A Novel Dynamic Mind Evolutionary Algorithm for Unit Economic Dispatch Problem

Pingfei Zhu, Lanxiang Wang, Yukai Li
State Grid Electric Power Research Institute
Beijing, China
{zhupingfei, wanglanxiang, liyukai}@sgepri.sgcc.com.cn

Yuyang Lai
School of Control and Computer Technology
North China Electric Power University
Beijing, China
284298549@qq.com

***Abstract*—Economic Dispatch (ED) is one of the optimization issues for improving the economic benefit of power plants. According to the framework of Mind Evolutionary Algorithm, we proposed a new developed Dynamic Mind Evolutionary Algorithm (DMEA) to solve the ED problem. Specifically, the economic model in power plants was built firstly. Secondly, an individual evaluation function is presented. Thirdly, simplex method was used to search the extreme value of each sub-group. Then, sub-groups are separated at the step "similartaxis operator", while the sub-groups with the same extreme value are assembled at the step "dissimilation operator", so that the extreme value of each local space can be found efficiently. Ultimately, it can avoid repeated search for the same space due to the record of the searched area. Including DMEA, three different methods were compared under the same illustration. The simulation results demonstrate the effect of DMEA.**

Keywords-Economic Dispatch; Dynamic Mind Evolutionary Algorithm; power plants.

I. INTRODUCTION

Economic Dispatch (ED) is a typical optimized matter [1] [2]. It is to distribute the load of each unit, with the basic constrained conditions for the operation of power plants, so as to minimize the cost or coal consumption of power generation [3]. It has become a hot spot for researchers in both domestic and foreign scholars. The issue of ED could be resolved efficiently and is at great accuracy. Traditional methods, such as quadratic programming [4], can only solve the continuous differentiable quadratic model; dynamic programming [5] will result in the "dimension disaster" as the variables and solution space increase. Fang et al., [6] propose an improved genetic algorithm which projects real coding method with diploid initial population ranking selection, adaptive genetic parameter and compressed space method. A continuous Hopfield neuronal network, which regards the solution of ED as the value of stable point in the multi-variable and nonlinear dynamic system, is proposed in [7]. In [8], Particle Swarm Optimization (PSO) is improved with both mixing the virtue of Genetic Algorithm and the disturbance part, which prevents the algorithm from the convergence of local minimum. In this paper, we propose a new developed type of Dynamic Mind Evolutionary Algorithm (DMEA) to solve the ED problem. Adopting the simplex search method, the algorithm can get rid of dependence on the expression of models.

Mind Evolutionary Algorithm, one of evolutionary algorithms, can imitate the evolution of human mind's thought. On the basis of the Standard Mind Evolutionary Algorithm, we suggest a dynamic distribution method of the sub-groups, splitting or assembling them in accordance with the relation among different group centers when the sub-groups become mature. Furthermore, the call-board has recorded the searched areas, to avoid the repeated search and enhance the efficiency of DMEA. The simulation results show that not only high speed of convergence but also high precision of solution are reached with the employment of DMEA in ED.

II. MATHEMATICAL MODELS FOR ECONOMIC DISPATCH IN THE ELECTRIC POWER SYSTEM

A. Objective Functions

The aim of ED model is to construct the functional relation between each unit load and coal consumption or between each unit load and the cost of power generation, then seek for the optimized minimum value of the model.

$$\min F = \min\{\sum_{i=1}^{n} F_i(P_i)\} \tag{1}$$

where F denotes the optimized object, n stands for the number of units, P_i represents the power of the ith unit and $F_i(P_i)$ is the fuel-cost function.

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \tag{2}$$

Eq. (2) is deduced based on the operating data of each power plant. a_i, b_i, c_i are the parameters of the ith unit.

In the real operation, the generating units with multivalve steam turbines exhibit a greater variation in the fuel-cost functions. The valve-point effect introduces ripples in the heat-rate curves. Taking this effect into consideration, the fuel-cost function, Eq (2) can be rewritten with a sine function part:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + E_i \tag{3}$$

$$E_i = \left| g_i \sin[h_i(P_{i\min} - P_i)] \right| \tag{4}$$

where g_i and h_i are both parameters of the algorithm, and $P_{i\min}$ is the minimum operating output of the ith unit.

B. Constraint Conditions

The operation constraints of the ith unit are as follows:

$$P_{i\min} \le P_i \le P_{i\max} \quad i = 1, 2, \cdots, n \tag{5}$$

where $P_{i\min}$ and $P_{i\max}$ are the lower and the upper operation limit of the ith unit, respectively.

