an adaptive particle swarm optimization (PSO) algorithm based on fuzzy control theory is proposed in this paper, and the optimal operation considering both power loss and voltage quality is realized. Firstly, the fuzzy membership curve is used to transform two objectives into one, the fitness value of latest step is introduced as input of fuzzy controller to adjust the controlling parameters of PSO dynamically. The proposed strategy was applied in solving the power flow issue in six terminals DC grid model, and corresponding results are presented to verify the effectiveness and feasibility of proposed algorithm.

Keywords: DC grid, Optimal power flow, Particle swarm optimization (PSO), Fuzzy control

1. Introduction

Power system needs to consider a series of optimization problems during the safe and efficient operation, for example, economic dispatch (ED) for minimizing fuel cost of generator unit [1, 2], hydro-thermal scheduling to collaborative hydro power generation [1, 3], optimal power flow (OPF) to optimize generation cost and transmission power loss [4], as well as optimal reactive power dispatch (ORPD) to improve voltage distribution and reduce voltage deviation [5]. The optimization goal is primary meet all kind of operation constraints, at the same time, makes the generation cost minimum or the social benefit of electric power system maximum. Thus, in context of increasing depletion of fossil fuel resources and the large-scale development of renewable energy, optimal operation becomes especially important in power system.

Based on VSC-HVDC technologies, multi-terminal high voltage direct current (MTDC) and DC grid which composed of multiple DC lines, also face the optimization problems of power balance constraints, power flow distribution and economic operation. Wind energy, photovoltaic and load are accessed to the grid through inverter, and its control system is mainly used to maximize track the output of wind and solar energy, or meet the users demand [6, 7]. For the system, they can be regarded as weak controlled terminals. By contrast, slack bus such as grid connected inverter and energy storage, have ability to adjust power flow, so is the main regulation means of DC grid. When branch number in DC grid is larger than station number n-1, the freedom of the system will be lack, scholars have put forward adding some DC power flow controller to improve the control ability. So far system level control strategies are mainly focused on master-slave margin control and multiple point voltage droop control, overall consider the power distribution characteristics and the voltage quality through design the slope and threshold of the P-V curve. However, this kind of coordination control is still stand on the maintaining the normal and safe operation level, cannot automatically adjust according to the situation of power flow distribution, so its economic load distribution capacity is low, and still a long distance to the expected characteristics of DC grid [8].

At present, the artificial intelligence technologies have been widely used in solving optimization problems, these methods have incomparable advantage in solving complex problems compared with traditional methods, has become mainstream methods of power system expansion planning, operation, modeling and analysis. Methods containing expert system [9], fuzzy control [10], simulated annealing algorithm [4], and so on. Aiming at the optimal power flow problem in DC grid, this paper proposed an adaptive PSO algorithm based on fuzzy control theory, used to adjust the setting value of multiple point voltage control in real time, to realize the multi objective optimization of minimum active power loss and minimum voltage deviation. Besides, the presented strategy is completely compatible with lower control hierarchy, occupies little communication data, hence, it has a promising application prospect.

2. System Structure and Model

A six terminal dendritic experimental platform is used as an equivalent of a large scale DC grid, the operation need to meet the requirement of both economic and security, and

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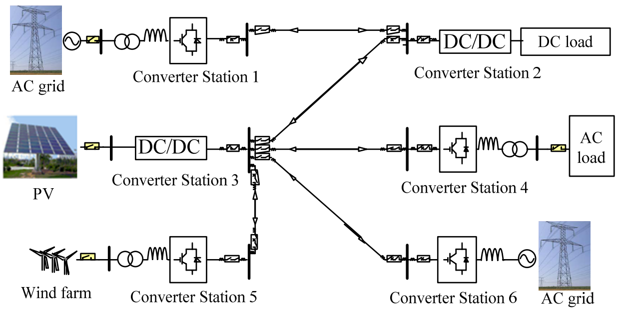

Fig. 1. Six-terminal dendritic DC grid experimental platform

set the optimization objective to minimize the power loss as well as voltage deviation, so that the mathematical model of optimization object is constructed [11].

