A Quantum Particle Swarm Optimization Algorithm with Available Transfer Capability

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Abstract—**Quantum particle swarm algorithm integrated the quantum behavior with particle swarm optimization algorithm, is used to settle the majorization question of calculating available transmission capability. And by using the software of Matlab to IEEE-30 bus system as an example of the simulation, after comparing the simulation results with the traditional particle swarm optimization algorithm results, we dissected the optimization performance and convergence speed of the above two algorithms, and verify the effectiveness of quantum particle swarm algorithm to settle the majorization question of the available transmission capability.**

Keywords* — *available transmission capacity; particle swarm optimization algorithm; quantum particle swarm optimization algorithm

With the gradual marketization of power system operation, building a strong smart grid has become an inevitable trend of development. At the same time, it is also the necessary demand to meet the high capacity, long distance power transmission and the high speed increase of the power load. The key problem is the selection of power transmission technology, and the method of improving the power transmission power and transmission ability of the existing transmission net. Energy transfer capability of power grid system， especially the Available Transfer Capability (ATC), has an important influence on the stable operation of the power grid and the smooth operation of the electricity market. The modern electricity system is approaching the limit of operation. The numeration of available transfer capability (ATC) has become a very important means. The concept can be expressed in the form of a formula[1], $ATC = TTC - TRM - CBM - ETC$,In the form: TTC is the total transfer capability; TRM is the transmission reliability margin; CBM is the capacity benefit margin; ETC is the existing transmission commitment.

Since Frans Van den Bergh has testified that the traditional particle swarm optimization[2-3](PSO) algorithm can not astringe to the global optimal solution, even the local optimal solution, and the test conclusion prove that the improvement of the convergence performance of many algorithms is limited. For settling the convergence question better, a new optimization algorithm—the Quantum-behaved Particle Swarm Optimization (QPSO) algorithm[4-7] , is applied to the calculation of the available transmission capacity.

I. THE QUANTUM-BEHAVED PARTICLE SWARM OPTIMIZATION ALGORITHM

In the QPSO algorithm, the spatial position of quantum particles can be depicted by wave function ψ(x,t).For the ψ(x,t), in the quantum space, the probability density function of a point can be obtained by the method of solving the Schrodinger equation. Then, after obtaining the probability density by the above method, the Monte Carlo simulation way is applied to calculate the particle position function, so that the particle locomotion formula of the QPSO algorithm can be obtained:

$$mbest(t) = \frac{1}{M}\sum_{i=1}^{M} p_i(t) = \left[\frac{1}{M}\sum_{i=1}^{M} p_{i1}(t), \frac{1}{M}\sum_{i=1}^{M} p_{i2}(t), \cdots, \frac{1}{M}\sum_{i=1}^{M} p_{id}(t)\right]$$

$$PP_{id}(t) = \varphi \cdot p_{id}(t) + (1-\varphi)\cdot p_{gd}(t) \qquad (1)$$

$$X_{id}(t+1) = PP_{id}(t) + \text{rand}(t)\cdot\beta(t)\cdot\left|mbest(t) - X_{id}(t)\right|\cdot\ln\left(\frac{1}{u(t)}\right)$$

In the form: In the optimization problem, M is the number of particles in the group, and in essence, it represents the number of potential solutions; d is the size of the particle; Pi (t) is the best position of the I particle in the group when calculating the I iteration, and its global optimal position is represented by Pg (t); PPid (t) represents the random point position between the two; mbest(t) shows the average optimal position of all particles in the group at the I iteration. Among them: $\varphi = radf\ (\ )$,the function $radf\ (\ )$ can come into being a random number that obeys uniform distribution between [0,1].Supposing:

$$\text{rand}(t) = \begin{cases} 1 & \text{if } radf\ (\ ) \le 0.5 \\ -1 & \text{if } radf\ (\ ) > 0.5 \end{cases}$$

In summary, formula (1) is The Quantum-behaved Particle Swarm Optimization Algorithm, QPSO algorithm for abbreviation.

II. ATC COMPUTING BASED ON QPSO ALGORITHEM

In this article, the optimal power flow model under the condition of system static security constraints is used as the basic calculation model, and the maximum active power of all the electric nodes in the electric area is used as the objective function:

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$$T_{ATC} = \max\left(\sum_{i\in S_G}\Delta P_{Gi}\right) \quad (2)$$

In the formula: Δ PGi is the burden active increment of the node i; The set of load nodes of the electric area is expressed as SG, $i = 1,2,3,\ldots, n$ (n is the amount of nodes in the system).

