Real-Coded Genetic Algorithm with Smart Mutation for Solving Nonconvex Economic Dispatch Problems

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Abstract
In this paper, real-coded genetic algorithm with smart mutation (RCGA-SM)is proposed to solve the economic dispatch (ED) problem. In the proposed method, the required controllingprocess is accomplished on the total amount of chromosomes and consequently there is no need to use penalty cost function for controlling sum of variables in solving economic dispatch problem. This method will begin to explore the optimal answer just within the logic and acceptable zone in addition to its capability in reducing the search range. In order to show the performance and the efficiency of the proposed method, the ED problem considering several constraints is solved in 6, 15and 40 units systems through the proposed technique. The proposed coding could effectively escape from infeasible solutions. Thereby search efficiency and solution quality are dramatically improved.The obtained results are compared with other advanced technical algorithms, which well depict the superiority of the RCGA-SM technique over the other compared methods.

Keywords: Economic dispatch; nonconvex optimization; penalty function; smart mutation.

1. Introduction
The ED aims to determine optimized sets of generators' output powers in a way that total grid load demand is provided with the least cost as the constraints' requires are well met. For simplicity, the cost function of each unit in ED problem is specified with a second order function and is solved through mathematical approaches [1-2]. In general, these mathematical approaches require information of cost function's derivation to solve the problem. It is important to note that the input-output features of generation plants are nonconvex, which is because of the existence of the prohibited zones, valve-point loading, etc. Therefore, the ED problem should be optimization of a nonconvex problem in the presence of constraints, which cannot be solved directly through the mathematical approaches.

{R.1:In recent decades, advanced heuristic techniques such as genetic algorithm [3-4], evolutionary programming [5], artificial bee colony algorithm [6-7], harmony search algorithm [8-9], differential evolutionary [10-11], particle swarm optimization [12-16] and Biogeography-based optimization [17-18] have been developed to solve nonconvex ED problem.}

RCGA is one of the initiative algorithms which is proper to solve the nonconvex optimization problems. The search technique in this algorithm depends on the population and the group of chromosomes. Simple concept, easy implementation, relative ability in continuing the program and parameters control even under error occurrence, and the calculative efficiency of this technique are some of the major advantageous of RCGA [19]. In spite of these advantageous, it may get trapped in local optimizations due to search ability limits, inappropriate and illogical mutations, and penalty factors existence in the presence of problems possessing heavy constraints.

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In some optimization problems the same as economic dispatch,it is necessary that the sum of the variables while optimizationconvergetoanexpected value. In solving this type of problem, a penalty factor is usually employed. Considering that a penalty factor is used to do this by increasing the cost, thus, some disadvantages such as the search space increase is unavoidable.This research proposes a novel coding based on RCGA in order to solve economic dispatch problems without using penalty factor.

The classic optimization approaches consisting penalty function have a certain week point, which is the selection of suitable value of penalty factor and as the penalty parameters are inappropriately selected, the problem getsmore serious and finding solutions becomes difficult [20].

In this paper, a new RCGA-based method is proposed tocontroltotal chromosomes' values in each iteration process with no need for penalty factors in order to converge the total chromosomes' values to the expected value and the efficiency of the method is examined in solving ED problem.

The RCGA-SM creates the initial population in acompletely random form considering the constraints associated with total chromosomes' value and its equation solution in a way that the sum of the chromosomes' values equals the expected value. It is managed in the next iterations in a way that the above constraint is not violated to make the algorithm find out the optimum cost just in alogical and acceptable zone in addition to the decreasesin the search range.

One of the other disadvantages of the genetic algorithm method falls in mutation creation strategy, where inappropriate chromosomes' values selection can practically violate the constraints and trappedthe algorithm in local optimum points.

In order to overcome such problemsin the proposed method, the values of one or more genes are changed in a logical and acceptable range to create a mutation in the offsets of each population.

In order to elucidate the advantages of the proposed method, ED problem solution through RCGA-SM is implemented on three systems with different generation units (6, 15, and 40 units) considering the effects of valve-point, existence of prohibited operational zones, ramp rate constraints, and the system losses. The results are compared with that of the new and efficient algorithms such as GAAPI [24], BBO [19], DE-BB0 [32], RCGA [23], QPSO [31], ICA-PSO [28], ACO [25], GA-PS-SQP [33], etc, which well shows the superiority of the proposed technique over the above approaches.

2. Formulation of Economic Dispatch Problem

2.1. Objective Function

The ED problem aims to minimize the total cost function of a power system considering the constraints. Total cost function and the simplified cost function of each generation unit are as follows, respectively:

$$F_T = \sum_{i=1}^{n} F_i(p_i) \tag{1}$$

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

Where F_T is the total generation cost, F_i is the cost function of the i^{th} generator, a_i , b_i , c_i are the cost coefficients of the i^{th} generator, P_i is the output power of the i^{th} generator and n is the number of generators.