Power balance constraint is given as:

$$\sum_{i=1}^{n} P_i = P_L + P_D \tag{6}$$

where P_L is the total loss of the grid system and P_D is the total load instruction.

III. DYNAMIC MIND EVOLUTIONARY ALGORITHM

A. Introduction of MEA

The natural evolution of biology depends on inheritance and natural selection. The evolution process persists thousands of years while the evolutionary process of human mind is relatively short. This is because human being is capable of adapting actively to the change of the natural environment and studying both self-consciously knowledge and experience from predecessor and other people. Meanwhile, the development of human mind is accelerated in the recent years with the development of information communication and many innovations have been acquired. Depending on which science and technology have been developed, these phenomena are called similartaxis and dissimilation, respectively. Derived from the Genetic Algorithm, Mind Evolutionary Algorithm simulates the evolution of the human thoughts, replacing crossover operator and mutation operator with "similartaxis operator" and "dissimilation operator". The set of all individuals is called a population. The population is divided into several groups distinguished into two categories: the winner groups and the temporary groups. "Similartaxis operator" performs local competition within subgroups among individuals and finds local optimal points out. Firstly, some individuals are distributed normally around one point. Then, their scores are computed and the one with highest score is the "winner". The winner, delegating the sub-group in the following dissimilation operator, participates in the global competition. "Dissimilation operator" performs global competition where "winners" of each sub-group from "similartaxis operator" compete with each other. After the "dissimilation operator", those points with high score are reserved for next round while the others are eliminated and replaced by new individuals distributed in the solution space. This makes the evolution of the population converge to the optimal point. Similartaxis operator refers to the process of each solution learning from the superior one while dissimilation operator stands for the competition among all groups and the search for new space. MEA enables the group search instead of individual one.

The search in MEA is realized by the similartaxis operator in every sub-group and dissimilation operator among different sub-groups, therefore, the construction, iteration and division of sub-groups have great influence on the performance of MEA. However, there are few elaborations about the process of constituting the sub-groups and the division of them. On the basis of the position of each individual in solution space, we try to split and assemble the sub-groups so as to find the local optimized solution for all sub-sections in similartaxis operator and to choose the global optimized one in dissimilation operator. Meanwhile, the eliminated and searched area is recorded on the call-board, preventing the repeated search for the solution space.

B. The solution of ED based on dynamic mind evolutionary algorithm

The issue of ED concerns a constrained, nonlinear optimization. With the construction of outer point penalty function, constrains are added to the evaluation expression, resulting in the search for optimum solution where the infeasible solution is also acceptable as the initial point.

$$\begin{aligned} &\min F' = \min\{\sum_{i=1}^{n} F_i(P_i) + \sigma_1 \sum_{j=1}^{l} (h(P))^2 + \sigma_2 \sum_{k=1}^{u} [\max\{0, g_j(P)\}]^2\} \\ &s.t \begin{cases} h_i(P) = 0, i = 1, 2, \cdots, l \\ g_j(P) \le 0, j = 1, 2, \cdots, u \end{cases} \end{aligned} \tag{7}$$

where $P = (P_1, P_2, \cdots P_n)^{\mathrm{T}}$ represents the output power of each unit, and l, u is the number of equation and inequation constraints in the model. σ_1 and σ_2 are the penalty coefficients of equation and inequation constraints, respectively. (7) is taken as the evaluation function for the whole DMEA.

Once the evaluation function is determined, the initial individual solution needs to be generated. Since the output of the generator must be restricted to the range between the lower limit and the upper limit, the former n-1 generators randomly engender their output power within the constraint shown in (5) while the output power of the last generator is attained according to (6). If the result is beyond the constraint of its lower or upper limits, the output power of the last generator should be recognized as lower or upper limit, which is closer to the calculation result.

