Many-objective Reactive Power Optimization Using Particle Swarm Optimization Algorithm Based on Pareto Entropy

Xu Zhuansun, Jielong Wu, Anming Zhu
Postdoctoral Scientific Research station
Shaanxi Electric Power Company
Xi'an China
zhuansunxu@hotmail.com

Tong Han, Yanbo Chen
Departmrent of Electrical and Electronic Engineering
North China Electric Power University
Beijing,China

Jin Ma
Departmrent of Electrical and Information Engineering
University of Sydney
NSW, Australia

***Abstract*—This paper presents a many-objective reactive power optimization model which consists of minimum active power loss, minimum node voltage deviation, maximum static voltage stability and maximum power supply capability. To efficiently solve this model, a novel approach by using particle swarm optimization is proposed. This approach is called many-objective particle swarm optimization algorithm based on Pareto entropy which adopts loose Pareto dominant relationship and maps the Pareto front from cartesian coordinate system to parallel cell coordinate system, thus designing evolutionary strategies using Pareto front's distribution entropy and entropy difference in the new coordinate system. The presented algorithm is capable to balance convergence and diversity of the approximate Pareto front. Moreover, cell dominant intensity and individual density are introduced to assess the individual environment fitness of the Pareto optimal solution, and we hereby design the selection strategy of the global best solution. Simulations based on the IEEE 14-bus systems demonstrate the effectiveness of the proposed model and the efficiency of the proposed algorithm.**

***Index Terms*-- Many-objective；reactive power optimization；particle swarm optimization algorithm.**

I. INTRODUCTION

Reactive power optimization plays an important role in the optimal operation of power systems. The objective of reactive power optimization is to optimize the security and economic of power system by control the output of VAR compensator, the tap ratios of transformer, generator voltage, in the condition of certain load level and satisfying operational constraints.

Conventional reactive power optimization considers minimum active power loss, minimum node voltage deviation or the combination of the above two objectives [1, 2]. And the weight method is universally used to solve the multi-objective reactive power optimization. However, different values of weight will lead to different optimization results [3]. Some researchers also proposes a multi-objective reactive power optimization model which consists of minimum active power loss, minimum node voltage deviation, maximum static voltage stability or the two of them [4,5]. To solve the multi-objective optimization problem, various algorithms, such as Multi-objective Particle Swarm Optimization[6], Multi-objective Genetic Algorithm[4], Pseudo Grdient based Particle Swarm Optimization[7], et al, have been proposed. The multi-objective reactive power optimization problem above is two-dimension or three-dimension, thereby making Pareto optimal solution can be obtained using conventional multi-objective evolutionary algorithm based on Pareto dominant.

Based on the conventional three-dimension multi-objective reactive power optimization model, this paper further takes maximum power supply capability into account, thereby leading a four-dimension multi-objective reactive power optimization model. For the high dimension of the model, we propose a many-objective particle swarm optimization algorithm based on Pareto entropy (PeMaOPSO). Simulations are carried on IEEE14-bus system to test the performance of the proposed approach.

II. POWER SUPPLY CAPABILITY BASED ON POWER FLOW ENTROPY

Power supply capability is affected by the maximum transfer capability of lines or transformers, and also the power flow distribution of power system. In general, a power system with more balanced power flow distribution surely has higher power supply capability.

Entropy can be used to measure the system's confusion status, and Ref. [8] introduces the concept of entropy to describe the equilibrium of power flow distribution. Here, we only introduces the expression of the index of power supply capability based on power flow distribution:

$$SC = \frac{e^{-H} - e^{-H_{min}}}{e^{-H_{max}} - e^{-H_{min}}} \tag{1}$$

Here, H expresses the power flow entropy which is the same as Ref. [8], and H_{min} and H_{max} are the minimize and maximize values of H, respectively. The larger power supply capability index SC reflects stronger power supply capability.

III. Formulation Of Many-objective Reactive Power Optimization

The existing reactive power optimization problems are usually modeled as a multi-objective optimization problem with goals of active power loss minimization, node voltage deviation minimization and static voltage stability maximization. Dispatch of reactive power distribution in reactive power optimization can lead to changes of node voltage and further changes of active power distribution. From this perspective, it is reasonable to regard reactive power optimization as a fine control of active power distribution. And the equilibrium of active power distribution directly affects power supply capability. Therefore, it's of great significance to introduce the index of power supply capability based on power flow entropy into reactive power optimization problem. This is the motivation of our approach.