2.1.1. ED Problem Considering the Valve-Point Effects

The generation units with multi steam valve create more variations in plant cost function. Since the existence of steam valves leads to ripple creation in plants' characteristics, the cost function would have a more nonlinear formula. Therefore, the cost function (2) should be replaced with the following cost function:

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + |e_i \times \sin(f_i \times (P_{i,\min} - P_i))| \tag{3}$$

Where e_i and f_i are the factors of the i^{th} unit, which reflect the effects of the valve-point. In addition, $P_{i,\min}$ is the minimum i^{th} unit generated power [10].

2.2. Equality and Inequality Constraints

2.2.1 Active Powers' Balance Equation

In order to balance the power, total units generated power should equal to the total required load and total transmission line losses. In other words:

$$\sum_{i=1}^{n} P_i = P_{load} + P_{loss} \tag{4}$$

where P_{load} is the total system load. Total transmission losses, P_{loss} , is a function of unit output power expressed as follows using the B factors [2]:

$$P_{loss} = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{io} P_i + B_{00} \tag{5}$$

2.2.2. Maximum and Minimum Power Limit

The output power of each generator should fall between the maximum and minimum powers of that generator corresponding to the following inequality:

$$P_{i,\min} \le P_i \le P_{i,\max} \tag{6}$$

where $P_{i,\min}$ and $P_{i,\max}$ are respectively the minimum and the maximum powers of the i^{th} unit.

2.2.3. Ramp Rate Limits

The actual operation interval of all power plants is restricted by their ramp rate limits. The ramp-up and ramp-down limits are considered as follows:

$$P_i - P_i^0 \le UR_i \text{ and } P_i^0 - P_i \le DR_i \tag{7}$$

where P_i^o is the previous i^{th} unit output power, UR_i and DR_i are the up-ramp and down-ramp limits of the i^{th} unit, respectively. In order to consider the ramp rates and the units output power constraints simultaneously, (6) and (7) could be combined as the following inequality:

$$\max\{P_{i,\min}, P_i^0 - DR_i\} \le P_i \le \min\{P_{i,\max}, P_i^0 + UR_i\} \tag{8}$$

2.2.4. ED Problem Considering the Prohibited Operating Zones

In some cases, the entire operating range of a generating unit is not always available due to executive physical limitations. Units might have some prohibited operating zones because of the existence of some deficiencies in machineries or in accessories. These deficiencies would lead to instability in some specific output power intervals [6]. Therefore, some additional constraints should be considered as follows for operational intervals of units with prohibited zones:

$$P_i \in \begin{cases} P_{i,\min} \le P_i \le P_{i,1}^l \\ P_{i,k-1}^u \le P_i \le P_{i,k}^l \\ P_{i,pzi}^u \le P_i \le P_{i,\max} \end{cases} \quad \begin{matrix} k = 2,3,\cdots,p_{zi} \\ i = 1,2,\cdots,n_{pz} \end{matrix} \tag{9}$$

where $P_{i,k}^l$ and $P_{i,k}^u$ are the lower and the upper bounds of the i^{th} unit prohibited zones, respectively and P_{zi} is the number of i^{th} unit prohibited zones and n_{pz} is the number of units fall in prohibited zone [21].

3. An Overview on Real-Coded Genetic Algorithm

The RCGA is inspired by the mechanism of genetic evolution in real life, which is composed of threeoperators: selection, crossover and mutation operators. More information on the performance of these operators is available in [22-23],But in general the selection operator assures that the best members remain in addition to orientation of values. The crossover operator creates two new offspring through parent solutions based on specific rules such as combination under different probabilities. The mutation operator varies some chromosomes of each population in random [22].

The operation of RCGA is in a way that a number of population members with lower fitness are eliminated and new offspring tabernacle in any iteration. The members remaining with high fitness function in any iteration differ in several problems and methods. If the number of the last remained population or individual in any iteration is n_{keep}, the individuals remaining with high fitness are C_j in which each population is comprised of the number of chromosomes and this number depends on the problem dimension.

$$C_j = \sum_{i=1}^{n} X_{ij} \qquad i = 1,2,3,\cdots,n \quad and \quad j = 1,2,3,...,n_{keep} \tag{10}$$

Individuals remaining inthe form of father chromosomes (c_m) or the mother one (c_f) in any iteration generate a new generation. The combination of parent chromosomes in each mating, results in two offspring. If the new offsprings are called c_m^{gen} and c_f^{gen} the followings are valid:

$$C_m^{gen} = a \times C_m + (1-a) \times C_f \tag{11}$$

$$C_f^{gen} = (1-a) \times C_m + a \times C_f \tag{12}$$

where x_{ij} is the i^{th} chromosome of j^{th} population or individual, while f and m are a function of j.

