ECONOMIC DISPATCH SOLUTION USING A REAL-CODED GENETIC ALGORITHM

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SUMMARY

In this paper, an efficient and practical real-coded genetic algorithms (RCGAs) has been proposed for solving the economic dispatch problem. The objective is to minimize the total generation fuel cost and keep the power flows within the security limits.

For each problem of optimization in genetic algorithms(GAs) there are a large number of possible encodings. Although binary representation is usually applied to power optimisation problems, in this letter we use a RCGAs , witch is a modified GAs employing real valued vectors for representation of the chromosomes. The use of real valued representation in the GAs has a number of advantages in numerical function optimization over binary encoding [1]. The efficiency of the GAs is increased as there is no need to convert chromosomes to the binary type, less memory is required, there is no loss in precision by discretization to binary or other values, and there is greater freedom to use different genetic operators.

A non-uniform arithmetic crossover operator was introduced into the RCGAs [1][2].

We used a non-uniform arithmetic crossover operator produces a complimentary pair of linear combinations produced from random proportions of the parents.

The non-uniform mutation operator is used to inject new genetic material into the population and it is applied to each new structure individually[2]. A given mutation involves randomly altering each gene with a small probability.

The proposed technique improves the quality of the solution and speed of convergence of the algorithm. The RCGAs developed is compared with a binary-coded genetic algorithm (BCGAs) and classical optimisation technique of Quasi-Newton (Broyden-Fletcher-Goldfarb-Shanno) [3].

The proposed approach has been tested on the IEEE 25-bus system [4].

Keywords: *economic dispatch, real-coded genetic algorithm, binary-coded genetic algorithm, non-uniform arithmetic crossover*

1. INTRODUCTION

The economic dispatch (ED) problem is one of the most important operational functions of the modern clay energy management system. The purpose of the ED is to find the optimum generation among the existing units, such that the total generation cost is minimized while simultaneously satisfying the power balance equations and various other constraints in the system.

The literature of the ED problem and its solution methods are surveyed in [5] and [6]. However, it is realized that the conventional techniques become very complicated when dealing with increasingly complex dispatch problems, and are further limited by their lack of robustness and efficiency in a number of practical applications.

Recently, a global optimization technique known as GAs which is a kind of the probabilistic heuristic algorithm has been studied to solve the power optimization problems. The GAs may find the several sub-optimum solutions within a realistic computation time.

The efficiency and the robustness of the proposed RCGAs are demonstrated by test functions. Then the RCGAs with simulated non-uniform arithmetic crossover, elitism and a non-uniform mutation are applied to ED problem.
In order to investigate its performance, the RCGAs developed is compared with a BCGAs previously employed and classical optimisation technique of Quasi-Newton (Broyden-Fletcher-Goldfarb-Shanno) [3]

The proposed approach has been tested on the IEEE 25-bus system [4].

2. PROBLEM FORMULATION

The ED problem may be expressed by minimizing the fuel cost of generator units under constraints. Depending on load variations, the output of generators has to be changed to meet the balance between loads and generation of a power system. The power system model consists of n generating units already connected to the system.

The ED problem can be expressed as:

$$\text{Min} \quad \sum_{i=1}^{NG} F_i(P_{Gi}) \tag{1}$$

$$F_i(P_{Gi}) = \left(a_i + b_i P_{Gi} + c_i P_{Gi}^2\right) \tag{2}$$

Where ai, bi and ci are the cost coefficients of the i-th generator and NG is the number of generators including the slack bus. P_{Gi} is the real power output of the i-th generator (MW). $F_i(P_{Gi})$ is the operating cost of unit i (\$/h).

Subjects to the following constraints:

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \qquad \text{for i= 1,…,NG} \tag{3}$$

$$\sum_{i=1}^{NG} P_{Gi} - D - P_L = 0 \tag{4}$$

Where

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_{Gi} B_{ij} P_{Gj} + \sum_{i=1}^{N} B_{0i} P_{Gi} + B_{00} \tag{5}$$

D : total demand (MW)
P_L : transmission losses (MW)
P_{Gi}^{max} : maximum generation output of the i-th generator
P_{Gi}^{min} : minimum generation output of the i-th generator
B : coefficients of transmission losses

GAs is a general stochastic optimization algorithm that was originally developed for solving unconstrained problems.