By introducing the index of power supply capability based on power flow entropy into conventional reactive power optimization problem, a novel many-objective reactive power optimization model can be expressed as:

$$\begin{cases} min\, F(X_1, X_2) = [f_1(X_1, X_2), f_2(X_1, X_2), f_3(X_1, X_2), f_4(X_1, X_2)] \\ s.t. g(X_1, X_2) = 0, h(X_1, X_2) \le 0 \end{cases} \tag{2}$$

and

$$f_1(X_1, X_2) = \sum_{k \in N_B} g_k \left(U_i^2 + U_j^2 - 2U_i U_j cos\theta_{ij}\right) \tag{3}$$

$$f_2(X_1, X_2) = \sum_{i \in N_l} \frac{\left|U_{li} - U_{li}^*\right|}{U_{li,max} - U_{li,min}} \tag{4}$$

$$f_3(X_1, X_2) = \sum\nolimits_{k \in N_B} FVSI_{ij} = \sum\nolimits_{k \in N_B} 4\left(\frac{U_j}{U_i} - \frac{U_j^2}{U_i^2}\right) \tag{5}$$

$$f_4(X_1, X_2) = \frac{e^{-H} - e^{-H_{min}}}{e^{-H_{max}} - e^{-H_{min}}} \tag{6}$$

where, $g(X_1, X_2) = 0$ and $h(X_1, X_2) \le 0$ are the power flow equations and bound constraints of the variables, respectively. Control variables $X_1 = [U_G^T, Q_C^T, T_B^T]^T$, where U_G^T is the vector of generator voltage, Q_C^T is the vector representing VAR compensator's output, T_B^T is the vector of under-load tap changing transformer ratio. State variables $X_2 = [U_L^T, Q_G^T]^T$, where U_L^T is the vector of load bus voltage, Q_G^T is the vector of generator's reactive power output. $f_1(X_1, X_2)$ denotes active power loss, N_B is the set of system branch, U_i is the voltage of a branch's head end, U_j is the voltage of a branch's end, θ_{ij} is the phase angle difference between a branch's two ends. $f_2(X_1, X_2)$ denotes node voltage deviation, N_l is the set of load bus, U_{li} is the actual voltage value of load bus i, U_{li}^* is the expected voltage value off load bus i, $U_{li,max}$ is the upper limit voltage value of load bus i, $U_{li,min}$ is the lower limit voltage value of load bus i. $f_3(X_1, X_2)$ denotes static voltage stability, and which is calculated by the fast voltage stability index(FVSI)[9,10]. $f_4(X_1, X_2)$ denotes the power supply capability based on power flow entropy, and the meaning of variables is the same as the above.

IV. Many-objective Particle Swarm Optimization Algorithm Based on Pareto Entropy

Generally multi-objective optimization algorithm based on Pareto dominant can solve multi-objective optimization problems with two or three objectives effectively. But when the dimension of objectives is more than three, the proportion of non-dominated individuals in population will increase rapidly, and even worse, most of individuals become non-dominated solutions. And there will be a degradation of algorithm's searching performance eventually [11]. Hu W et.al [12] proposed a multi-objective particle swarm optimization based on Pareto entropy, which has a good optimization performance for many-objective optimization problem. However, this algorithm doesn't take the high dimension of optimization problem into account. For solving the many-objective reactive power optimization problem, a new approach called many-objective particle swarm optimization methodology based on Pareto entropy (PeMaOPSO) is proposed in this paper.

PeMaOPSO approach has the almost same algorithm flow as the second generation multi-objective particle swarm optimization. And we will introduce the differences between them emphatically in next part.