After N initial solutions are produced, as many as $k(n+1)$ solutions are generated according to the normal distribution randomly around the first N initial solutions which become the centers of different sub-groups. Meanwhile, the positions of all these solution points aforementioned are recorded on the local call-boards of each sub-group. Then the strategy of similartaxis operator is implemented in accordance with simplex search method. Firstly, a simplex is formed with $n+1$ adjacent solutions in a sub-group. Assume $F'(x_1) > F'(x_2) > \cdots > F'(x_{n+1})$, i.e., the solution x_1 has the highest fuel cost while x_{n+1} has the lowest one. It is assumed that $x_{n+2}$is the geometric center of

the polygon whose peaks are $x_2, x_3, \cdots, x_{n+1}$. Point x_{n+3} is chosen to satisfy the following equation:

$$x_{n+3} = 2x_{n+2} - x_1 \quad .$$

where x_{n+3} is called the reflection point of x_1 with respect to x_{n+2}. $F'(x_{n+3}) < F'(x_{n+1})$ indicates the correct search direction. x_{n+4} is defined as follows

$$x_{n+4} = x_{n+2} + \alpha(x_{n+2} - x_1) \quad .$$

where $\alpha > 1$. $F'(x_{n+4}) < F'(x_{n+3})$ indicates the favorable expansion and x_1 should be replaced by x_{n+4} to form a new simplex. If $F'(x_{n+4}) < F'(x_{n+3})$, x_1 should be replaced by x_{n+3} to form a new simplex.

If $F'(x_{n+1}) < F'(x_{n+3}) < F'(x_n)$ according to (8), x_1 should be replaced directly by x_{n+3} to form a new simplex. However, $F'(x_n) < F'(x_{n+3}) < F'(x_1)$ indicates that x_{n+3} is overextended. x_{n+5} is defined as follows

$$x_{n+5} = x_{n+2} + \beta(x_{n+3} - x_{n+2}) \quad (10)$$

where $\beta < 1$, x_1 is replaced by x_{n+5} to form a new simplex.

If $F'(x_{n+3}) > F'(x_1)$, reference to (8), the new vertex of simplex should be located between x_{n+2} and x_1. x_{n+6} is defined as follows

$$x_{n+6} = x_{n+2} + \beta(x_{n+2} - x_1) \quad (11)$$

If $F'(x_{n+6}) < F'(x_1)$, x_1 should be replaced directly by x_{n+6} to form a new simplex. Otherwise, it is considered that all of the points in the direction $x_1 x_{n+2}$ have higher fuel cost than x_1. In this case, a new simplex is formed among x_{n+1} and the midpoints from $x_1 x_{n+1}, x_2 x_{n+1}, \cdots, x_n x_{n+1}$ and the simplex search is repeated.

Therefore, in the algorithm, whatever the situation is, a new simplex can be always found which at least has one vertex with lower fuel cost compared with the original simplex. The algorithm is repeated until the termination criterion for the convergence is satisfied.

After the similartaxis operator of all solutions are finished in one sub-group, *k* optimized solutions are obtained, two of which, x_1'、x_2', are chosen randomly and $F'(x_1') < F'(x_2')$ is assumed. $x_3' = x_1' + \gamma(x_2' - x_1')$, $\gamma < 1$ is calculated. If $F'(x_1') < F'(x_2') < F'(x_3')$, the sub-group has more than one extreme area and thus it should be split. After that, the split sub-group goes into the similartaxis operator process again until it can't be split any more.

Similartaxis operator is followed by Dissimilation operator. Firstly, two best solutions x_1^{best}, x_2^{best} from neighboring sub-groups are chosen randomly. Suppose that $F'(x_1^{best}) < F'(x_2^{best})$, $x_3'' = x_1^{best} + \gamma(x_2^{best} - x_1^{best})$, $\gamma < 1$ is calculated. If $F'(x_1^{best}) < F'(x_3') < F'(x_2^{best})$ or $F'(x_3') < F'(x_1^{best}) < F'(x_2^{best})$, these two neighboring sub-groups are situated within an area sharing the same local extreme and should be assembled. Then, these two sub-groups are combined. When none of these sub-groups can be assembled any more, so that the number of sub-groups can be *N*, on the one hand, the worst sub-groups are eliminated if the number of sub-groups excesses *N*. On the other hand, if the number of them is smaller than *N*, new sub-groups are generated.

After the similartaxis operator of sub-groups is finished, the evaluation of superior solutions from all sub-groups are sorted. The last N_T sub-groups in the ranking list are deleted and N_T newly-born sub-groups are generated.