2.1 Topology of DC grid

The physical simulation platform of six-terminal DC grid which mentioned in the previous chapter is shown as Fig.1. Each terminal connect to DC grid by a DC breaker, if any failure occurs at one terminal during operation, it will be cut off by shutdown the connected DC breaker, and enter into N-1 fault operation mode.

1#, 6# terminals are the access points to AC grid, so they are slack nodes. 2# terminal is DC load, 3# terminal is photovoltaic generation system, 4# terminal is AC load, while 5# is wind power generation system. All these terminals are connected to a host computer by optical fiber, scanning the running state and power flow distribution of each terminal, meanwhile sent control instructions to two slack nodes after optimizing calculation, so that to realize the purpose of regulating power flow. The instructions will be issued every few minutes, valve level and station level controller will operates locally, so that the voltage setting value would keep constant while instruction is not updated or communication fails. Because the 2#, 3#, 4# and 5# terminals are both connected by power electronics devices, its AC side or low-voltage side can be adjusted automatically when voltage fluctuating, thus can be regarded as a power port. Its output power is only related to external factors such as wind speed, light intensity and user's needs.

2.2 Minimum power loss/voltage deviation model

Power loss is the main factor affecting the efficiency of DC grid. In order to calculate the sum of branch loss, it can be written as following formula refers to corresponding AC system:

$$\min P_{loss} = \sum_{i=1}^{6}\sum_{j=1}^{6} g_{ij} \times (U_i - U_j)^2 \tag{1}$$

Where U_1~U_6 are the terminal voltages respectively, g_{ij} are the branch conductance from terminal i to j, in this platform, there are five branches. Substantially, the power conversion loss as well as generator's mechanical loss also contribute to the power loss, for sake of simple illustrate, not considered here.

Terminal voltage is another important indicator to test the safety and power quality of DC grid, therefore, the voltage deviation is regarded as one of objective function to maintain system voltage stability. As follows,

$$\min \Delta V = \sum_{i=1}^{6}\left(\frac{U_i - U_i^*}{\Delta V_{i\max}}\right) \tag{2}$$

Where U_i^* are the rating voltage of the nodes, and ΔV_{imax} are maximum allowable voltage deviation. For example, refer to the requirement of AC grid's standard GB12325-2008,"powerquality—deviation of supply voltage", the voltage deviation of 20kV power grid or below should limited to 7% of the nominal voltage.

2.3 Constraints

2.3.1 Power flow constraint

The steady-state operating point of the system is only determined by injected power through converter and DC side voltage of each terminal, while the supporting capacity and line inductance do not affect power flow distribution. The power balance constraint equations can be written according to the KCL and KVL's law.

$$\begin{aligned}
&(U_1 - U_2)g_{12} = I_1\\
&(U_2 - U_3)g_{23} = I_2 + I_1\\
&(U_3 - U_5)g_{35} = -I_5\\
&(U_3 - U_4)g_{34} = -I_4\\
&(U_3 - U_6)g_{36} = -I_6\\
&P_i = U_i I_i\\
&\sum I_i = 0
\end{aligned} \tag{3}$$

Where I_1~I_6 are current injected into the system from each port, P_2~P_5 are power of distributed generation and load respectively, they are known; U_1, U_6 are the voltage of slack nodes, they are setting value, also is known, and the rest are unknown variables. Therefore, there are 10 nonlinear equations containing 10 unknown variables, so it can be solved by fixed point iteration or Newton method. *Matlab* provides a *fsolve* function, which offer a quick solution after setting the initial state, then the terminal voltage and branch current distribution could be obtained.