Parameter a is a random number falls in [0, 1].

The mutation operator randomly changes some chromosomes of the offspring of each population.

In this paper, a new approach is proposed in which the selection and the mutation operators are selected inlogical intervals.

4. The Proposed Method

4.1. Controlling Each Population's Chromosome Values in the First Iteration

In solving ED problem through RCGA, the control process is carried out on the optimum response of total chromosomes through applying the penalty factors to tend the chromosomes' total values towards the expected value. This is accomplished in a way that the chromosomes are separately and randomly valued within the specified range and they are fined in proportion with the difference with the expected value at the end of iteration if the chromosomes' total values do not fall in the expected range. Here, the expected chromosomes' total value equals to the follows:

$$G_i = \lambda + \delta \tag{13}$$

$$\delta = \sum_{y=1}^{m} f_y(Z_y) \qquad y = 1,2,3,...,m \tag{14}$$

where λ is a constant value associated with the given data and $f(z)$ is a value calculated applying chromosomes' values in the related formula in iteration and its number m depends on the problem multi objective dimension, for example in solving ED problems m is equal to 1 and $\delta = P_{loss}$.

In the proposed method, it is initially assumed that $\delta = 0$ and according to the following relations, the first iteration's parameters are valued as the controlled random values in a way that the chromosomes' total value equals λ.

In the following relations, the parameters are considered as follows:

x_{ij} = the value of i^{th} chromosome of the j^{th} population

In the RCGA-SM, the relations are solved through (15) and (16) respectively related to chromosomes' total constraints and each chromosome's value and the value of each chromosome is valued randomly in controlled form to satisfy (15). The solution of the equations is as follows:

$$\lambda = \sum_{i=1}^{n} X_{ij} \qquad i = 1,2,3,...,n \tag{15}$$

$$X_{i,\min} \le X_{ij} \le X_{i,\max} \tag{16}$$

where x_{ij} isthe value of i^{th} chromosome of the j^{th} population and n is the maximum number of chromosome in each population.

$$X_{ij} = X_{ij,\min} + r_{ij} \times (X_{ij,\max} - X_{ij,\min}) \tag{17}$$

Assuming the followings valid:

$$X_{tj} = X_{ij} - X_{ij,\min} \tag{18}$$

$$X_{sj} = X_{ij,\max} - X_{ij,\min} \tag{19}$$

$$X_{tj} = r_{ij} \times X_{sj} \tag{20}$$

With combined equations (15), (17) and (18) the followings are obtained:

$$\sum_{t=1}^{n} X_{tj} + \sum_{i=1}^{n} X_{ij,\min} = \lambda \tag{21}$$

$$\sum_{t=1}^{n} X_{tj} = \lambda - \sum_{i=1}^{n} X_{ij,\min} \tag{22}$$

In order to reform (22) from equality to inequality form and create an interval for random values selection, it is necessary to subtract the value of a chromosome falls in its own interval from this value. Therefore, the following is valid:

X_{mj} is one of the randomly selected chromosomes. Therefore, According to equation (16), the range of this chromosome is equal: $X_{mj,\min} \le X_{mj} \le X_{mj,\max}$, now, by separating this chromosome, equation (18) converted from equality to inequality. In other words:

$$\sum_{t=1}^{n} X_{tj} - X_{mj} \le \Big(\sum_{\substack{i=1\\ i\ne m}}^{n} r_{ij} \times \sum_{\substack{s=1\\ s\ne m}}^{n} X_{sj}\Big) \le \sum_{t=1}^{n} X_{tj} \tag{23}$$

The r_{ij} value of all chromosomes can be randomly but in a controlled form determined easily applying (23) within the above range.

For example, the following is valid in order to calculate the r_{ij} value of the h^{th} chromosome:

$$\frac{\left(\sum_{t=1}^{n} X_{tj} - X_{mj} - \Big(\sum_{\substack{i=1\\ i\ne m\\ i\ne h}}^{n} r_{ij} \times \sum_{\substack{s=1\\ s\ne m\\ s\ne h}}^{n} X_{sj}\Big)\right) \le r_{hj} \times X_{hj}}{\left(\sum_{t=1}^{n} X_{tj} - \Big(\sum_{\substack{i=1\\ i\ne m\\ i\ne h}}^{n} r_{ij} \times \sum_{\substack{s=1\\ s\ne m\\ s\ne h}}^{n} X_{sj}\Big)\right)} \tag{24}$$

Assuming the followings valid:

$$A = \frac{\sum_{t=1}^{n} X_{tj} - X_{mj} - (\sum_{\substack{i=1 \\ i \neq m \\ i \neq h}}^{n} r_{ij} \times \sum_{\substack{s=1 \\ s \neq m \\ s \neq h}}^{n} X_{sj})}{X_{hj}} \quad (25)$$

$$B = \frac{\sum_{t=1}^{n} X_{tj} - (\sum_{\substack{i=1 \\ i \neq m \\ i \neq h}}^{n} r_{ij} \times \sum_{\substack{s=1 \\ s \neq m \\ s \neq h}}^{n} X_{sj})}{X_{hj}} \quad (26)$$

One random value within [0 1] is considered in order to obtain A and B values of not yet calculated r_{ij} value of the chromosomes.

