SOLVING ECONOMIC DISPATCH PROBLEM OF THERMAL UNITS USING ARTIFICIAL IMMUNE NETWORK ALGORITHM

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Abstract*. The objective of the Economic Dispatch Problem (EDP) of electric power generation, whose characteristics are complex and highly nonlinear, is to schedule the committed generating units outputs so as to meet the required load demand at minimum operating cost while satisfying all unit and system equality and inequality constraints. Recently, as an alternative to the conventional mathematical approaches, modern heuristic optimization techniques such as simulated annealing, evolutionary algorithms, neural networks, ant colony, and taboo search have been given much attention by many researchers due to their ability to find an almost global optimal solution in EDPs. Based on the probability distribution functions, this paper discusses the use of the optimization procedures based on artificial immune network theory. The optimization approaches based on artificial immune network are validated for a test system consisting of 13 thermal units whose incremental fuel cost function takes into account the valve-point loading effects.*

Keywords*: optimization, thermal units, artificial immune network.*

1. INTRODUCTION

The Economic Dispatch Problem (EDP) is to determine the optimal combination of power outputs of all generating units to minimize the total fuel cost while satisfying the load demand and operational constraints. It plays an important role in operation planning and control of modern power systems. Under a new deregulated electricity industry, power utilities try to achieve high operating efficiency to produce cheap electricity. Therefore, precise generation costs analysis (Walters and Sheblé, 1993) and several constraints, such as transmission capacity and system security are very important issues in the economic dispatch problems. Due to the nature of large scale, nonlinear generation cost and multiple constraints, EDP problem combines a highly nonlinear, nonconvex and computationally difficult environment with a need for optimality (Lin *et al*., 2001).

Over the past few years, a number of approaches have been developed for solving the EDP using the dynamic programming, linear programming, homogenous linear programming, and nonlinear programming techniques (Wood and Wollenberg, 1994). In these numerical methods for solving the EDP, an essential assumption is that the incremental cost curves of the units are piecewise-linear monotonically increasing functions. Unfortunately, the input-output characteristics of modern power generating units are inherently highly nonlinear because of valve-point loadings, multi-fuel effects, and others. Furthermore, they may lead to multiple local minimum points of the cost function. Classical dispatch algorithms require that these characteristics be approximated, even though such approximations are not desirable as they may lead to suboptimal solutions and hence huge revenue losses over time (Liu and Cai, 2005).

Recently, the some major types of stochastic search, including the simulated annealing (Basu, 2005), the genetic algorithms (Walters and Sheblé, 1993; Yalcinoz and Altun, 2001), differential evolution (Coelho and Mariani, 2006), evolutionary programming (Yang *et al*., 1996), ant colony (Song and Chou, 1999) and particle swarm optimization (Victoire and Jeyakumar, 2004) were applied to solve the EDP. One of these modern heuristic optimization paradigms is the Artificial Immune System (AIS).

Nature and in particular biological systems have always been fascinating to the human experts due to its complexity, flexibility, and sophistication. The nervous system inspired the evolution of artificial neural networks. In a similar manner the immune system motivated the emergence of an AIS (Agarwal *et al*., 2006). As per Castro and Von Zuben (2002), AIS can be defined as an abstract ormetamorphic computational system using ideas gleaned from the theories and components of immunology.

The biologic immune system in human being or other living beings is a complex dynamic system formed by many distributed individuals (antibodies) in mutual action. It has twofold characteristics of individual distinction and integral variety, and has many abilities such as learning, memory, self-regulation, and pattern recognition and feature extraction and so on (Yuan and Chu, 2007).

A meta-heuristic optimization approach employing AIS called opt-aiNET algorithm to solve the EDP is proposed in this paper. The aiNET algorithm is a discrete immune network algorithm based on the artificial immune systems paradigm that was developed for data compression and clustering (De Castro and Von Zuben, 2001), and was also extended slightly and applied to optimization to create the algorithm opt-aiNET (De Castro and Timmis, 2002). Opt-aiNET, proposed in De Castro and Von Zuben (2001), evolves a population, which consists of a network of antibodies (considered as candidate solutions to the function being optimized). These undergo a process of evaluation against the objective function, clonal expansion, mutation, selection and interaction between themselves.