So as to compute the value of ATC, we must satisfy the requirements of inequality constraints for power flow equation equality constraints and normal function of the system. This thesis uses the AC power flow model according to the characteristics of ATC, listing equality constraint equations:

$$\begin{cases} P_{Gi} - P_{Li} - V_i\sum_{j=1}^{n} V_j\left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right) = 0 \\ Q_{Gi} - Q_{Li} - V_i\sum_{j=1}^{n} V_j\left(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}\right) = 0 \end{cases} \quad (3)$$

In the formula: PGi、QGi respectively denote active and reactive power of generator i;PLi、QLi respectively indicate active and reactive power on the load node i; n is the total number of nodes; Vi、θi、Vj、θj are the voltage amplitude and phase angle of node i and j respectively; θij=θi-θj;Gij+jB represents the correspondence elements in the admittance matrix Y of the system node. According to formula (3), we can eliminate the equality constraint by calculating the tidal current and then reduce the dimension of the problem. In power flow calculation, generators in the generation area should be set as equilibrium nodes. In the system, The control variables are the increase in active power of generators except the balance node in the power supply area and the increase in active power and reactive power of all load nodes in the receiving area. The multidimensional space formed by coordinates of each dimension set up with the active power grow of generators except the balance nodes in the supply area and the active power and reactive power increase of all the load nodes in the receiving area is used as the search space of the ATC quantum-behaved particle swarm optimization algorithm, and its dimension is the quantity of the active power of generators except the balance nodes in the supply area and the active and reactive power of all the load nodes in the receiving domain.

Under normal conditions, the capacity constraints of the thermal stability of transmission lines, the constraints of the active and reactive power of generators and the voltage constraints of all the nodes of the system together constitute the inequality constraints of the system operation, that is:

$$\begin{cases} P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \\ Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \\ P_{Li}^{\min} \le P_{Li} \le P_{Li}^{\max} \\ Q_{Li}^{\min} \le Q_{Li} \le Q_{Li}^{\max} \\ V_i^{\min} \le V_i \le V_i^{\max} \\ \left|V_i^2 G_{ij} - V_i V_j\left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right)\right| \le P_{ij}^{\max} \end{cases} \quad (4)$$

In the above inequality constraints, i is used to represent a node of a generator in a power system, and its active and reactive power is represented by P_{Gi} and Q_{Gi} respectively; the maximum and minimum values of the two are respectively expressed by $P_{Gi}^{\min}$, $Q_G^{\min}$, $Q_G^{\min}$ and $Q_G^{\max}$;The active and reactive power entering i node load is represented by PLi and QLi respectively; The maximum and minimum values of the active and reactive power of the load node i are expressed as $P_{Li}^{\max}$, $P_{Li}^{\min}$, $Q_{Li}^{\max}$ and $Q_{Li}^{\min}$;the voltage amplitude of nodes i and j are expressed as Vi and Vj; The voltage phase angle difference between node i and node j is expressed as θ ij θij; in the power system, the elements contained in the two node admittance matrices can be expressed with Gij+Bij; the maximum value of the thermal stability power of the transmission lines with the i and j as the two endpoints at the head and the tail is expressed as $P_{ij}^{\max}$.

The penalty function can be used to simplify complex constrained optimization problems to unconstrained optimization problems, and the QPSO algorithm can be used to obtain the results. The generalized objective function is composed of the original objective function, the adjustable penalty factor and all the given constraint condition. In the iterative calculation, the numerical value of the penalty factor can be changed according to the degree of violation of the constraint conditions. The adaptive penalty function is constructed through the following method:

$$\begin{cases} F(x) = f(x) + p(t,x) \\ p(t,x) = h(t)\sum_{i=1}^{n}\theta_i \times \left|\min\left(g_i(x),0\right)\right|^{\alpha_i} \end{cases} \quad (5)$$

In the formula: the value of penalty function is controlled by the number of iterations and penalty factors, which is presented as P(t,x); the penalty factor is $\left|\min\left(g_i(x),0\right)\right|$;the penalty coefficient of penalty function is h(t) and θi; the number of iterations is $h(t) = t\sqrt{t}$;the punishment of the penalty function is αi. The value of the penalty factor can determine the values of θi and αi.

The computation model of the ATC problem is expressed in the form of minimization.

$$T_{ATC} = -\min\left(-\sum_{i\in S_G} P_{Li}\right) \quad (6)$$

Sort each part of formula (4), (5), (6) and use gk(x)≥0 to represent the k inequality. Then according to the construction of penalty function, the formula (2) can be constructed into a generalized objective function by means of formula(5).

$$Fitness\ (x) = F(x) = -\sum_{i\in S_G} P_{Li}^{\Delta} + P(t,x) \quad (7)$$

The generalized objective function of the optimization problem can be transformed freely and can be used as the fitness function of the algorithm. This fitness function has the function of evaluating the performance of particles.