2.3.2 Control variables constraint

The setting value of U_1, U_6 should meet the requirement of maximum permitted voltage deviation ΔV_{imax}, thus the constraint conditions are

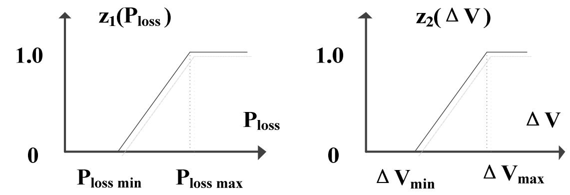

Fig. 2. Fuzzy membership curve

$$U_i^* - \Delta V_{i\max} \le U_i \le U_i^* + \Delta V_{i\max} \tag{4}$$

2.3.3 State variables constraint

State variables U_2~U_5 in DC grid should also satisfy the constraint (4), at the same time, currents are limited by the maximum permissible current $I_{i\max}$.

$$I_{i\min} \le I_i \le I_{i\max} \tag{5}$$

2.4 Single objective conversion of multi-objective optimization

For proposed multi objective model, the local search ability of PSO algorithm can be used to find enough solutions and form the Pareto optimal solution set, but it is more difficult to make satisfactory decision among them, so this paper convert the multi objective to single one and then utilize the minimax method to optimize solution. Firstly, the above minimum power loss model and minimum voltage deviation model are necessary to translate into [0, 1] interval fuzzy membership function. Trapezoidal membership curve is used as shown in Fig. 2.

The subscript 'min' and 'max' are lower and upper bounds of the corresponding variables respectively. Here, the upper limits of power loss and voltage deviation are not necessarily selected according to the physical limit or standard, it can be further reduced according to the expected optimization effect. Select the larger value of two target membership functions to construct the objective function, as shown in formula (6). Then, the optimization problem can be converted to minimization problem of a single objective function, such as formula (7).

$$z = \max\left[z_1(P_{loss}), z_2(\Delta V)\right] \tag{6}$$

$$\min z = \min\max\left[z_1(P_{loss}), z_2(\Delta V)\right] \tag{7}$$

3. Improved PSO Algorithm

3.1 Conventional PSO algorithm

Particle swarm optimization is an evolutionary algorithm based on swarm intelligence proposed by Dr. Kennedy and Professor Eberhart. Its characteristics are easy to implement, parallel search and high computing efficiency, is able to find the global optimal solution by a large probability. In recent years, PSO has been applied in many field of power system, such as power network planning [12], automatic generation control (AGC) and ED [13], optimal power flow and reactive power optimization [14], and so on. As well, compared to other evolutionary computation techniques, PSO can be expanded to handle both continuous and discrete variables easily, and more easy to handle various constraints. In PSO algorithm, each particle represents a set of possible solution and all particles constitute the swarm, each particle in the space will adjust its speed and position according to historical information of both their own and the swarm, until satisfy the convergence conditions, which means the optimal solution is found. Its iterated update function is as follows

$$\begin{aligned} v_{id}^{k+1} &= wv_{id}^{k} + c_1 r_1 (Pb_{id}^{k} - x_{id}^{k}) + c_2 r_2 (Gb_d^{k} - x_{id}^{k}) \\ x_{id}^{k+1} &= x_{id}^{k} + v_{id}^{k+1} \end{aligned} \tag{8}$$

Where v_{id}^k, x_{id}^k are velocity and position of particle '*i'*, in '*d'*th dimension and '*k'*th iteration. w is inertia weight. c_1, c_2 are learning factors of individual and swarm, also called acceleration factor. Pb_{id}^k is best position found by ith particle (personal best) in '*d'*th dimension and '*k'*th iteration, while Gb_d^k is the best position found by swarm (global best). r_1, r_2 are random numbers in the interval [0, 1].

It can be seen from (8), if the inertia weight w is 0, the search process of PSO is a process which gradually shrinking through iterative search space, thus it shows local search ability. When inertia part is added, the particle has the ability to expand search space. In order to explore a larger area in early iterations, determine the approximate range of the optimal solution quickly, and local fine search in late stage, we adopt a linear decreasing inertia weight to accelerate the convergence rate. As the formula (9)

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{k_{\max}} \times k_n \tag{9}$$

Where $w_{\max}$, $w_{\min}$ are maximum and minimum weight, while k_n, $k_{\max}$ are current and maximum times of iterations. Generally, in practical engineering the algorithm has a quite good performance when select w as 0.7298, and c_1, c_2 equal to 1.49618 [15].