An EDP with 13 unit test system using nonsmooth fuel cost function (Sinha *et al.*, 2003) is employed in this paper for demonstrate the performance of the proposed opt-aiNET method. The results obtained with the opt-aiNET approach were analyzed and compared with those obtained in recent literature.

The rest of the paper is organized as follows: section 2 describes the EDP, while section 3 explains the concepts of opt-aiNET method. Section 4 presents the simulation results of the 13 thermal units whose incremental fuel cost function takes into account the valve-point loading effects. Lastly, section 5 outlines our conclusion.

2. DESCRIPTION OF ECONOMIC DISPATCH PROBLEM

The objective of the economic dispatch problem is to minimize the total fuel cost at thermal power plants subjected to the operating constraints of a power system. Therefore, it can be formulated mathematically with an objective function and two constraints. The equality and inequality constraints are represented by equations (1) and (2) given by:

$$\sum_{i=1}^{n} P_i - P_L - P_D = 0 \tag{1}$$

$$P_i^{min} \le P_i \le P_i^{max} \tag{2}$$

In the power balance criterion, an equality constraint must be satisfied, as shown in equation (1). The generated power should be the same as the total load demand plus total line losses. The generating power of each generator should lie between maximum and minimum limits represented by equation (2), where P_i is the power of generator *i* (in MW); *n* is the number of generators in the system; P_D is the system's total demand (in MW); P_L represents the total line losses (in MW) and P_i^{min} and P_i^{max} are, respectively, the output of the minimum and maximum operation of the generating unit *i* (in MW). The total fuel cost function is formulated as follows:

$$min\ f = \sum_{i=1}^{n} F_i(P_i) \tag{3}$$

where F_i is the total fuel cost for the generator unity *i* (in \$/h), which is defined by equation:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \tag{4}$$

where a_i, b_i and c_i are coefficients of generator *i*.

A cost function is obtained based on the ripple curve for more accurate modeling. This curve contains higher order nonlinearity and discontinuity due to the valve point effect, and should be refined by a sine function. Therefore, equation (4) can be modified (Wood and Wollenberg, 1994), as:

$$\tilde{F}_i(P_i) = F(P_i) + \left| e_i sin\left(f_i \left(P_i^{\min} - P_i \right) \right) \right| \quad \text{or} \tag{5}$$

$$\tilde{F}_i(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| e_i sin\left(f_i \left(P_i^{\min} - P_i \right) \right) \right| \tag{6}$$

where e_i and f_i are constants of the valve point effect of generators. Hence, the total fuel cost that must be minimized, according to equation (3), is modified to:

$$min\ f = \sum_{i=1}^{n} \tilde{F}_i(P_i) \tag{7}$$

where $\tilde{F}_i$ is the cost function of generator *i* (in \$/h) defined by equation (6). In the case study presented here, we disregarded the transmission losses, P_L; thus, $P_L = 0$.

3. OPTIMIZATION METHOD BASED ON opt-aiNET APPROACH

AISs are learning and optimization methods that can be used for the solution of many different types of optimization problems (Dasrupta, 1999; Huang, 1999; De Castro and Timmis, 2003; Luh and Chuen, 2004; Kalinli and Karaboga, 2005; Chen and You, 2005). Artificial immune systems are devised chiefly based on the following properties of the biologic immune system:

(i) *Ability to produce diversified antibodies*. By means of cell differentiation, the immune system produces large numbers of varied antibodies to resist different antigens. This property can maintain individual variety in evolutionary process of the artificial immunization algorithm, thus improve the global search capability of the algorithm, and avoid falling into local optimum.

(ii) *Self-regulation*. The balance mechanism in biological immune system can automatically regulate the production of antibodies by inhibition or promotion, so that it can produce appropriate and necessary antibodies. This property corresponds to the inhibition or promotion of antibody concentration in the AIS, which improve the local search capability of the algorithm.

(iii) *Immune memory*. Some cells that have produced some certain antibodies are preserved as memory cells. If the same antigens relevant to those antibodies are encountered afterwards, the relevant memory cells shall be rapidly stimulated to produce a great quantity of the same antibodies. With this property of memory and recognition of the antigen in the algorithm, searching pace can be expedited and global search capability can be raised (Yuan and Chu, 2007).

