Artificial Immune Algorithm for Practical Power Economic Dispatch Problems

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Abstract—**This paper proposes an artificial immune algorithm with a multiplier updating method (AIA-MU) for practical power economic dispatch (PED) considering units with prohibited operating zones (POZ). The AIA equipped with a migration operation can efficiently search and actively explore solutions. The multiplier updating (MU) is introduced to handle the system constraints. To show the advantages of the proposed algorithm, two examples are investigated, and the computational results of the proposed method are compared with that of the previous methods. The proposed approach integrates the AIA and the MU, revealing that the proposed approach has the following merits - ease of implementation; applicability to non-convex fuel cost functions of the POZ; better effectiveness than previous methods, and the requirement for only a small population in applying the optimal PED problem of generators with POZ.**

Index Terms—**Power economic dispatch, artificial immune algorithm, prohibited operating zones.**

I. INTRODUCTION

Power generators may possess some POZ between their minimum and maximum generation limits, because of the practical limitations of power plant elements. Operating in those zones may cause amplification of vibrations in a shaft bearing, which must be avoided in practice. The PED problem becomes a non-convex optimization problem because the prohibited regions separate the decision space into disjoint subsets constituting a non-convex solution space [1]. Furthermore, utilities must maintain some generation capacity as spinning reserve to serve loads in the event that operating units or other equipment suddenly or unexpectedly failed.

Many approaches have been adopted to resolve such PED problems with POZ and spinning reserve. Lee *et al.* [1] decomposed the non-convex decision space into a small number of subsets such that each of the associated dispatch problems, if feasible, was solved via the conventional Lagrangian relaxation approach. Fan *et al.* [2] defined a small and advantageous set of decision space with respect to the system demand, used an algorithm to determine the most advantageous space, and then utilized the λ-δ iterative method to find the feasible optimal dispatch solution. For infeasible solutions, they re-dispatch the units using some heuristic rules to probe the neighborhood for feasibility.

To adequately solve the dispatch problem for units with POZ and spinning reserve, solution techniques that do not directly rely on the incremental cost function formulation but perform a direct search of the solution search space are required. Such solution techniques include: Hopfiled model of neural network [3], [4], genetic algorithm (GA) [5], and evolutionary programming (EP) [6], evolutionary strategy optimization (ESO) [7], particle swarm optimization with time varying acceleration coefficients (PSO-TVAC) [8]. Su *et al.* [3] employed a linear input-output model for neurons, enabling the development of an operational model for rapidly resolving the PED problems. Yalcinoz *et al.* [4] proposed an improved Hopfield neural network that used a slack variable technique to handle inequality constraints by mapping process for obtaining the weights and biases. Orero *et al.* [5] presented a penalty function approach to handle the POZ and spinning reserve constraints. Pereira-Neto *et al.* [7] used the ESO for solving the non-convex problem of power system. Chaturvedi *et al.* [8] employed the PSO-TVAC method to avoid the premature convergence for the POZ and spinning reserve of the PED problem.

AIA [9] is inspired by immunology, immune function and principles observed in nature. AIA is a very intricate biological system which accounts for resistance of a living body against harmful foreign entities. It is now interest of many researchers and has been successfully used in various areas of research [9], [10].

II. SYSTEM FORMULATION

Generally, the PED problem with some units possessing POZ can be mathematically stated as follows [11]:

$$Minimize \quad \sum_{i=1, i\in\Omega}^{N_p} F_i(P_i) = \sum_{i=1}^{N_p} F_i\left(c_i P_i^2 + b_i P_i + a_i\right) \quad (1)$$

where $F_i(P_i)$ is the fuel cost function of the unit i, P_i is the power generated by unit i, a_i, b_i, and c_i are cost coefficients of generator i, N_p is the number of on-line units, and Ω is the set of all on-line units. The PED problem subject to the following constraints:

A. Power Balance Constraints

The equality constraint of the power balance is given by:

$$\sum_{i=1}^{N_p} P_i = P_d + P_L \quad (2)$$

where P_d is the system load demand, and P_L is the transmission loss.

B. System Limits

The generating capacity constraints are written as:

$$P_i^{\min} \le P_i \le P_i^{\max}, \qquad i = 1, \cdots, n_p \qquad (3)$$

where $P_i^{\min}$ and $P_i^{\max}$ are the minimum and maximum power outputs of unit i.