III. EXAMPLE ANALYSIS

The system has 6 generators, 22 load nodes and 41 branches, which are divided into 3 electricity areas. Each power area has 2 generators, and 7 contact lines has set up between the power regions of the whole system. The whole system structure is shown in Figure 2. In the figure, node 1 is used to balance the power of the entire grid, known as a balanced node; nodes 2, 13, 22, 23, 27 are PV nodes, and the others are PQ nodes, as shown in Figure 1.

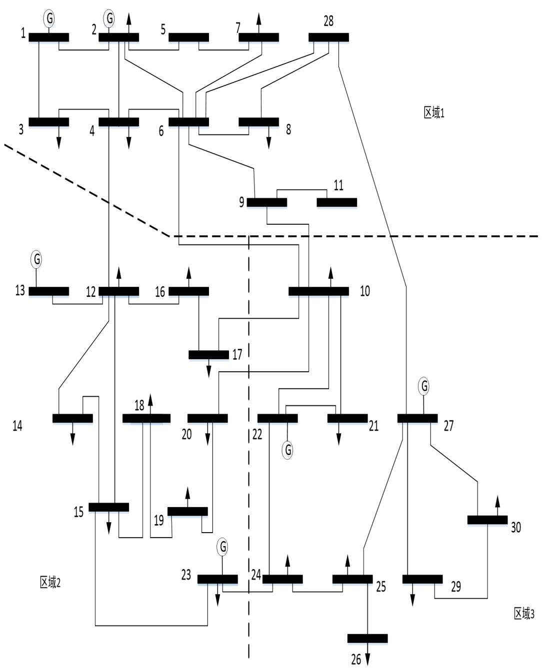

Figure 1. IEEE-30 node system

A. Parameter setting

The particle swarm optimization (PSO) algorithm and quantum-behaved particle swarm optimization (QPSO) algorithm ,set the same parameters of the IEEE-30 node system in the simulation process are used to simulate the available transmission capacity. The convergence speed and majorization ability of the quantum particle swarm optimization are evaluated by comparing and analyzing the simulation results. Example parameter setting:

In the particle swarm and quantum particle swarm al gorithm, the number of particles is 50, the value of the p opulation size M is 100, the learning factor c1=c2=2, the active power of the node of the power generation area is 100MW, the original variable is taken as the base state power flow value; Inertia weight ω： ω max=0.9， ω min=0.4;In the generalized objective function, the penalty function and the penalty function use piecewise functions respectively:

$$\theta_i = \begin{cases} 10, & penalty\ \ factor \le 0.01 \\ 20, & penalty\ \ factor \le 0.1 \\ 100, & penalty\ \ factor \le 1 \\ 300, & other \end{cases}$$

$$\alpha_i = \begin{cases} 1, & penalty\ factor \le 1 \\ 2, & otehr \end{cases}$$

B. Calculation process

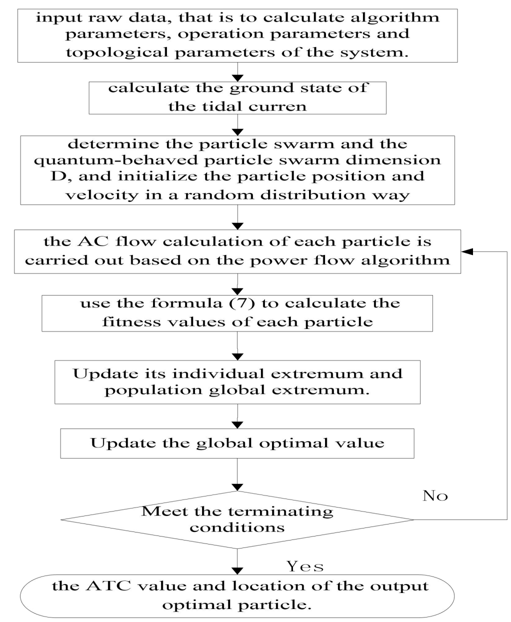

Figure 2. Flow of quantum particle swarm optimization in the basic state of ATC

C. Calculation process

So as to illustrate the function of the quantum-behaved particle swarm optimization (QPSO) algorithm in this paper, the best solution of the available transmission capacity between different regions is compared with the results obtained by the particle swarm optimization algorithm. The outcome is indicated in Table 1.