A. Coordinate Transformation

PeMaOPSO algorithm transforms the high dimension Pareto front into a two-dimensional plane with the form of parallel coordinate. The new coordinate system is called parallel cell coordinate system (PCCS). The transformation formula is

$$L_{k,m} = \left\lceil K \frac{f_{k,m} - f_m^{min}}{f_m^{max} - f_m^{min}} \right\rceil. \tag{7}$$

where $\lceil x \rceil$ is a top integral function. $k = 1, 2, \ldots, K$, and K is the number of external archive's individuals in current iteration. $m=1,2,\ldots,M$, and M is the number of objectives. f_m^{max} and f_m^{min} are the maximum and minimum of the m th objective in current Pareto front. $L_{k,m}\in\{1,2,\ldots K\}$ is the integer labelling after $f_{k,m}$ mapped to PCCS, which denotes the m^{th} cell coordinate component of the k^{th} non-dominated solution.

B. Pareto Entropy and Entropy Difference

In PCCS, we can measure distribution uniformity of the approximate Pareto front by entropy. In the t^{th} iteration, Pareto entropy of the approximate Pareto front in external archive is calculated as follows:

$$Entropy(t)=-\sum_{k=1}^{K}\sum_{m=1}^{M}\frac{Cell_{k,m}(t)}{KM}\log\frac{Cell_{k,m}(t)}{KM} \tag{8}$$

where $Cell_{k,m}(t)$ is the number of cell coordinate components which fall on the k th row and the m th column cell, after approximate Pareto front mapped to PCCS.

In two adjacent iteration of the $t-1$ th and the t^{th}, entropy difference which reflects variation degree of the approximate Pareto front can be calculated as follows:

$$\Delta Entropy(t)=Entropy(t)-Entropy(t-1) \tag{9}$$

C. Individual Density in PCCS

PeMaOPSO algorithm's updating strategy of external archives is the same as the second generation multi-objective particle swarm optimization's, but only the individual density is assessed by individual density in PCCS.

When approximate Pareto front in external archive has been mapped to PCCS, individual density of any solution $P_i\left(i=1,2,\ldots,K\right)$ among which is calculated as:

$$Density(P_i)=\sum_{j=1,j\neq i}^{K}\frac{1}{PCD(P_i,P_j)^2} \tag{10}$$

where $PCD(P_i,P_j)$ denotes the parallel cell distance between P_i and P_j and can be calculated as:

$$PCD\left(P_i,P_j\right)=\begin{cases}0.5, & if\ \forall m, L_{i,m}=L_{j,m}\\ \sum_{m=1}^{M}\left|L_{i,m}-L_{j,m}\right| & if\ \exists m, L_{i,m}\neq L_{j,m}\end{cases} \tag{11}$$

where $L_{i,m}$ is calculated by formula (3).

D. Loose Pareto Dominant Relationship

PeMaOPSO algorithm adopts loose Pareto dominant relationship to decrease the proportion of non-dominated individuals in population. In loose Pareto dominant relationship, we judge Pareto dominant relationship between solution x and solution y after solution x reduced $(1-\varepsilon)$ times, and then determine the dominant relationship. Loose Pareto dominant relationship is shown graphically in Figure 1.

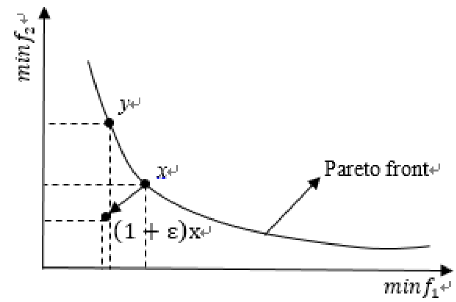

Figure 1. Loose Pareto dominant relationship.

E. Cell Dominant Intensity

A new concept, cell dominant intensity, is introduced in PCCS for assessing convergence of Pareto optimal solutions in external archive.

Definition of cell dominant: Be similar as Pareto dominant, cell dominant replaces objective vector in Pareto dominant with PCCS vector.

Definition of cell dominant intensity: Cell dominant intensity $S_c(x)$ of a Pareto optimal solution $x\in A$ is defined as the number of other Pareto optimal solutions in A which are cell dominated by x.

F. Assessment of Population's Evolution Status

Population's evolution status is divided into three cases and which's judgment principle (JP) are as follows:

- JP of convergence status: $\left|\Delta Entropy(t)\right|>\delta_c$.
- JP of diversity status: $\delta_s>\left|\Delta Entropy(t)\right|<\delta_c$.
- JP of stagnation status: $\left|\Delta Entropy(t)\right|<\delta_s$.

where $\delta_c=\frac{2}{H}log2$, $\delta_s=\frac{2}{MK}log2$, H is the member quantity of external archive, M is the number of objectives, K is the maximum member quantity of external archive.