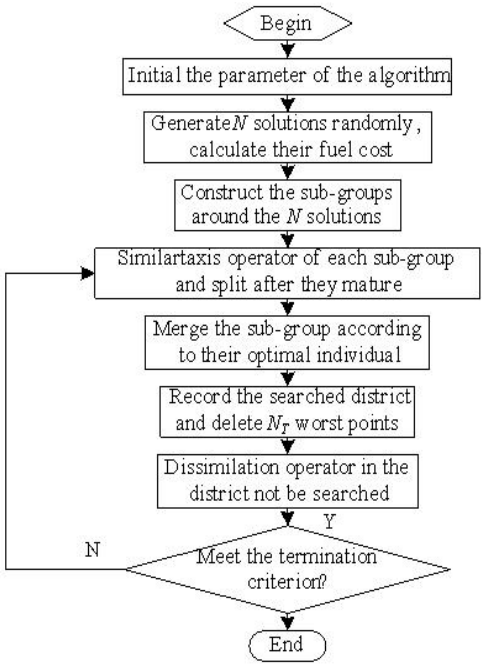

Figure 1. Flow chart of DMEA

Before the generation of new sub-groups in DMEA, it is required to record the information of the searched areas on the overall call-board. For either the deleted sub-groups or the remaining sub-groups, the position of the optimized solution should be recorded and the initial solution, which is farthest from the optimized solution in each sub-group, should also be recorded on the local call-board before the deletion. Moreover, the searched area is such defined that all the points are closer to the optimized solution in comparison with the farthest initial one. Hence, the initial solutions of the newly-born sub-groups cannot go beyond the range of unsearched area. Otherwise, the initialization is restarted. Having got the new sub-groups, the similartaxis operator of both the new sub-groups and the merged sub-groups are executed. The circular procedure is repeated until the termination condition is satisfied.

After the parameters are set up, two parts are included in the algorithm, similartaxis operator and dissimilation operator. The flow chart is shown in figure 1.

IV. SIMULATION RESULTS

The 13-generator system in [9] is chosen as an example. The valve-point effect of the units is concerned while the power loss is neglected. To take the advantage of group search, we set N=30. Meanwhile, we also set $N_T = 10$ to guarantee a higher rate of elimination so that one third of the group could be updated during each round of iteration. Empirically, we set $\sigma_1 = \sigma_2 = 20$, $\alpha = 1.5$, $\beta = 0.5$, $\gamma = 0.5$. The limit of iterations is I=400. The parameters of the units can be found in [9].

The result curve is shown in Fig. 2. The curve of DMEA has a steep decline slope in the beginning. It is shown that the algorithm has strong search capability because it finds local extremum quickly. As shown in Fig. 2, an acceptable solution is found after 130th generation. Because the search space becomes smaller and smaller, the so-far optimum solution does not change significantly. The results of DMEA and other literatures are listed in Table 1. Instead of single point search, DMEA can find as many local extremum points as possible, and take the best one as the final solution. Compared with the other intelligent algorithms, DMEA achieves a superior performance.