C. System Spinning Reserve Constraints

Units with spinning reserve can be are given as:

$$\sum_i S_i \ge S_R \qquad (4)$$

$$S_i = \min\left\{ \ (P_i^{\max} - P_i), \quad S_i^{\max} \right\} \quad \forall i \in (\Omega - \omega) \ (5)$$

$$S_i = 0 \qquad \forall i \in \omega \qquad (6)$$

where S_i is spinning reserve contribution of unit i in MW, S_R stands system spinning reserve requirement in MW, $P_i^{\max}$ is maximum generation limit of unit i, $S_i^{\max}$ denotes maximum spinning reserve contribution of unit i, and ω is set of all on-line units with prohibited zones. Due to a unit with prohibited zones may operate into one of its zones while system load is regulating, it is shown in (6) that this kind of units should not contribute any regulating reserve to the system. In other words, system spinning reserve requirement must be satisfied by way of regulating the units without prohibited zones.

D. Units with POZ

The unit operating range denotes the effects of a generator with POZ [5]:

$$P_i^{\min} \le P_i \le P_{i,1}^l \qquad or$$

$$P_{i,j-1}^u \le P_i \le P_{i,j}^l, \quad j = 2, \cdots, n_i \qquad or \qquad (7)$$

$$P_{i,ni}^u \le P_i \le P_i^{\max}, \qquad \forall i \in \omega$$

where $P_{i,j}^l$ and $P_{i,j}^u$ respectively are the lower and upper bounds of prohibited zone j of unit i, and n_i is the number of prohibited zones in unit i.

Clearly, the entire operating region of a dispatching unit with n_i prohibited zones is divided into (n_i+1) disjoint operating sub-regions. The total number of decision sub-spaces caused by that division may be counted as follows:

$$N = \prod_{i \in \omega} (n_i + 1) \qquad (8)$$

Equation (8) shows that the total number of decision sub-spaces rises extremely quickly as the number of units with prohibited zones rises.

III. THE PROPOSED ALGORITHM

A. The AIA

In AIA [10], mimics these biological principles of clone generation, proliferation and maturation. The main steps of AIS based on clonal selection principle are activation of antibodies, proliferation and differentiation on the encounter of cells with antigens, maturation by carrying out affinity maturation process, eliminating old antibodies to maintain the diversity of antibodies and to avoid premature convergence, selection of those antibodies whose affinities with the antigen are greater.

In order to emulate AIA in optimization, the antibodies and affinity are taken as the feasible solutions and the objective function respectively.

B. The MU

Michalewicz *et al.* [12] surveyed and compared several constraint-handling techniques used in evolutionary algorithms. Among these techniques, the penalty function method is one of the most popularly used to handle constraints. In this method, the objective function includes a penalty function that is composed of the squared or absolute constraint violation terms. Powell [13] noted that classical optimization methods include a penalty function have certain weaknesses that become most serious when penalty parameters are large. More importantly, large penalty parameters ill condition the penalty functions so that obtaining a good solution is difficult. However, if the penalty parameters are too small, the constraint violation does not contribute a high cost to the penalty function. Accordingly, choosing appropriate penalty parameters is not trivial. Herein, the MU [14] is introduced to handle this constrained optimization problem. Such a technique can overcome the ill conditioned property of the objective function.

Considering the nonlinear problem with general constraints as follows:

$$\min_x F(x)$$
$$subject \quad to \quad h_k(x) = 0, \quad k = 1, ..., m_e \qquad (9)$$
$$g_k(x) \le 0, \quad k = 1, ..., m_i$$

where $h_k(x)$ and $g_k(x)$ stand for equality and inequality constraints, respectively.

The augmented Lagrange function (ALF) [13] for constrained optimization problems is defined as:

$$L_a(x, v, \upsilon) = f(x) +$$
$$\sum_{k=1}^{m_e} \alpha_k \left\{ [h_k(x) + v_k]^2 - v_k^2 \right\} + \sum_{k=1}^{m_i} \beta_k \left\{ \langle g_k(x) + \upsilon_k \rangle_+^2 - \upsilon_k^2 \right\} \qquad (10)$$

where α_k and β_k are the positive penalty parameters, and the corresponding Lagrange multipliers $v = (v_1, ..., v_{m_e})$ and $\upsilon = (\upsilon_1, ..., \upsilon_{m_i}) \ge 0$ are associated with equality and inequality constraints, respectively.