G. Selection Strategy of the Global Best Solution

Let the number of objectives be M, external archive be A, and the population's evolution status $Status=\{Convergence, Diversity, Stagnation\}$. Figure 2 explains the selection strategy of the global best solution gbest.

In Figure 2, function $\mathrm{Top}(D\,|\,S,n,\mathrm{'ASC'}\,|\,\mathrm{'DESC'})$ is to return the top n members from set D or S in the way of 'ASC' (ascending) or 'DESC' (descending). Function $\mathrm{RandSelect}(C)$ is to select a member from set C at random.

In addition, selection strategy of the personal best solution is as same as global best solution's.

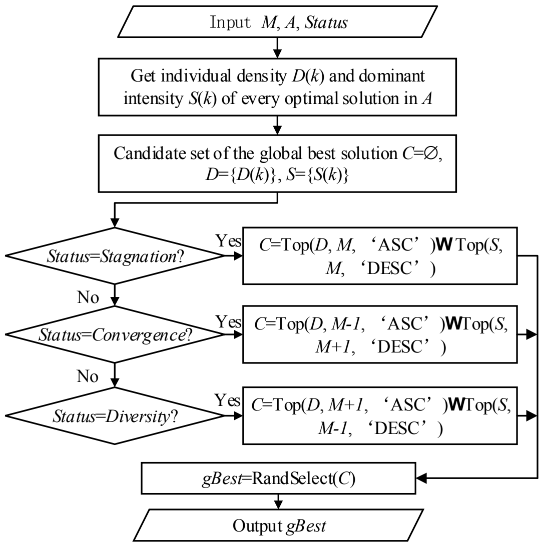

Figure 2. Flow chart of selection strategy of global best solution.

H. Algorithm Flow of PeMaOPSO Algorithm

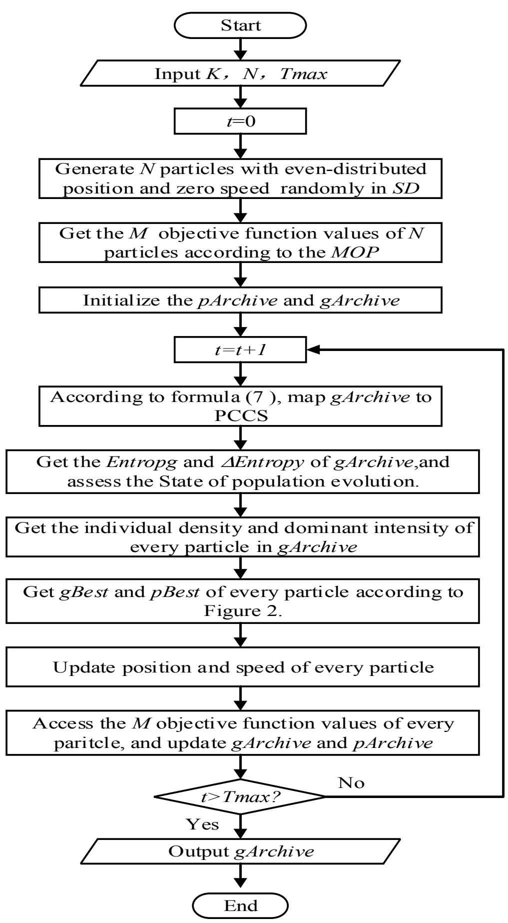

Figure 3. Flow chart of PeMaOPSO algorithm

For a optimization problem *MOP* with *M* objectives, searching space of *D* decision variables is *SD*, the maximum member quantity of external archive is *K*, the number of particles is *N*, the maximum number of iterations is *Tmax*, global external archive is *gArchive*, personal external archive is *pArchive*, the global best solution is gbest, the personal best solution is *pBest*. Storage and maintenance strategies of external archive can refer to [12]. So the flow chart of PeMaOPSO algorithm is given in Figure 3.