By applying an exterior penalty function we transform a constrained non-linear ED problem into an unconstrained problem.

We can rewrite the problem shown in (1) as

$$F_m(P_G, r_k) = \sum_{i=1}^{NG} F_i(P_{Gi}) + \frac{1}{r_k} \cdot B.h^2 \tag{6}$$

Where the value of the penalty coefficient r_k is checked at each iteration.

The constant B is defined as

$$\begin{cases} B > 0 & if \qquad h \ne 0 \\ B = 0 & if \qquad h = 0 \end{cases} \tag{7}$$

h is the equality constrained defined as

$$h = \sum_{i=1}^{NG} P_{Gi} - D - P_L \tag{8}$$

3. GENETIC ALGORITHMS

GAs are well-known stochastic methods of global optimization based on the evolution theory of Darwin [7]. They have successfully been applied in different real-world applications.

GAs was originally developed for solving unconstrained problems. Recently, many variants of GAs have been developed for solving constrained nonlinear programming. Most of these methods were based on penalty formulations that transform (1) into an unconstrained function $F_m(P_G,r_k)$ (6), consisting of a sum of the objective and the constraints weighted by penalties, and use GAs to minimize $F_m(P_G,r_k)$.

GAs, unlike strict mathematical methods, have the apparent ability to adapt to nonlinearties and discontinuities commonly found in power systems [8].

The basic idea behind GAs is to mathematically imitate the evolution process of nature.

The algorithms are based on the evaluation of a set of solutions, called population.

The population is treated with genetic operations. At the iteration i the population Xi consists of a number of N individuals x_j, that is, solutions, where N is called a population size. The population is initialized by randomly generated individuals.

The individuals can be encoded using either binary or real numbers. We use the latter because of their popularity.

Each individual xj = $(x_1, \ldots, x_n)$ is a vector of variables. Each variable is a real number.

The suitability of an individual is determined by the value of the objective function, to be called a fitness function.

A new population is generated by the genetic operations selection, crossover and mutation. Parents are chosen by selection and new offsprings are produced with crossover and mutation. All these operations include randomness. The success of the optimization process is improved by elitism where the best individuals of the old population are copied as such to the next population.

4. REAL-CODED GENETIC ALGORITHM

For each problem of optimization in GAs there are a large number of possible encodings. Although binary representation is usually applied to power optimisation problems, in this letter we use a RCGAs, witch is a modified GAs employing real valued vectors for representation of the chromosomes. The use of real valued representation in the GAs has a number of advantages in numerical function optimization over binary encoding [1][2]. The efficiency of the RCGAs is increased as there is no need to convert chromosomes to the binary type, less memory is required, there is no loss in precision by discretization to binary or other values, and there is greater freedom to use different genetic operators. For the real valued representation, the *k*-th chromosome C_k can be defined as follows [1][2][9]:

$$C_k=[P_{k1}, P_{k2}, \ldots, P_{kn}] \quad k=1,2,\ldots,popsize \tag{9}$$

where popsize means population size and P_{ki} is the generation power of the *i*-th unit at *k*-th chromosome. Reproduction involves the creation of new offspring from the mating of two selected parents or mating pairs. It is thought that the crossover operator is mainly responsible for the global search property of the GA. A non-uniform arithmetic crossover operator was introduced into the RCGAs [1][2][9].

We used a non-uniform arithmetic crossover operator produces a complimentary pair of linear combinations produced from random proportions of the parents. The heuristic crossover operator produces a child that is a linear extrapolation away from the better parent along the direction of the vector joining the two parents.

Two chromosomes, selected randomly for crossover, C_i^{gen} and C_j^{gen}, may produce two offspring, $C_i^{gen}+1$ and $C_j^{gen}+1$, which is a linear combination of their parents, i.e.,

$$C_i^{gen+1} = a.\, C_i^{gen} + (1-a).\, C_j^{gen} \tag{10}$$

$$C_j^{gen+1} = (1-a).\, C_i^{gen} + a.\, C_j^{gen} \tag{11}$$

where a is a random number in range of [0,1].

The non-uniform mutation operator is used to inject new genetic material into the population and it is applied to each new structure individually[2]. A given mutation involves randomly altering each gene with a small probability.