The contour of the ALF does not change shape between generations while constraints are linear. Therefore, the contour of the ALF is simply shifted or biased in relation to the original objective function, $f(x)$. Consequently, small penalty parameters can be used in the MU. However, the shape of contour of La is changed by penalty parameters while the constraints are nonlinear, demonstrating that large penalty parameters still create computational difficulties. Adaptive penalty parameters of the MU are employed to alleviate the above difficulties, and Table I presents computational procedures of the MU. More details of the MU have shown in [15].

TABLE I: COMPUTATIONAL PROCEDURES OF THE MU

Step 1. Set the initial iteration $l = 0$. Set initial multiplier, $v_k^l = v_k^0 = 0, k = 1,...,m_e$, $\upsilon_k^l = \upsilon_k^0 = 0, k = 1,...,m_i$, and the initial penalty parameters, $\alpha_k > 0$, $k = 1,...,m_e$ and $\beta_k > 0$, $k = 1,...,m_i$. Set tolerance of the maximum constraint violation, ε_k (e.g. $\varepsilon_k = 10^{32}$), and the scalar factors, $\omega_1 > 1$ and $\omega_2 > 1$.

Step 2. Use a minimization solver, e.g. AIA, to solve $L_a(x, v^l, \upsilon^l)$. Let x_b^{l} be a minimum solution to the problem $L_a(x, v^l, \upsilon^l)$.

Step 3. Evaluate the maximum constraint violation as $\hat{\varepsilon}_k = \max\{ \max_k |h_k|, \max_k \max(g_k, -\upsilon_k) \}$, and establish the following sets of equality and inequality constraints whose violations have not been improved by the factor ω_1:

$$I_E = \{ k : | h_k | > \frac{\varepsilon_k}{\omega_1}, \quad k = 1, \cdots, m_e \}$$

$$I_I = \{ k : | \max(g_k, -\upsilon_k) | > \frac{\varepsilon_k}{\omega_1}, \quad k = 1, \cdots, m_i \}$$

Step 4. If $\hat{\varepsilon}_k \geq \varepsilon_k$, let $\alpha_k = \omega_2 \alpha_k$ and $v_k^{l+1} = v_k^l / \omega_2$ for all $k \in I_E$, let $\beta_k = \omega_2 \beta_k$ and $\upsilon_k^{l+1} = \upsilon_k^l / \omega_2$ for all $k \in I_I$, and go to step7. Otherwise, go to step 5.

Step 5. Update the multipliers as follows:
$$v_k^{l+1} = h_k(x_b^l) + v_k^l$$
$$\upsilon_k^{l+1} = \langle g_k(x_b^l) + \upsilon_k^l \rangle_+ = \upsilon_k^l + \max\{g_k(x_b^l) - \upsilon_k^l\}$$

Step 6. If $\hat{\varepsilon}_k \leq \varepsilon_k / \omega_1$, let $\varepsilon_k = \hat{\varepsilon}_k$ and go to step 7. Otherwise, let $\alpha_k = \omega_2 \alpha_k$ and $v_k^{l+1} = v_k^l / \omega_2$ for all $k \in I_E$, and let $\beta_k = \omega_2 \beta_k$ and $\upsilon_k^{l+1} = \upsilon_k^l / \omega_2$ for all $k \in I_I$. Let $\varepsilon_k = \hat{\varepsilon}_k$ and go to step 7.

Step 7. If the maximum iteration reaches, stop. Otherwise, repeat steps 2 to 6.

Fig. 1 displays the flow chart of the proposed algorithm, which has two iterative loops. The ALF is used to obtain a minimum value in the inner loop with the given penalty parameters and multipliers, which are then updated in the outer loop toward producing an upper limit of L_a. When both inner and outer iterations become sufficiently large, the ALF converges to a saddle-point of the dual problem [15]. Advantages of the proposed AIA-MU are that the AIA efficiently searches the optimal solution in the economic dispatch process and the MU effectively tackles system constraints.