3.2 Fuzzy design

There is a considerable amount of computation during the PSO searching, so that a faster convergence rate in application of power flow optimization is necessary. Due to the search process is nonlinear and complex, a decreasing inertia weight sometimes cannot reflect the true search process. For this purpose, Yuhui Shi and others has proposed a technology dynamically adjust the inertia

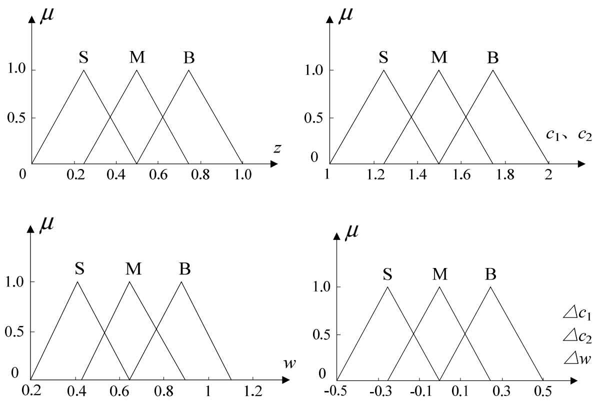

Fig. 3. Membership of input/output variables

weight by using fuzzy inference engine [16], introduce the best evaluation parameter CBPE of each iteration as a input of fuzzy controller and dynamic adjust parameter w. Based on this, this paper further proposes that using control parameter w, c_1, c_2 in previous step as well as fitness value of current step z as the inputs of fuzzy controller, to adjust these parameters in next step calculation, to make it converge more quickly.

Firstly, the scope of input output should be clear, so control parameters should be restricted to the specified range according to experience, that is $0.2 \le \omega \le 1.1$, $1 \le c_1 \le 2.0$, $1 \le c_2 \le 2.0$, the rate of output parameter in each iteration is restricted within [-5%,+5%]. Fitness function z has been transformed to range [0, 1] through fuzzy membership curve as shown in Fig.2.

Due to these parameters only need a minor adjustment, in order to reduce the number of control rules, set the input and output fuzzy partition number to three, its membership function is shown in Fig. 3. In which, the fuzzy language S represent 'small', M represent 'medium' and B represent 'big'.

3.3 Rule design of fuzzy control

The establishment of fuzzy control rules is generally based on expert experience and knowledge, the adjustment of the control parameters of the PSO algorithm is as follows [17]:

(1) As the formula (9), the fitness value z is relatively 'small' at the latter stage of the iteration, so the inertia weight w should reduced, learning factor of individual c_1 and swarm c_2 should increased to enhance the local search ability.

(2) In the early stage of iteration, experience of individual particles should be highlighted to expand the search area while the fitness value z is relatively 'big', which means c_1 increased and c_2 decreased. However in the latter stage, experience of the swarm should be enlarged to accelerate convergence, thus c_1 decreased and c_2 increased.

The above experiences were sorted into fuzzy control rules as Table 1 to 3:

Table 1. Fuzzy rules of Δc_1

z	c1		
	S	M	B
S	B	M	S
M	B	M	S
B	B	M	M

Table 2. Fuzzy rules of Δc_2

z	c2		
	S	M	B
S	B	M	M
M	B	M	S
B	M	M	S

Table 3. Fuzzy rules of Δw

z	c2		
	S	M	B
S	M	S	S
M	B	M	S
B	B	M	M

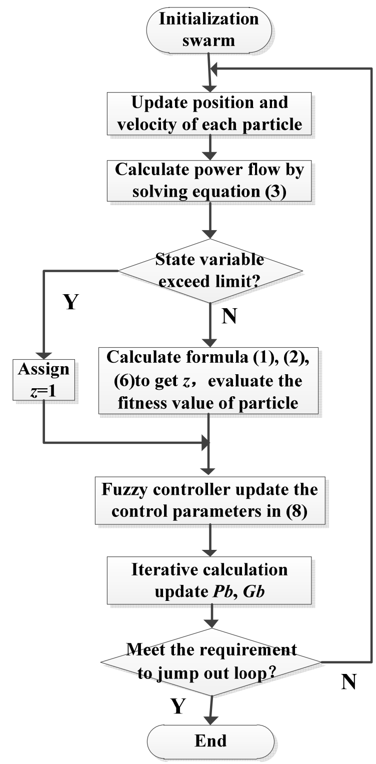

Fig. 4. Flow chart of algorithm

After fuzzy inference, the maximum overall average membership function rule (MOM) is adopted in clearness calculation, then the control parameters are updated by formula (10), so as to achieve the fuzzy controller design.