TABLE I. COMPARISON OF THE OPTIMAL SOLUTIONS OF TWO ALGORITHMS IN EACH REGION

Regional pair	*P*(ATC)/MW	
	PSO	QPSO
$1 \to 2$	108.08	104.45
$2 \to 1$	56.63	60.38
$1 \to 3$	106.56	104.08
$3 \to 1$	94.45	98.93
$2 \to 3$	43.52	50.49
$3 \to 2$	66.37	88.23

In this paper, the results of QPSO calculation in area 3→2 are used to illustrate the power adjustment process in the transmission area and the receiving area. In area 3→2, there are two generators in the region 3 of the transmission area, and assume that all generators in the other regions are generated by the ground state power flow. In the QPSO calculation process, a generator of region 3 is used as a balancing machine, which means that the node 27 is used as a balance node, then another generator, the node 22,is used as a control variable in the QPSO algorithm. There are 8 load nodes in area 2, and assume that the node loads in other regions are based on the ground state power flow. The active and reactive power of all load nodes in the region 2 is used as the control variable in the QPSO algorithm, that is, there are 16 control variables. Then there are 17 control variables in the whole region 3→2, so the dimension of the algorithm is 17 , that is, the QPSO algorithm is optimized in the 17 dimension space.

In the result of the program operation, the active power is 44.20168MW.With generator 27 as the balancing machine, the program output value is 92.5236MW, while the ground state power of generators 27 and 22 are 26.91 and 21.59MW respectively. In the case of not considering CBM, TRM,ATC3 → 2= 92.5236 + 44.20168 - 26.91 - 21.59=88.22528MW.Similarly, the available transfer capability in other areas can be worked out. When calculating the traditional particle swarm optimization algorithm, the active output is 46.40872MW in the running result of the PSO program, and the program output value of generator 27 is 68.4582MW,the other parameters are the same: ATC3 → 2=68.4582+ 46.40872-26.91-21.59 = 66.36692MW.

In this paper, we take the convergence curve of the QPSO algorithm in region 2→3 as an example and compare the stability with the PSO algorithm. The result is shown in Table 2.

TABLE II. QPSO AND PSO ALGORITHMS ARE USED TO CALCULATE THE ATC RESULTS OF 2-3 REGIONS AND THE COMPARISON of the number of iterations respectively

algorithm	2→3region		variance
	averagevalue/MW	t (Self use）/s	
PSO	43.52944	118.5593（26.6406）	5.32
QPSO	50.48604	117.1611（26.3321）	4.33

We can found through the above results:1)The average value of the 10 calculations by QPSO algorithm is larger, which indicates that QPSO algorithm has better global search ability and its accuracy is higher;2)In time consuming, the time used by QPSO to call other functions and the time of using its own algorithms are less than the time used by the PSO algorithm, which indicates that the QPSO algorithm can find the optimal solution quickly;3)For the variance of each optimization result, the variance calculated by the QPSO algorithm is relatively small, which can reflect the stronger stability of the QPSO algorithm (The variance in the table refers to the variance of the 30 optimal solutions obtained by optimization for 30 times).

The comparison of convergence curves between the QPSO algorithm and the PSO algorithm is shown in Figure 3.As can be seen from Figure 3, under the same starting point, the QPSO algorithm first reached the optimal solution at the 77 iteration, and the curve has a large slope, which shows that the convergence ability of the QPSO algorithm is strong.

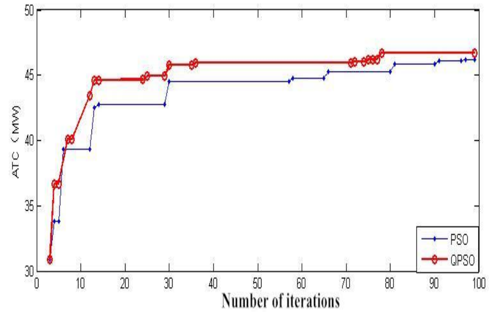

Figure 3. Comparison of algorithm QPSO and PSO convergence curve

IV. CONCLUSION

In this study, a new method, quantum particle swarm optimization (PSO), is proposed to calculate available transfer capability. By comparing and analyzing the results of ATC calculated by QPSO algorithm and PSO algorithm, We can draw a conclusion that QPSO algorithm has been excellent performance and faster convergence speed. The algorithm is more reasonable and effective. ATC can satisfy the security stability of the system, and can also satisfy the load demand to the maximum. Thus, the optimal allocation of resources can be realized, and the economic benefit is also improved. The QPSO algorithm proposed in this paper has strong global search ability, but it needs further improvement in jumping out of local search capability; The QPSO algorithm is superior to the PSO algorithm in convergence performance and stability, but there is no big difference in time consuming, Therefore, it is necessary to conduct in-depth research on the speed of the algorithm.

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