V. CASE STUDY

In this section, simulations are carried on IEEE14-bus systems to test the performance of the proposed approach. Under-load tap changing transformer branches are branch 4-7, 4-9 and 5-6. VAR compensator buses are bus 4, 5 and 9. The upper and lower limits of each variable are shown in TABLE I~III. Maximum active power active power transmission capacities of each branch are shown in TABLE IV.

TABLE I. Parameters and limits of generations

Bus	$Q_{G.max}/pu$	$Q_{G.min}/pu$	$U_{G.max}/pu$	$U_{G.min}/pu$
2	0.5	-0.4	1.1	0.9
3	0.4	0	1.1	0.9
6	0.24	-0.06	1.1	0.9
8	0.24	-0.06	1.1	0.9

TABLE II. Limits of PQ nodes and transformer taps

$U_{load.max}/pu$	$U_{load.min}/pu$	$T_{k.max}/pu$	$T_{k.min}/pu$
1.06	00.94	1.05	0.95

TABLE III. Limits of reactive power sources and voltage

$Q_{c.max}/pu$	$Q_{c.min}/pu$	$U_{c.max}/pu$	$U_{c.min}/pu$
0.24	-0.12	1.05	0.95

Note: Transformers and VAR compensators both have 10 taps.

TABLE IV. Maximum active power transmission capacity of branches(*MPC*)

Branch	1-	1-5	2-3	2-4	2-5	3-4	4-5
MPC/pu	1.	0.8	0.8	0.7	0.6	0.3	0.7
Branch	4-	4-9	5-6	6-	6-	6-	7-8
MPC/pu	0.	0.2	0.5	0.1	0.1	0.2	0.1
Branch	7-	9-	9-	10-	12-	13-	
MPC/pu	0.	0.0	0.1	0.0	0.0	0.1	

Before optimizing, we set the values of generators voltage and transformers ratio to 1.0 pu. By load flow calculation, we can get the values of four objective functions.And the values of f_1 to f_4 are 0.15066, 0.24908, 1.13688 and 0.99753 respectively..

Figure 4 shows the result of final approximate Pareto front in PCCS. And we can conclude that optimized by

PeMaOPSO algorithm, final approximate Pareto front of many-objective reactive power optimization problem shows good uniformity and diversity. In other words, we have obtained good Pareto optimal solutions.

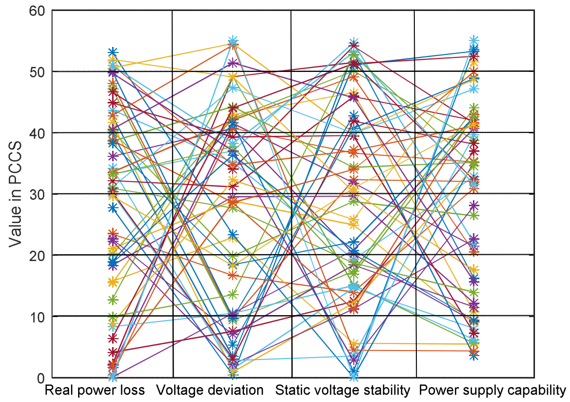

Figure 4. Approximate Pareto front in PCCS

Figure 5 shows part of Pareto optimal solutions in parallel coordinate system (for clearness, we only select 9 Pareto optimal solutions). Compared with the values of objective functions before optimizing in Table 5, we can see that after optimization, active power loss, node voltage deviation, static voltage stability and maximum power supply capability are all improved greatly.

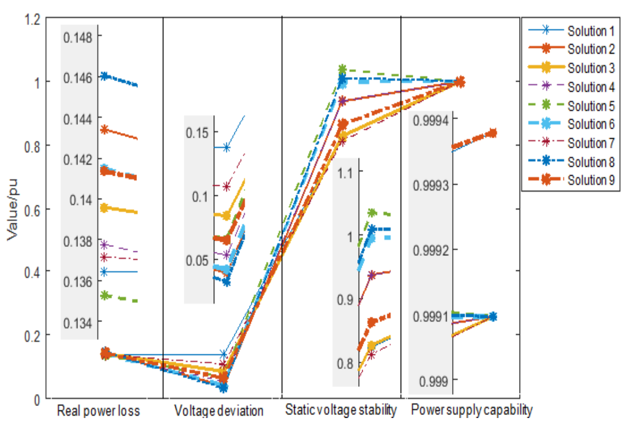

Figure 5. Part of Pareto optimal solutions.