A meta-heuristic optimization approach employing artificial immune networks called opt-aiNET algorithm to optimize the solving of an EDP in this paper. Opt-aiNET is capable of performing local and global search, as well as to adjust dynamically the size of population (Campelo *et al*., 2006). Opt-aiNET creates a memory set of antibodies (points in the search space) that represent (over time) the best candidate solutions to the objective function. Opt-aiNET is capable of either unimodal or multimodal optimization and can be characterized by five main features: (i) the population size is dynamically adjustable; (ii) it demonstrates exploitation and exploration of the search space; (iii) it determines the locations of multiple optima; (iv) it has the capability of maintaining many optima solutions; and (v) it has defined stopping criteria.

The steps of opt-aiNET are summarized as follows (Coelho and Alotto, 2007):

Initialization of the parameter setup

The user must choose the key parameters that control the opt-aiNET, i.e., population size (M), suppression threshold (s_s), number of clones generated for each cell (N_c), percentage of random new cells each iteration (d), scale of affinity proportion selection (b), and maximum number of iterations allowed (stop criterion), N_{gen}.

Initialization of cell populations

Set iteration t=0. Initialize a population of i=1,..,M cells (real-valued n-dimensional solution vectors) with random values generated according to a uniform probability distribution in the n dimensional problem space. Initialize the entire solution vector population in the given upper and lower limits of the search space.

Evaluation of each network cell

Evaluate the fitness value of each cell (in this work, the objective of the fitness function is to minimize the cost function).

Generation of clones

Generate a number N_c of clones for each network cell. The clones are offspring cells that are identical copies of their parent cell.

Mutation operation

Mutation is an operation that changes each clone proportionally to the fitness of the parent cells, but keeps the parent cell. Clones of each cell are mutated according to the affinity (Euclidean distance between two cells) of the parent cell. The affinity proportional mutation is performed according to equations (8) and (9), given by:

$$c' = c + \alpha \cdot N(0,1) \qquad \text{(Gaussian opt-aiNET approach)} \tag{8}$$

$$\alpha = \rho^{-1} e^{-f^*} \tag{9}$$

where c' is a mutated cell c, $N(0,1)$ is a Gaussian random variable of zero mean and unitary standard deviation, ρ is a parameter that controls the decay of the inverse exponential function, and f^* is the objective function of an individual normalized in the interval [0,1].

Other two opt-aiNET approaches are also presented in this paper. The approaches are modifications of equation (8) given by

$$c' = c + \alpha \cdot U(0,1) \qquad \text{(Uniform opt-aiNET approach)} \tag{10}$$

$$c' = c + \alpha \cdot C(0,1) \qquad \text{(Cauchy opt-ainET approach)} \tag{11}$$

where $U(0,1)$ and $C(0,1)$ are uniform and Cauchy probabilities density functions, respectively, in the range [-5,5].

Evaluation the fitness of all network cells

Evaluate the fitness value of all network cells of the population including new clones and mutated clones.

Selection of fittest clones

For each clone select the most fit and remove the others.

Determination of affinity of all network cells

Determine the affinity network cells and perform network suppression.

Generate randomly d network cells

Introduce a percentage d of randomly generated cells. Set the generation number for $t = t + 1$. Proceed to step of *Evaluation of each network cell* until a stopping criterion is met, usually a maximum number of iterations, t_{max}. The stopping criterion depends on the type of problem.

4. CASE STUDY OF ECONOMIC DISPATCH PROBLEM WITH 13 THERMAL UNITS

This case study consists of 13 thermal units of generation with the effects of valve-point loading, as given in Table 1. The data shown in Table 1 are also available in Wong and Wong (1994) and Sinha *et al.* (2003). In this case, the load demand expected to be determined is P_D = 1800 MW.

Table 1. Data for the 13 thermal units.