Let us suppose $C = (c_1, \ldots, c_i, \ldots, c_n)$ a chromosome and $c_i \in [up_i, low_i]$ a gene to be mutated. Next, the gene, $c_i^{\prime}$, resulting from the application of non-uniform mutation [2].

The gene $c_i^{\prime}$ can be defined as follows:

$$c_i^{\prime} = C_i + mut\_scale \,.\, d_i \,.\, randn \tag{12}$$

Where:
$d_i = up_i - low_i$
mut_scale is normally set to 0.1
randn is Normally distributed random numbers.

An elitist GAs search is used and guarantees that the best solution obtained so far in the search is retained and used in the following generation, and thereby ensuring no good solution already found can be lost in the search process.

5. ECONOMIC DISPATCH USING GENETIC ALGORITHM

RCGAs is a probabilistic search technique, which generates the initial parent vectors distributed uniformly in intervals within the limits and obtains global optimum solution over number of iterations. The implementation of RCGAs is given below.

The initial population is generated after satisfying the equation (3). The elements of parent vectors (P_{Gi}) are the real power outputs of generating units distributed uniformly between their minimum and maximum limits.

The fitness function is used to transform the cost function value into a measure of relative fitness. The fitness function is given in equation (6).

The selection is based on the cost of parent vectors $F_m(P_{Gi})$ with the corresponding cost of offspring vectors $F_m(P_{Gi}^{\prime})$ in this population. The best vector having minimum cost, whether parent vector p_i or offspring vector $P_{Gi}^{\prime}$ is selected for the new parent for the next generation.

An non-uniform arithmetic crossover operator is used. After crossover is completed, non-uniform mutation is performed. In the mutation step, a random real value makes a random change in the m-th element of the chromosome. After mutation, all constraints are checked whether violated or not. If the solution has at least one constraint violated, a new random real value is used for finding a new value of the m-th element of the chromosome. Then, the best solution so far obtained in the search is retained and used in the following generation. The RCGAs process repeats until the specified maximum number of generations is reached. The flowchart of RCGAs is shown in Fig. 1.

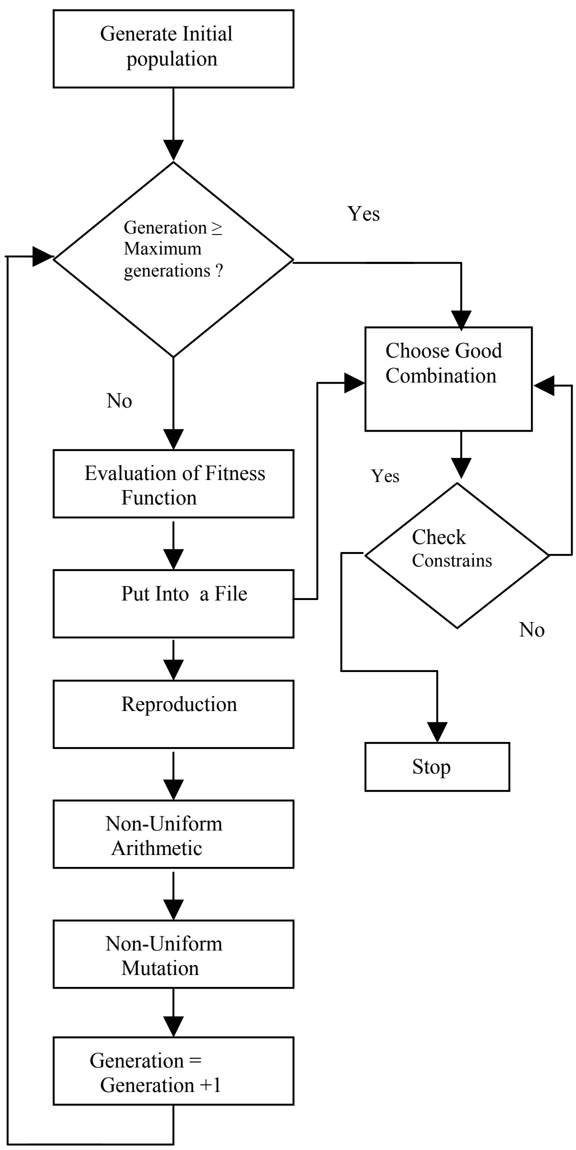

Fig. 1 Flowchart of RCGAs

6. SIMULATION RESULTS

The proposed approach is tested on the IEEE 25-bus system[4]. The cost functions in dollars per hour were as follows:

$F_1 (P_{G1}) = 0.0015\, P_{G1}^2 + 1.8\, P_{G1} + 40$
$F_2 (P_{G2}) = 0.0030\, P_{G2}^2 + 1.7\, P_{G2} + 60$
$F_3 (P_{G3}) = 0.0012\, P_{G3}^2 + 2.1\, P_{G3} + 100$
$F_4 (P_{G4}) = 0.0080\, P_{G4}^2 + 2.0\, P_{G4} + 25$
$F_5 (P_{G5}) = 0.0010\, P_{G5}^2 + 1.9\, P_{G5} + 120$

Power generation limits:

$100 \le P_{G1} \le 300$
$80 \le P_{G2} \le 150$
$80 \le P_{G3} \le 200$
$20 \le P_{G4} \le 100$
$100 \le P_{G5} \le 300$

The system load P_D was 730 MW.
Transmission losses P_L are computed using the B coefficients.
The proposed method was implemented in Matlab 5.3 with P-III 731MHz system.

The parameter settings to execute RCGAs are:
Population size Npop = 30
Number of iterations maxgen = 300
Probability of crossover $P_c = 0.8$
Probability of mutation $P_m = 0.08$

The minimum cost and active power generations are presented in Tab.1.

P_{G1}^{opt} (MW)	P_{G2}^{opt} (MW)	P_{G3}^{opt} (MW)	P_{G4}^{opt} (MW)	P_{G5}^{opt} (MW)	cost ($/h)	Time (sec)
213.68	127.46	141.93	29.53	258.86	2010.8	1.60

Tab. 1 Results of RCGAs

Fig. 2 shows the generation cost evolution during the iterative procedure.

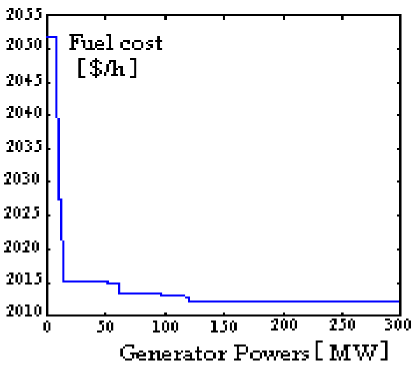

Fig. 2 The generation cost evolution during the iterative procedure

In Tab. 2, the results of proposed method (RCGAs) are compared with the results of BCGAs and BFGS.

It is seen that there is a negligible difference in the optimal values of cost between the RCGAs and BCGAs.

The BFGS method produced a higher operation cost than other methods.

The RCGAs demonstrated faster convergence then BCGAs.

The total computational time of the RCGAs is far less than for the BCGAs.

	RCGAs	BCGAs	BFGS
P_{G1}^{opt} (MW)	213.68	206.72	211.30
P_{G2}^{opt} (MW)	127.46	121.64	126.30
P_{G3}^{opt} (MW)	141.93	151.82	151.29
P_{G4}^{opt} (MW)	29.53	33.21	71.24
P_{G5}^{opt} (MW)	258.86	258.05	211.31
cost ($/h)	2010.8	2011.0	2029.3
time (sec)	1.60	4.78	0.0

Tab. 2 Results of RCGAs compared with BCGAs and BFGS methods

7. CONCLUSION

In this paper a new RCGAs has been presented and compared with a BCGAs and classical optimisation technique of BFGS, the proposed method has been applied to the economic dispatch problem.

The proposed technique improves the quality of the solution and reduce the computation time.

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BIOGRAPHY

Hamid Bouzeboudja was born on 04.03.1965. In 1993 he graduated at the Electrotechnical Department of the Faculty of Electrical Engineering at University (USTO) in Algeria. He defended his "Magister" in the field of optimal power flow problems in 1996; his thesis title was "Optimal Power Flow". His scientific research is focusing an practical methods based on genetic algorithms for solving the economic dispatch problem of complex systems.

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