$$
\begin{aligned}
c_1(k+1) &= c_1(k)(1+\Delta c_1(k)\%) \\
c_2(k+1) &= c_2(k)(1+\Delta c_2(k)\%) \\
\omega(k+1) &= \omega(k)(1+\Delta \omega(k)\%)
\end{aligned}
\tag{10}
$$

3.4 PSO optimization procedure

Make two slack nodes operate in constant DC voltage mode under capacity constraints, station level and valve level control are operated independently, which means follow the dispatching instruction when well communicate, but maintain voltage setting value and work safely when communicate fails.

Set the particle dimension to two, representing the voltage setting value of two slack nodes, U_1 and U_6, their position need to meet the range of constraints (4). Real time evaluates the constraint (4) and (5) while in the loop, when state variable is beyond limit, assigned its fitness value to 1, which means directly excluded from the optimization results. The flow chart of PSO process shows in Fig. 4.

4. Simulation Studies

Six terminals DC grid model is built in Matlab/Simulink, three types of controller are designed respectively, which are P-V_{dc} voltage droop controller [18], OPF controller based on standard PSO (according to the fixed control parameters in Section 3.1) as well as improved PSO algorithm. The system parameters of the platform are given in following Table 4:

Select the number of particle as 30, initial inertia weight w as 0.73, learning factor c_1 and c_2 as 1.496, maximum iteration as 2000 times, and the iteration exit error is 10^{-20}, which means when reduced proportion of fitness value in one step is less than this error, it can be considered the global optimum is found. The loop will end when any condition is satisfied. The above is programmed by m file in Matlab.

4.1 Comparison of optimization performance

Aiming at sending-end system, whose renewable energy power generation is greater than load consumption; and receiving-end system, whose power generation is less than load, the simulation has carried out for comparison. The power flow distribution, power loss and mean value of voltage deviation are shown in Table 5. Due to the optimal solution are unique, no matter proposed strategy or standard PSO, thus their performance optimization results are combined in this chapter.

Table 4. Main parameters of the platform

	parameter
voltage level	500V
capacity of AC connected terminal 1# & 6#	10kVA
capacity of load terminal 2# & 4#	10kW
capacity of photovoltaic terminal 3#	5kW
capacity of wind terminal 5#	10kW
Branch equivalent impedance	1Ω

Table 5. Simulation results

(a) Optimization results of sending-end system

Working condition	Strategy	Voltage distribution	Voltage deviation/ Power loss
P_2=-2kW P_3=4kW P_4=-1kW P_5=7kW	Voltage droop control	U_1=502.3;U_2=507.1 U_3=515.7;U_4=513.8 U_5=529;U_6=505.4	12.21V 384.1W
	Proposed controller	U_1=502.6;U_2=506.4 U_3=514.2;U_4=512.2 U_5=527.4;U_6=502.8	**10.95V** **383.2W**

(b) Optimization results of receiving-end system

Working condition	Strategy	Voltage distribution	Voltage deviation/ Power loss
P_2=-5kW P_3=2kW P_4=-7kW P_5=2kW	Voltage droop control	U_1=495.7;U_2=486.7 U_3=488;U_4=473.2 U_5=492.1;U_6=495.9	11.4V 380.3W
	Proposed controller	U_1=510.2;U_2=501.4 U_3=502.7;U_4=488.3 U_5=506.6;U_6=510.3	**7.15V** **357.3W**

Table 6. Comparison of computing time/iteration times

		Computing time/Iteration times in 3 trials		
Sending-end grid	Standard PSO	383.8s 866	415s 813	230.6s 478
	Improved PSO	108.1s 283	57.09s 154	113s 292
Receiving-end grid	Standard PSO	160.6s 464	139.8s 406	154.7s 442
	Improved PSO	60.12s 175	75.35s 228	88.98s 275

Simulation result shows, compared to conventional voltage droop control, proposed PSO algorithm in this paper obtained a better performance in both voltage deviation and power loss under both working conditions. The receiving-end grid reached 37.3% decrease in voltage deviation while power loss gained 6% decline. The sending-end grid also reduced 10.3% in voltage deviation.