Thermal unit	P_i^{min}	P_i^{max}	a	b	c	e	f
1	0	680	0.00028	8.10	550	300	0.035
2	0	360	0.00056	8.10	309	200	0.042
3	0	360	0.00056	8.10	307	150	0.042
4	60	180	0.00324	7.74	240	150	0.063
5	60	180	0.00324	7.74	240	150	0.063
6	60	180	0.00324	7.74	240	150	0.063
7	60	180	0.00324	7.74	240	150	0.063
8	60	180	0.00324	7.74	240	150	0.063
9	60	180	0.00324	7.74	240	150	0.063
10	40	120	0.00284	8.60	126	100	0.084
11	40	120	0.00284	8.60	126	100	0.084
12	55	120	0.00284	8.60	126	100	0.084
13	55	120	0.00284	8.60	126	100	0.084

Each optimization method was implemented in MATLAB (MathWorks). All the programs were run on a 3.2 GHz Pentium IV processor with 2 GB of Random Access Memory (RAM). In each case study, 50 independent runs were made for each of the optimization methods involving 50 different initial trial solutions for each optimization method. In this paper, the opt-aiNET approach is adopted using 16,000 cost function evaluations in each run.

In this case study, the population size N was 20, the stopping criterion t_{max} was 800 generations. The setup of opt-aiNET algorithm used was: suppression threshold = 5, percentage of newcomers: d=50%, scale of the affinity proportional selection using a linear reduction of b with initial and final values of 0.1 and 6 in each run, respectively, and the number of clones generated for each cell is N_c=10.

A key factor in the application of optimization methods is how the algorithm handles the constraints relating to the problem. In this work, the penalty-based method proposed in Coelho and Mariani (2006) was used.

The simulation results obtained are given in Table 2, which shows that the opt-aiNET with Cauchy operator succeeded in finding the best solution for the tested methods. The best results obtained for solution vector P_i, i=1,..,13 using opt-aiNET with Cauchy operator was 17963.9571 $/h, as shown in Table 3.

Table 4 compares the results obtained in this paper with those of other studies reported in the literature. Note that in studied case, the result reported here using opt-aiNET with Cauchy operator is comparatively lower than recent studies presented in the literature, except to the simulation results using hybrid particle swarm with SQP (Sequential Quadratic Programming) method proposed in Victoire and Jeyakumar (2004).

Table 2. Convergence results (50 runs) of a case study of 13 generating units with valve point and $P_D = 1800$ MW.

Optimization Method	Type	Equation	Minimum Cost ($/h)	Mean Cost ($/h)	Maximum Cost ($/h)	Standard Deviation of Cost ($/h)
opt-aiNET	Gaussian	eq. (8)	18070.3593	18248.2837	18494.4318	62.2774
opt-aiNET	Uniform	eq. (10)	18065.9600	18201.7937	18335.5056	62.8032
opt-aiNET	Cauchy	eq. (11)	17976.8619	18200.6771	18335.5056	61.0332

Table 3. Best result (50 runs) obtained using opt-aiNET approach with Cauchy operator.

Power	Generation (MW)	Power	Generation (MW)
P_1	628.3191	P_8	109.3998
P_2	74.7991	P_9	109.7676
P_3	298.1378	P_{10}	40.0000
P_4	60.0000	P_{11}	40.0000
P_5	109.8578	P_{12}	55.0000
P_6	109.8660	P_{13}	55.0000
P_7	109.8527	$\sum_{i=1}^{13} P_i$	1800.0000

Table 4. Comparison of case study results for fuel costs presented in the literature.

Optimization Technique	Case Study with 13 Thermal Units
Evolutionary programming (Sinha *et al.*, 2003)	17994.07
Particle swarm optimization (Victoire and Jeyakumar, 2004)	18030.72
Hybrid evolutionary programming with SQP (Victoire and Jeyakumar, 2004)	17991.03
Hybrid particle swarm with SQP (Victoire and Jeyakumar, 2004)	17969.93
Opt-aiNET approach using Cauchy operator proposed	17976.8619

5. CONCLUSION

This paper presents opt-aiNET approaches for solving an EDP of power systems. The opt-aiNET methodologies were successfully validated for a test system consisting of 13 thermal units whose incremental fuel cost function takes into account the valve-point loading effects.

Simulation results show that the proposed opt-aiNET approaches are applicable and effective in the solution of EDPs. In this context, the result reported here using opt-aiNET with Cauchy operator is comparatively lower than recent studies presented in the literature, except to the results using hybrid particle swarm with SQP proposed in Victoire and Jeyakumar (2004).

The opt-aiNET has great potential to be further applied to many ill-conditioned problems in power system planning and operations. In future research, the authors will be proposed the opt-aiNET approaches for multiobjective environmental/economic power dispatch problems.

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