Now the following is valid: $A \le r_{hj} \le B \to r_{hj} = A + r \times (B - A)$. Parameter r is a random value causes random r_{hj} value selection within the controlled interval.

This process continues until the r_{hj} values of all chromosomes except the m^{th} one are selected. Finally, the following can be applied to calculate r_{mj} of the x_{mj}^{th} chromosome:

$$\sum_{t=1}^{n} X_{tj} = \sum_{\substack{t=1 \\ t \neq m}}^{n} X_{tj} + X_{mj} \times r_{mj} \quad (27)$$

$$\sum_{t=1}^{n} X_{tj} = \sum_{\substack{i=1 \\ i \neq m}}^{n} r_{ij} \times \sum_{\substack{s=1 \\ s \neq m}}^{n} X_{sj} + (r_{mj} \times X_{mj}) \quad (28)$$

$$r_{mj} = \frac{\sum_{t=1}^{n} X_{tj} - (\sum_{\substack{i=1 \\ i \neq m}}^{n} r_{ij} \times \sum_{\substack{s=1 \\ s \neq m}}^{n} X_{sj})}{X_{mj}} \quad (29)$$

Finally, (17) can easily be applied to calculate the values of each chromosome since r_{ij} values are known. Now, the chromosome total value equals to λ, and applying the obtained values in $f(z)$, the variable part of the problem for any iteration is calculated. This is a constant value, which can simply be added randomly to the chromosomes capable of facing with value increase to equalize the chromosomes' total values in the first iteration to G_i value.

4.2. Controlling Each Population's Chromosome Values in the Next Iteration

In order to correct the values of each chromosome, the low valued chromosomes of the population should be eliminated and substituted with new generations. Since the new positions of a chromosome may sometimes not satisfy the constraints, the instruction of facing with constraints is executed. The instruction related to the constraints and range of each chromosome, is applied initially and the constraint associated with the group response is applied then in a way that the necessity of equalization of chromosomes' total value and λ parameter in (15) is provided assuming $\delta = 0$. This is accomplished in a way that the chromosomes' total value of each population stays equal to the λ value as the values of thechromosomes randomly vary in the related interval. Now, the chromosomes values can be calculated applying the obtained chromosomes' values on $f(z)$. Simply, this value is constant and can be randomly added to one or more chromosomes capable of facing with value increase. This is carried out until the chromosomes' total value of each population equals to G_i value. This random variation of one or more chromosome causes a kind of mutation in the algorithm and makes the algorithm to ride through the local optimum points.

Through this technique, the chromosomes' total value of each population always equals with the desired and the problem aimed value and it decreases the search zone in addition to theoptimum cost find out in the logical and acceptable zone. Therefore, the programs run time decreases considerably.

The flowchart of program run is well illustrated in Fig (1).

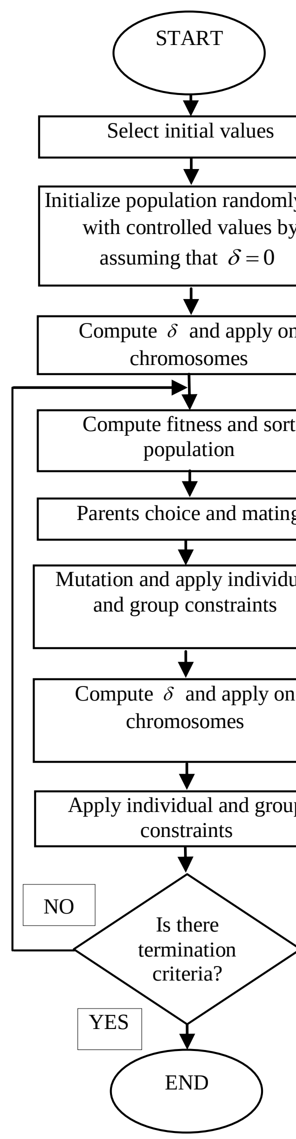

Fig (1): Procedure of the RCGA-SM

4.3. Creating Mutation in the proposed Method

One of the major problems of genetic algorithm technique lies in mutation creation manner. Inappropriate chromosomes values selection can practically cause constraints violation, run time increase, and algorithm trapped in local optimum points.