IV. SYSTEM SIMULATIONS

This section investigates two examples to illustrate the effectiveness of the proposed algorithm with respect to the quality of the solution obtained. The first example compares the proposed AIA-MU with the previous methods in terms of production cost for a 5-unit system. The second example compares the AIA-MU with the previous methods in terms of production cost for a 15-unit system, in which four units (Units 2, 5, 6 and 12) have POZ.

The proposed AIA-MU was directly coded using real values, and the computation was implemented on a personal computer (P5-3.0 GHz) in FORTRAN-90. Setting factors utilized in these examples were as follows: the population size N_p was set to 5 for the proposed AIA-MU, and iteration numbers of the outer loop and inner loop were set to (outer, inner) as (50, 5000) for examples of 1 and 2. For most setting of the parameters, the proposed method is able to converge satisfactorily.
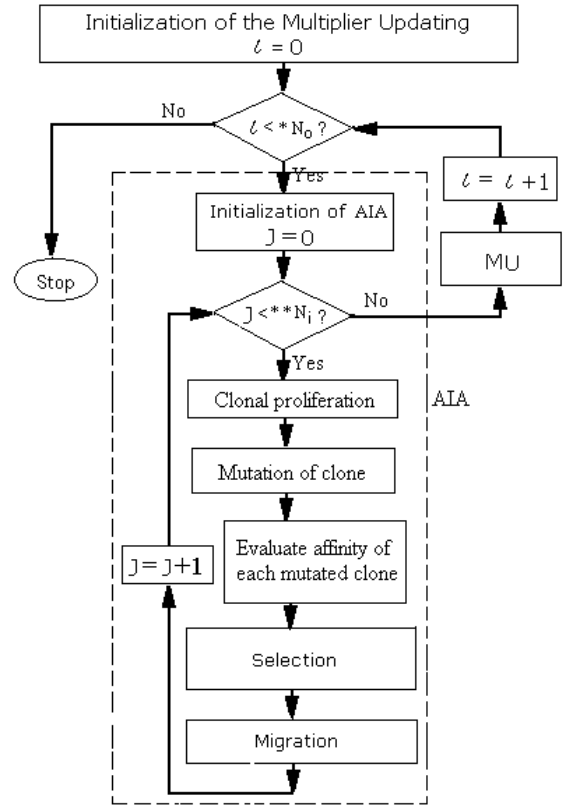

Fig.1 The flow chart of the AIA-MU
* N_0 : maximum number of iterations of outer loop
** N_i : maximum number of iteartions of inner loop

Fig. 1. The flow chart of thr AIA-MU.

A. Example 1

This example system has five on-line units with the following input-output cost functions:

$$F_i(P_i) = 350 + 8P_i + 0.01P_i^2 + 1 \cdot 10^{-6} P_i^3 \, \$/h \quad (11)$$

where $i = 1, ..., 5$. The operating limits are 120 MW $< P_i <$ 450MW for $i = 1, 2, ..., 5$. Units 1, 2 and 3 have POZ as defined in [2], these zones result in a non-convex decision space composed of 27 convex sub-spaces. The system load demand P_D and spinning reserve S_R are 1175 MW and 100 MW, respectively.

For comparison, Table II lists the computational results of the proposed AIA-MU, the λ-δ Method [2], and the EP Method [6]. The total cost obtained by the AIA-MU is satisfactory compared with that obtained by the λ-δ method [2] and the EP method [6].

TABLE II: COMPUTATIONAL RESULTS OF THE PREVIOUS METHODS AND THE PROPOSED IGAMUM FOR EXAMPLE 1

Items	λ-δ Method [2]	EP Method [6]	AIA-MU
P_1 (MW)	238.33	240.00	238.13
P_2 (MW)	210.00	210.00	210.00
P_3 (MW)	250.00	250.00	250.00
P_4 (MW)	238.33	223.07	238.46
P_5 (MW)	238.33	251.93	238.41
Total power (MW)	1,174.99	1,175.00	1,175.00
Total cost ($/h)	11,492.51	11,493.23	11,492.50

Fan *et al.* [2] defined a small and advantageous set of decision space with respect to the system demand, used an

algorithm to determine the most advantageous space, and then utilized the λ - δ iterative method to find the feasible optimal dispatch solution. For infeasible solutions, they re-dispatch the units using some heuristic rules to probe the neighborhood for feasibility. The AIA-MU combines the AIA and the MU. The AIA can efficiently search and actively explore solutions, the MU avoids deforming the augmented Lagrange function and resulting in difficulty of solution searching. Unlike the method [2], it requires neither the decomposition of the non-convex decision space nor the determination of the advantageous set of decision space before solving via this conventional approach.