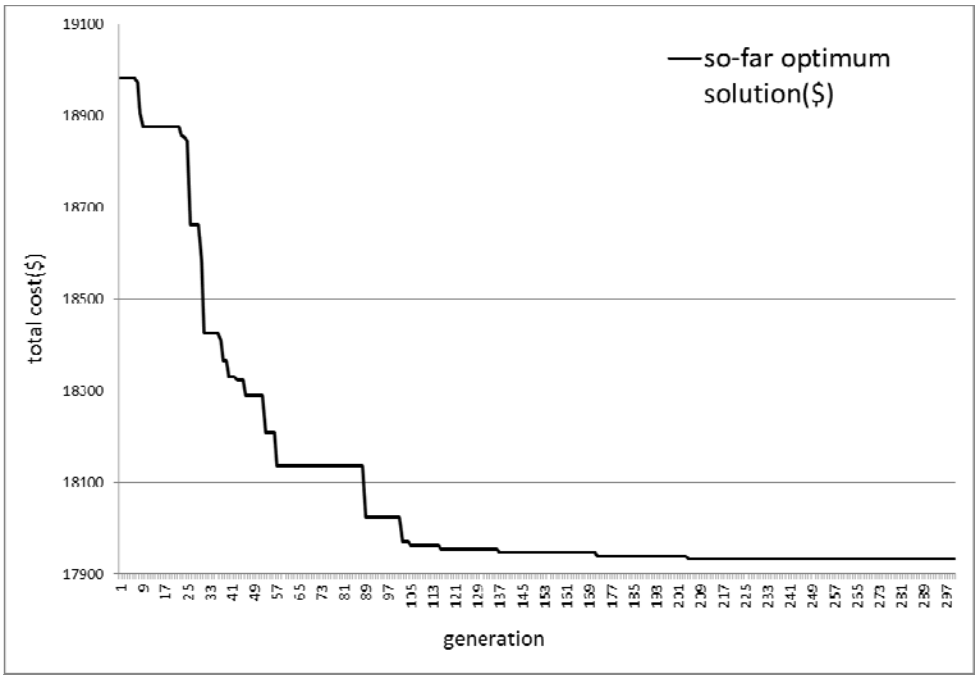

Figure 2. The curve of total coal cost by DMEA

TABLE I. THE RESULT COMPARISON OF DIFFERENT METHODS

Unit[MW]	Methods			Unit[MW]	Method		
	XPSO	*FXPSO*	*DMEA*		*XPSO*	*FXPSO*	*DMEA*
P1	510.16	502.24	505.39	P8	98.256	97.674	101.59
P2	246.05	278.94	237.06	P9	100.43	88.133	102.59
P3	266.31	222.64	273.00	P10	40.00	40.014	40.001
P4	102.33	104.83	98.83	P11	40.00	40.015	40.001
P5	96.938	108.31	95.412	P12	55.00	55.012	55.001
P6	93.827	98.193	94.935	P13	55.00	55.019	55.001
P7	95.704	108.98	101.19	All-in cost/$	17934.00	17934.80	17933.00

V. CONCLUSIONS

On the basis of MEA, a dynamic sub-groups division method is proposed which renders solutions in different extreme areas to be separated so that the pertinence of similartaxis operator searching is strengthened. Furthermore, the searched areas are noticed on the overall call-board to avoid repeated search. The modification of MEA algorithm can increase the convergence rate. In addition, in utilizing the simplex search method in the similartaxis operator, the algorithm exhibits a better adaption to different kinds of models. Therefore, DMEA can be applied directly to the AGC system in the power plant or local area network of EMS system, and achieve an optimal scheduling scheme.

ACKNOWLEDGMENT

This work was financially supported by the Science and Technology Project of SGEPRI (State Grid Electric Power Research Institute) entitled "Development and Application of the System for Electric Vehicle Charging/Battery Swap Network Operating and Management", the Science and Technology Projects of SGCC entitled "Research on the Integrated Supporting Technologies for Intelligent Marketing Business based on the International IEC-CIM/CIS Standard" and "Research on the Information Processing and Typical Applications for Electric Internet of Things".

REFERENCES

[1] S. M. Sajjadi, A. S. Yazdankhah and F. Ferdowsi, "A new gumption approach for economic dispatch problem with losses effect based on valve-point active power", Electric Power Systems Research, Vol. 92, Nov. 2012, pp. 81-86.

[2] G. C. Liao, "Integrated isolation niche and immune genetic algorithm for solving Bid-Based dynamic economic dispatch", International Journal of Electrical Power & Energy Systems, Vol. 42, Nov. 2012, pp. 264-275.

[3] T. Niknam, H. D. Mojarrad and H. Z. Meymand, "Non-smooth economic dispatch computation by fuzzy and self-adaptive particle swarm optimization", Applied Soft Computing, Vol. 11, Mar. 2011, pp. 2805-2817.

[4] Y. Fan, L. Zhang. "Real-time economic dispatch with line flow and emission constraints using quadratic programming", IEEE Transactions on Power Systems,Vol. 13, May 1998, pp. 320-25.

[5] S. S. Kumar and V. Palanisamy, "A.dynamic programming based fast computation hopfield neural network for unit commitment and economic dispatch", Electric Power Systems Research, Vol. 77, June 2007, pp. 917-925.

[6] Y. J. Fang and C. L. Cui, "An improved accelerating genetic algorithm and its application in dynamic load distribution of units", East China Electric Power , Val. 38, May 2010, pp. 0717-0720.

[7] W. J. Wan, K. Y. Zhou and J. Q. Xu,"Dynamic system on economic dispatch among thermal power units" Proceedings of the 2005 Chin. Soc. for Elec. Eng.(CSEE), Jan. 2005, pp. 125-129.

[8] Y. H. Hou, L. J. Lu, X. F. Xiong, S. J. Cheng and Y. W. Wu, "Enhanced particle swarm optimization algorithm and its application on economic dispatch of power systems", Proceedings of the 2004 Chin. Soc. for Elec. Eng.(CSEE), Jul. 2004, pp.95-100.

[9] N. Sinha, R. Chakrabarti and P. K.. Chattopadhyay, "Evolutionary programming techniques for economic load dispatch", IEEE Transactions on Evolutionary Computation,Vol. 7, Feb. 2003, pp. 83-94.