In order to overcome such problem, in the RCGA-SM technique, inspired by the mutation of heritage and according to the fact that a percentage of baby's (offspring) genes are not exactly similar with that of the parents but close to their genes' characteristics, the values of one or more gene vary in the logical and acceptable range considering individual and group constraints to create a mutation in the offspring of each population.

The creation of mutation in offspring, in the proposed technique falls in the fact that eventually the chromosomes' total values equal to λ obtained by (13). At the first stage, it is carried out changing (13) as follows:

$$G_i = \lambda + \delta + M_q \quad (30)$$

$$M_q = (\sum_{i=1}^{n}(x_{ij,\max}) - \lambda) \times r \times u \quad (31)$$

Where u falls in [0.3 , 0.7] value of which equals to 0.7 at the first iteration and decreases as the iterations number increases. Parameter r is a random value falls in [0 , 1] applying of which in (31) results in varied mutation amount in each population.

Now, the values of one or more chromosomes require to totally exceeding to M_q in their own constraint interval to validate (30). It is important to note that the share of each chromosome in providing M_q value is randomly an increasable value of it within the related constraints interval.

At the second stage, (13) should equal to G_i value as previous: $G_i = \lambda + \sum_{y=1}^{m} f_y(Z_y)$.

Therefore, it is necessary to decrease the values of one or more chromosomes randomly down to M_q in related constraint interval to satisfy (13). This random increase in the values of one or more chromosomes up to M_q, and the same randomly value decrease in chromosomes of a population causes a kind of mutation and variation of some chromosomes' values. Through this technique, the algorithm would not trap in local optimum points and it would continuously accomplish the searching process until the last program iteration.

5. ED Problem Solution through the RCGA-SM

In order to apply the proposed method on the ED problem, the 4.1 and 4.2 parts' relations vary as follows:

According to the fact that the load amount is constant (λ in (13)), at the first stage considering no losses in (13), $(f(z)) = 0$, the primary population is selected in controlled random intervals in a way that the chromosomes' total values equal to load amount. In order to achieve this, (13), (14), (15), and (16) vary as follows:

$$G_i = \lambda + \delta \quad (33)$$

$$\lambda = P_{load} = \sum_{i=1}^{n}(P_i) \quad (34)$$

$$\delta = P_{loss} \quad (35)$$

$$P_{ij,\min} \le P_{ij} \le P_{ij,\max} \quad (36)$$

$$P_{ij} = P_{ij,\min} + r_{ij} \times (P_{ij,\max} - P_{ij,\min}) \quad (37)$$

$i = 1,2,3,...,n_{variable}$ and $j = 1,2,3,...,n_{population}$

Since the selection interval of random chromosomes values in this technique is controllable, the effects of the ramp rate constraints can easily be applied when they are under consideration. Through this, the chromosomes' total random values are fully controllable.

The problem solution process through the RCGA-SM matching the flowchart of Fig.1 is as the following steps:

Step 1: primary validating and population forming, considering the load amount and individual and group constraints.

Step 2: if there are losses, apply the chromosomes values of each population in the losses equation (5), calculate the losses value, and distribute the losses in some chromosomes randomly until the chromosomes' total values equals to the generators' provided power amount.

Step 3: calculate the costs and sort the population on the costs base.

Step 4: the act of mating and producing new offspring (crossover).

Step 5: applying the mutation and correcting the new offspring' chromosomes to meet the constraints related to each chromosome and total chromosomes.

Step 6: apply the chromosomes values of each population on (8), calculate the losses amount, and randomly distribute the losses amount in some chromosomes in a way that (13) is not violated.

Step 7: go to Step 3 if the program's finishing criterion is not satisfied

6. Numerical Experiments

This section presents the results of simulations carried out on three different test cases in order to evaluate the robustness and performance of the proposed GA-based coding. In addition, thecomparison of these results with other relevant and valid methods reported in the literature will be given. To verify the feasibility and effectiveness of the proposed approach, 50 independent trails were performed and the quality of solving the problem and convergence characteristics were evaluated. {R.5:The proposed algorithm is implemented using the MATLAB 7.0 software and run on a PC with Intel(R) Core(TM) i3-2330M CPU 2.20 GHz2 GB RAM.To implement proposed algorithm, some RCGA parameters should be predefined. In the proposed RCGA-SM for all test cases, the initial population size is set to100, the optimal value of Nkeep is set to 30 percent of initial population and the probability of mutation is set to 0.03.}

The proposed method is implemented on three different power systems.

a) A system with 6 power units containing prohibitedoperating zones, ramp rates constraints, and network losses.

b) A system with 15 units containing prohibited operatingzones, ramp rates constraints, and network losses.

c) A system with 40 power plants with valve-point effects.