B. Example 2

To further demonstrate the effectiveness of the proposed method, a larger practical system of units with POZ having non-convex cost functions and spinning reserve was addressed in this example, which is identical to that used by Lee *et al.* [1]. The remaining units will contribute with

regulating reserves [16]. This system supplies a 2650MW load demand with 200MW as spinning reserve. This system has 15 on-line units supplying a system demand of 2650MW. Among these dispatching generators, units 2, 5 and 6 have three POZ, and unit 12 has two POZ, forming 192 decision sub-spaces for this realistic system. The implementation of this example can be represented as follows:

$$L_a\left(x,v,\upsilon\right)= f\left(x\right)+\alpha_1\left\{\ \left[h_1\left(x\right)+v_1\right]^2-v_1^2\ \right\}$$
$$+\sum_{k=1}^5\beta_k\left\{\ \left\langle g_k\left(x\right)+\upsilon_k\right\rangle_+^2-\upsilon_k^2\ \right\} \tag{12}$$

$$\text{objective}:\ \min_{x=\left(P_1,P_2,...P_{15}\right)}\ f\left(x\right)=\sum_{i=1}^{15}\ F_i\left(P_i\right) \tag{13}$$

$$\text{subject to}\ \ h_1:\ \ \sum_{i=1}^{15}P_i-P_d-P_L=0 \tag{14}$$

$$g_1:P_2^{150}\le P_2\le P_{2,1}^{185},or\quad P_{2,1}^{225}\le P_2\le P_{2,2}^{305},or\quad P_{2,2}^{335}\le P_2\le P_{2,3}^{420},or\quad P_{2,3}^{450}\le P_2\le P_2^{455}$$
$$g_2:P_5^{105}\le P_5\le P_{5,1}^{180},or\quad P_{5,1}^{200}\le P_5\le P_{5,2}^{260},or\quad P_{5,2}^{335}\le P_5\le P_{5,3}^{390},or\quad P_{5,3}^{420}\le P_5\le P_5^{470}$$
$$g_3:P_6^{135}\le P_6\le P_{6,1}^{230},or\quad P_{6,1}^{255}\le P_6\le P_{6,2}^{365},or\quad P_{6,2}^{395}\le P_6\le P_{6,3}^{430},or\quad P_{6,3}^{455}\le P_6\le P_6^{460} \tag{15}$$
$$g_4:P_{12}^{20}\le P_{12}\le P_{12,1}^{30},or\quad P_{12,1}^{55}\le P_{12}\le P_{12,2}^{65},or\quad P_{12,2}^{75}\le P_{12}\le P_{12}^{80}$$
$$g_5:S_R-\sum_{i=1}^{15}S_i\le 0$$

TABLE III: COMPARED RESULTS WITHOUT LOSS OF THE PREVIOUS METHODS AND THE AIA-MU

Items	λ-δ [1]	λ-δ [2]	Hopfield [3]	Hopfield [4]	AIA-MU
P_1 (MW)	450	450.0	449.4	454.6976	449.9995
P_2 (MW)	450	450.0	450	454.6976	450.0001
P_3 (MW)	130	130.0	130	129.3512	130.0000
P_4 (MW)	130	130.0	130	129.3512	130.0000
P_5 (MW)	335	335.0	335	244.9966	335.0001
P_6 (MW)	455	455.0	455	459.6919	455.0003
P_7 (MW)	465	465.0	464.9	464.6916	465.0000
P_8 (MW)	60	60.0	60	60.0938	60.0000
P_9 (MW)	25	25.0	25	25.0496	25.0000
P_{10} (MW)	20	20.0	20	89.1023	20.0000
P_{11} (MW)	20	20.0	20	20.0338	20.0000
P_{12} (MW)	55	55.0	55	63.1815	55.0002
P_{13} (MW)	25	25.0	25	25.0527	25.0000
P_{14} (MW)	15	15.0	15	15.0044	15.0000
P_{15} (MW)	15	15.0	15	15.0044	15.0000
TP (MW)	2650	2650	2649.3	2650.0002	2650.0000
sum_S_i (MW)	235	235.0	235.7	231.8996	235.0005
TC ($/h)	32,549.8	32,544.99	32,538.4	32,568	32,544.9705
CPU_time(s)	-	-	-	-	4.88