VI. CONCLUSION

In this paper, by considering the effect of reactive power optimization to power system fully, a many-objective reactive power optimization model consisted of minimum active power loss, minimum node voltage deviation, maximum static voltage stability and maximum power supply capability is proposed. For the high dimension of the model, we propose a new algorithm — PeMaOPSO algorithm. PeMaOPSO algorithm adopts loose Pareto dominant relationship, and maps the Pareto front from cartesian coordinate system to PCCS. According to status of population assessed by Pareto entropy and entropy difference, and individual environment fitness assessed by cell dominant intensity and individual density, evolutionary strategies with equilibrium and adaptivity are designed. The effectiveness of PeMaOPSO algorithm has been tested through IEEE14-bus system. Results show that PeMaOPSO algorithm has the ability to obtain Pareto optimal solutions with good uniformity and diversity, and improve the system performance greatly. So as a new attempt, PeMaOPSO algorithm has heuristic significance to solve power system optimization problem with high dimension.

VII. REFERENCES

[1] Kursat Ayana, Ulas Kılıc "Artificial bee colony algorithm solution for optimal reactive power flow", International Journal of Applied Soft Computing, vol. 12, pp. 1477–1482, May 2012.
[2] K. Vaisakh, P. Kanta Rao "Differential Evolution Based Optimal Reactive Power Dispatch for Voltage Stability Enhancement", Journal of Theoretical and Applied Information Technology, vol. 4, pp. 700-709, 2008.
[3] Sharma, T.; Srivastava, L., "Evolutionary Computing Techniques for Optimal Reactive Power Dispatch: An Overview and Key Issues," Communication Systems and Network Technologies (CSNT), 2014 Fourth International Conference on , vol., no., pp.507,511, 7-9 April 2014.
[4] P. Aruna Jeyanthy, D. Devaraj "Multi-Objective Genetic Algorithm for Reactive Optimization Inclusing Voltage Stability", International Journal of Engineering Science and Technology, vol. 2 (7), pp. 2715-2729, Oct 2010.
[5] D. Godwin Immanue and Dr. C. Chritober Asir Rajan "A Multi Objective Genetic Algorithm approach to Reactive Power and Voltage Control in Power System", International Journal of Research in Engineering and Technology (IJRET), vol. 2, pp. 174-178, 2013.
[6] Congyu Zhang, Minyou Chen and Ciyong Luo "A Multi-objective Optimization Method for Power System Reactive Power Dispatch", in proceedings of the Intelligent Control and Automation (WCICA), 28th World Congress, pp. 6-10, July 2010.
[7] Dung Anh Le, Dieu Ngoc "Optimal Reactive Power Dispatch by Pseudo-Gradient Guided Particle Swarm Optimization", in proceedings of the IPEC, Conference on Power & Energy, pp. 7-12, December 2012.
[8] Cao YJ, Wang GZ, et al. "An Identification Model fir Self-organized Criticality of Power Grids Based on Power Flow Entropy", Automation of Electric Power Systems, vol. 35, pp. 1-5, Apr 2011.
[9] Musirin, I.; Rahman, T.K.A., "Novel fast voltage stability index (FVSI) for voltage stability analysis in power transmission system," Research and Development, 2002. SCOReD 2002. Student Conference on , vol., no., pp.265,268, 2002.
[10] Musirin, I.; Rahman, T.K.A., "On-line voltage stability based contingency ranking using fast voltage stability index (FVSI)," Transmission and Distribution Conference and Exhibition 2002: Asia Pacific. IEEE/PES , vol.2, no., pp.1118,1123 vol.2, 6-10 Oct. 2002.
[11] Kong WJ, Jing L, Chai TY. "Survey on large-dimensional mult-i objective evolutionary algorithms", Control and Decision,vol. 25, pp. 331-326, Mar 2010.
[12] Hu W, Yen GG, Zhang X. Multiobjective particle swarm optimization based on Pareto entropy. Ruan Jian Xue Bao/Journal of Software, 2014,25(5):1025-1050.