6.1. system with 6-unit

The experimentations are carried out on a system with six power units considering prohibitedoperating zones, ramp rate constraints and network losses. The system provides total 1263 MW load amount. The input data and B factors of network losses exist in [15]. The number of primary population and the program iteration are 100. The algorithm's convergence scheme is illustrated in Fig (2). As it is obvious, in RCGA-SM, the search zone is limited due to elimination of penalty cost function and effective control on the chromosomes' total values. Here, the algorithm just tries to find out the optimum cost in a logical and acceptable zone and consequently, it converges to the optimum responses in the primary algorithm iterations. As it is shown, the algorithm reaches to 15443 $/h just in the first eight iteration. The RCGA and the PSO start points with penalty factors in Fig (2) well show the negative effects of the penalty factor application and cause increases the search region size.

As it is shown in Fig (2), the RCGA-SM reaches to its minimum value in the initial iterations due to the search within the logical zone.

Table (1): Best power output for 6 generator system

Unit (MW)	GA [23]	PSO [15]	BBO [19]	RCGA-SM
P1	474.81	447.50	447.3997	446.8308
P2	178.64	173.32	173.2392	173.2352
P3	262.21	263.47	263.3163	263.8920
P4	134.28	139.06	138.0006	139.1612
P5	151.90	165.48	165.4104	165.4544
P6	74.18	87.13	87.07979	86.8378
TP	1276.03	1276.01	1275.446	1275.41
P_{loss}	13.02	12.958	12.446	12.4121
TC	15459.00	15450	15443.09	15442.6551
T/I	---	0.06	0.0325	0.007888

*TP: total power [MW], TC: total cost [$/h], T/I: cpu time/iteration [sec.]

Table (2): Comparing among different methods after 50 trials (6 generator system)

Methods	Maximum cost ($/h)	Minimum cost ($/h)	Average cost ($/h)
RCGA	15524	15459	15469.00
GAAPI	15449.85	15449.78	15449.81
PSO	15492	15450	15454
BBO	15443.096	15443.096	15443.0964
RCGA-SM	15442.659	15442.655	15442.657

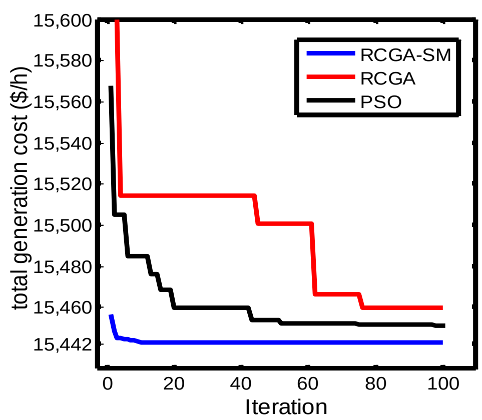

Fig (2): Convergence characteristic of 6-unit system

In Table (1), the results obtained using the proposed method are compared with advanced and efficient methods.

The results of Table (1), shows the superiority of the RCGA-SM over the other new and efficient algorithms from cost and losses amount viewpoint. In the proposed method, the program run time is significantly decreased in comparison with the other algorithms because the find out process is just accomplished in logical zone and consequently considerable decrease in calculation burden occurs and the program calculation decreases in fitness section. The run time with 100 iterations equals to 0.7888 sec, where the run time of a single iteration is 0.007888 sec, which is 7 times less than that of PSO algorithm and 4 times less than BBO.

Table (2) well shows that the proposed technique is robust in comparison with the other algorithms and converges to the optimum responses in each program execution.

6.2. system with 15-unit

The experimentations are carried out on a system with fifteen power plants considering prohibited operatingzones, ramp rate constraints and network losses. The system provides total 2630 MW load amount. The input data and B factors of network losses exist in [15].

The number of iteration and the initial population are 300 and 100 respectively. The convergence pattern of the proposed algorithm on a 15-generator system is shown in Fig (3). As it is obvious, in RCGA-SM, the search range decreases by effective controlling on the chromosomes' total values and it starts to find out the optimum points just within the logical and acceptable range.

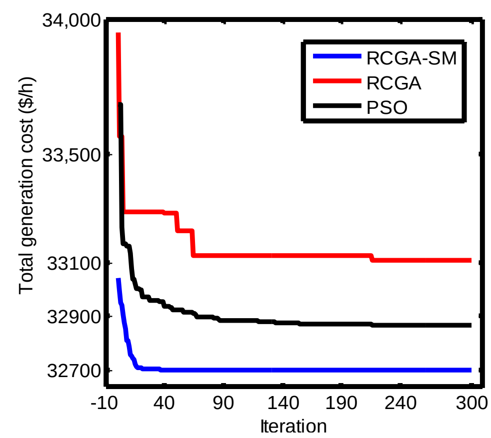

Fig (3) : Convergence characteristics of 15-unit system

The GA and PSO algorithms' start points with penalty factors shown in Fig (3) well show the negative effects of applying penalty factors and increase the search region. It is obvious from the convergence pattern of the genetic algorithm that the applied mutations are not appropriate and cause the algorithm trapped in local optimum points and increases the required iteration numbers.