TABLE IV: COMPARED RESULTS CONSIDERING LOSS OF THE PREVIOUS METHODS AND THE AIA-MU

Items	GA [17]	SA [17]	HDE [17]	VSHDE [17]	AIA-MU
P_1 (MW)	415.85	413.22	455.00	454.74	455.0000
P_2 (MW)	450.00	167.67	336.16	**424.96***	450.0000
P_3 (MW)	111.87	99.91	128.39	129.87	130.0000
P_4 (MW)	121.46	21.36	129.92	129.99	130.0000
P_5 (MW)	340.84	449.20	420.00	**397.36***	335.0000
P_6 (MW)	455.00	296.28	418.73	500.00	460.0000
P_7 (MW)	333.78	360.15	443.03	464.75	430.1175
P_8 (MW)	81.84	287.99	60.00	60.00	60.0000
P_9 (MW)	115.48	155.27	41.42	25.89	25.0000
P_{10} (MW)	60.59	138.81	107.17	20.75	84.5692
P_{11} (MW)	31.78	47.85	20.00	20.00	20.0000
P_{12} (MW)	55.00	76.97	79.59	75.86	80.0000
P_{13} (MW)	70.39	81.91	36.98	25.06	25.0000
P_{14} (MW)	26.22	52.94	22.02	15.13	15.0000
P_{15} (MW)	36.34	52.95	15.00	15.00	15.0000
TP (MW)	2,704.46	2,702.49	2,713.40	2,719.35	2,714.6867
P_L(MW)	56.45	52.49	63.41	69.35	64.6867
sum_S_i (MW)	307.86	218.90	246.65	230.53	264.8825
TC ($/h)	33,538.27	34,174.45	33,343.37	**33,282.17#**	33,259.3055
CPU_time(s)	-	-	-	-	5.02

* An unit loading in a prohibited zone
# An infeasible result

This complex optimization problem contains one objective function with fifteen variable parameters, $(P_1, P_2, \ldots, P_{15})$, one equality constraint, (h_1) and five inequality constraints, since four units have the POZ, $(g_1$ to $g_4)$, and the spinning reserve constraint (g_5).

Table III lists five algorithms of this problem with POZ and spinning reserve constraints obtained by two λ-δ methods, two Hopfield methods and the proposed AIAE-MU. Computational results demonstrate that the proposed method is a little better than the two λ-δ methods and the Hopfield method. Even though the Hopfield method has a little less total cost than the proposed method, but its total generated power is 2649.3 MW, which is 0.7 MW less than the system load demand. In table III, the *sum_S$_i$* and *CPU_time* stand the sum of spinning reserve and simulation time obtained from the method, respectively. Table III reveals that the proposed AIA-MU not only has the lowest total cost (*TC*) of all methods tested, but also generates the exact total power (*TP*) for the system constraints of (14) and (15), showing that the proposed algorithm is more effective than other methods for the practical PED problem with POZ.

Moreover, Table IV shows compared results obtained with the previous variable scaling HDE (VSHDE) [17], the GA [17], simulated annealing (SA) [17] and the propose AIA-MU for the system with the transmission loss. The result obtained by the VSHDE method is an infeasible solution, because generations of Unit 2 and Unit 5, $(P_2$ and $P_5)$, are located in POZ, respectively. The proposed algorithm also yields better solution quality than other methods in the PED problem considering POZ.

V. CONCLUSIONS

An efficient method for solving the optimal PED problem considering POZ was proposed. The proposed approach integrates the AIA and the MU, showing that the proposed algorithm has the following merits: 1) ease of implementation; 2) applicability to non-convex fuel cost functions of the POZ; 3) better effectiveness than the previous method, and 4) the need for only a small population. System simulations have shown that the proposed approach has the advantages mentioned above for solving optimal PED problems of the system with POZ.

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