4.2 Comparison of convergence characteristics

For more insight regarding the significance of proposed PSO strategy, some transient processes are observed. The computing time and iteration times are recorded in Table 6, three times for each condition.

Data shows, although the number of iterations and computing time vary under the same condition, improvement in convergence is obvious. The new method only uses about half the time.

The global best values Gb_d^k are tracked, and two typical curves are selected for comparison. Fig. 5 visually explains why improved algorithm is faster.

Monitoring fitness value during iterative calculation, we can see the convergence rate of each algorithm directly, as shown in Fig. 6.

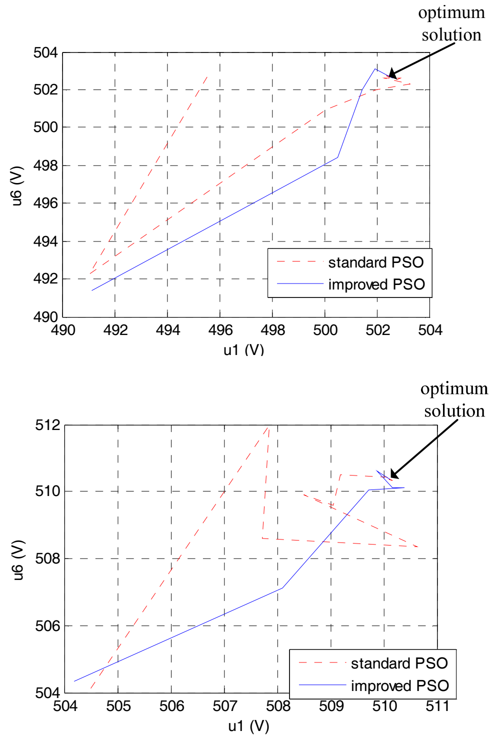

Fig. 5. Trace of global best value

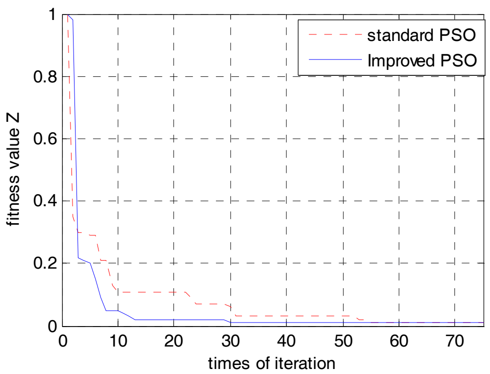

Fig. 6. Convergence contrast between two PSO algorithms

Through fitness curve recording from the data, we can see improved PSO falls slower than standard PSO in the first few steps, but in following iteration it shows its fast convergence characteristics, eventually find the global optimal solution through fewer iterations.

5. Conclusion

This paper introduces the PSO algorithm to solve the optimal power flow controlling problem in MTDC or DC grid, a fuzzy controller is introduced to improve convergence of standard PSO algorithm, dynamic adjusting three control parameters to make a better convergence rate. In order to compare the effectiveness of the proposed method, a six terminal dendritic DC grid model has been built in Matlab, a multiple point voltage controller and a standard PSO controller are designed. The simulation results show that the introduction of PSO algorithm brings optimization in both power loss and voltage deviation. Besides, the improved PSO scheme would have a better convergence rate. In simulation calculation, it saves about half the computing time. So it can be considered to be of practical value.

It is worth point out that, although the proposed algorithm is able to take into account the operation of both economy and voltage quality, however, the method of turning multi objective into single is still one make decision before optimization. Therefore, although a non-dominated solution could be solved, it is not necessarily the preference of the decision maker. Multi objective PSO could be used to solve the Pareto optimal solution set, thus more choices could be provided to decision maker to make a decision.

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