Table (3): Best power output for 15-generator system

Unit (MW)	GAAPI [24]	SOH_PSO [27]	PSO [15]	RCGA -SM
P1	454.70	455.00	439.11	455.0000
P2	380.00	380.00	407.97	380.0000
P3	130.00	130.00	119.63	130.0000
P4	129.53	130.00	129.99	130.0000
P5	170.00	170.00	151.06	170.0000
P6	460.00	459.96	459.99	460.0000
P7	429.71	430.00	425.56	430.0000
P8	75.35	117.53	98.56	76.3573
P9	34.96	77.90	113.49	53.9575
P10	160.00	119.54	101.11	160.0000
P11	79.75	54.50	33.91	80.0000
P12	80.00	80.00	79.95	80.0000
P13	34.21	25.00	25.00	25.00000
P14	21.14	17.86	41.41	15.0000
P15	21.02	15.00	35.61	15.0000
TP	2660.36	2662.29	2662.4	2660.3149
Ploss	30.36	32.28	32.43	30.3100
TC	32732.95	32751.39	32858	32700.3490
T/I	NA	0.0936	NA	0.009988

The results shown in Table (3) depict the priority of the proposed method over the other techniques. The obtained cost amount through the proposed method equals to 32700 $/h. The line losses in this method equal to 30.31 MW, which is the least among the others. The run time with 300 iterations is 2.9964 sec. time to iteration of proposed method is 0.009988 sec.

Table (4): Comparing of different methods after 50 trials (15-generator system)

Methods	Maximum cost ($/h)	Minimum cost ($/h)	Average cost ($/h)
GA [15]	33337.00	33113.00	33228.00
GAAPI [24]	32756.01	32732.95	32735.06
PSO [15]	33331	32858	33039
SOH_PSO [27]	32945	32751	32878
PSO-SIF [1]	32709.92	32706.8800	32707.7900
Ɵ-PSO [34]	32,744.0306	32,706.6856	32,711.4955
RTO [35]	32715.18	32701.81	32704.53
RCGA-SM	32700.4603	32700.3490	32700.3909

The minimum and the mean obtained resultsthrough different approaches after 50 iterations are shown in Table 4. The search within the logical range and proper mutations increases the robustness of proposed method. Therefore, the algorithm obtains responses in each implementation. As it is obvious, the genetic algorithm in each implementation results in differently, which show the inappropriate mutations of this algorithm.

6.3. system with 40-unit

The experimented system contains 40 power plants and the input dada are given in [10]. Total demanded load is 10500 MW. The program iteration number and the initial population are 2000 and 100, respectively.

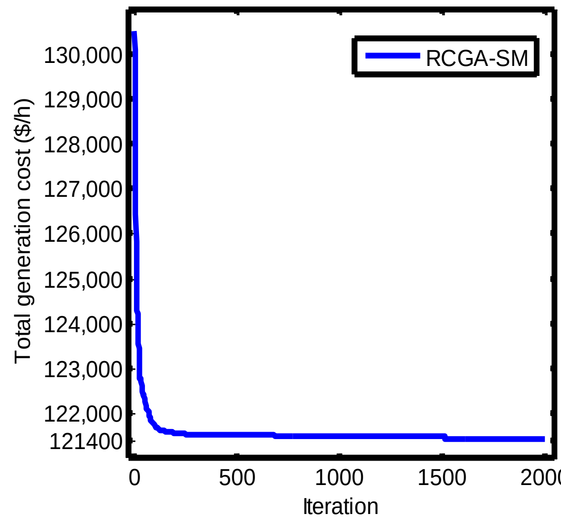

Fig (4): Convergence characteristics of 40-generator system

Fig (4): shows the convergence pattern of the RCGA-SM for a 40-generator system considering the valve-point effects. The convergence of the function in the initial iterations and facing with no trap in local optimum points and finding out optimum points in the 1550th iteration shows the logical mutations in the algorithm convergence pattern and the efficiency of the proposed mutation.

Table (5): Best power output for 40-generator system

Unit (MW)	RCGA-SM	DE-BBO [32]	BBO [19]	ICA-PSO [28]	QPSO [31]
P1	110.8016	110.7998	110.0465	110.80	111.20
P2	110.8008	110.7998	111.5915	110.80	111.7
P3	97.4000	97.3999	97.6007	97.41	97.40
P4	179.7336	179.7331	179.7095	179.74	179.73
P5	87.8004	87.9576	88.3060	88.52	90.14
P6	139.9999	140.0000	139.9992	140.00	140.00
P7	259.5996	259.5972	259.6313	259.60	259.60
P8	284.5999	284.5997	284.7366	284.60	284.80
P9	284.6000	284.5997	284.7801	284.60	284.84
P10	130.0006	130.0000	130.2484	130.00	130.00
P11	94.0003	168.7998	168.8461	168.80	168.80
P12	94.0008	94.0000	168.8461	94.00	168.80
P13	214.7593	214.7598	214.7038	214.76	214.76
P14	394.2792	394.2794	304.5894	394.28	304.53
P15	394.2791	394.2794	394.2761	394.28	394.28
P16	394.2790	304.5196	394.2409	304.52	394.28
P17	489.2791	489.2794	489.2919	498.28	489.28
P18	489.2796	489.2794	489.4188	489.28	489.28
P19	511.2794	511.2794	511.2997	511.28	511.28
P20	511.2789	511.2794	511.3073	511.28	511.28
P21	523.2795	523.2794	523.4170	523.28	523.28
P22	523.2794	523.2794	523.2795	523.28	523.28
P23	523.2794	523.2794	523.3793	523.28	523.29
P24	523.2792	523.2794	523.3225	523.28	523.28
P25	523.2794	523.2794	523.3661	523.28	523.29
P26	523.2794	523.2794	523.4362	523.28	523.28
P27	10.0005	10.0000	10.0531	10.00	10.01
P28	10.0007	10.0000	10.0113	10.00	10.01
P29	10.0000	10.0000	10.0030	10.00	10.00
P30	87.8021	97.0000	88.4775	96.39	88.47

P31	190.0000	190.0000	189.9983	190.00	190.00
P32	189.9997	190.0000	189.9881	190.00	190.00
P33	190.000	190.0000	189.9663	190.00	190.00
P34	164.7998	164.7998	164.8054	164.82	164.91
P35	199.8783	200.0000	165.1267	200.00	165.36
P36	194.5131	200.0000	165.7695	200.00	167.19
P37	109.9989	110.0000	109.9059	110.00	110.00
P38	109.9997	110.0000	109.9971	110.00	107.01
P39	109.9988	110.0000	109.9695	110.00	110.00
P40	511.2796	511.2794	511.2794	511.28	511.36
TC	121412.8705	121420.89	121426.953	121413.2022	121448.21

As seen from Table (6), the proposed method is robust compared with other techniques and reaches the approximately similar responses in each implementation. In Tables (5 and 7), the results obtained from the proposed method are compared with that of the advanced GA and PSO algorithms and the algorithms using the penalty factor.

Table (6): Comparing of different methods after 50 trials (40-generator system)

Methods	Maximum cost ($/h)	Minimum cost ($/h)	Average cost ($/h)
RCGA-SM	121435.4698	121412.8705	121415.1364
PSO	122607.91	121751.33	122020.75
DE-BBO	121420.8968	121420.8948	121420.8952
BBO	121688.6634	121426.953	121508.0325
QPSO	NA	121448.21	121508.0325
ICA-PSO	121453.56	121413.20	121428.14

Table (7): Minimum generation cost obtained by different methods on 40-generating unit system

Method	Minimum cost ($/h)
RCGA-SM	121412.8705
PSO [28]	121751.339
GA-PS-SQP[33]	121458.14
MPSO [28]	122252.26
S PSO [19]	122049.66
BF-NM [30]	121423.63
UHGA [28]	121424.48
CBPSO-RVM[26]	121555.32
ACO[25]	121532.41
IGAMU [28]	121819.25
DEC-SQP [28]	121741.97
ESO [29]	121630.96
RCGA[23]	121418.5425
FAPSO-NM [36]	121418.3000
FA [2]	121415.0500
MDE [37]	121414.7900
FPA [36]	121414.6185

The results well show the priority of the RCGA-SM. The obtained cost equals to 121412 $/h, which finds out better results compared with GAAPI [24], BBO [19], DE-BB0 [32], RCGA [23], QPSO [31], ICA-PSO [28], ACO [25], GA-PS-SQP [33] techniques.

7. Conclusions

This paper proposes a new technique to solve the optimization problemsin which the required control is applied on the total problem variables and the penalty cost is not applied. The RCGA-SM is successfully implemented on three nonconvex economic dispatch problems considering several constraints. In this method, the required control is applied on the chromosomes' total values, which decreases the search region within a logical and acceptable zone.Some of the advantages of proposed RCGA-SMare fast convergence towards the optimum responses in the initial iterations, short program run-time, no trap in local optimum points because ofthe logical mutations, algorithm's robustness, and its convergence towards the similar responses in each program implementation.

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