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An Improved Catastrophic Genetic Algorithm and Its Application in Reactive Power Optimization

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Abstract

This paper presents an Improved Catastrophic Genetic Algorithm (ICGA) for optimal reactive power optimization. Firstly, a new catastrophic operator to enhance the genetic algorithms' convergence stability is proposed. Then, a new probability algorithm of crossover depending on the number of generations, and a new probability algorithm of mutation depending on the fitness value are designed to solving the main conflict of the convergent speed with the global astringency. In these ways, the ICGA can prevent premature convergence and instability of genetic-catastrophic algorithms (GCA). Finally, the ICGA is applied for power system reactive power optimization and evaluated on the IEEE 14-bus power system, and the application results show that the proposed method is suitable for reactive power optimization in power system.

1. Introduction

The reactive power optimization (RPO), which is a non-linear planning problem with the traits of discrete, multiple variables and multiple constraints, has a significant influence on secure and economic operation of power systems. It is an effective approach to improve voltage level, decrease network losses and maintain the power system running under normal conditions. In this field, many traditional methods have been used, including linear programming (LP) [1], nonlinear programming (NLP) [2], and interior point methods (IPM) [3]. But, there are some drawbacks in these conventional methods that can limit their application in RPO, such as the complexity of algorithms, poor convergence properties, and the difficulty of dealing with dispersed variables.

Recently, Genetic Algorithm (GA) has been widely used to RPO [4-7]. GA has been theoretically and empirically proven to provide robust search in complex spaces. Numerous papers and dissertations establish the validity of the technique in optimization and control applications [8].

However, it is known that the main shortcoming of GA is premature [9,10]. To overcome this, Genetic-Catastrophic Algorithm (GCA) is presented in [11], in which a new operator, catastrophic operator, is proposed to recover the population diversity when premature is happened.

Since the notion of GCA is proposed, there were several researches. Meiying liao [12] analyze the mechanism of catastrophic operator in GA, Yongjun Zhang [13] presented an improved catastrophic operator to enhance the diversity of the small size populations. Others, GCA have been successfully used in many fields of power system, such as RPO [13], optimal power purchase planning [14] and optimal configuration of switching devices in distribution system [15].

The GCA mentioned above is mainly concentrated on improving the searching capability of SGA, but ignoring the instability caused by catastrophic operator. In this paper, based on the analysis of mechanism of GCA, an Improved Catastrophic Genetic Algorithm (ICGA) is proposed. In ICGA, a new catastrophic operator is designed for improving the stability of the proposed method, Besides, in order to improve the GA's convergent speed and searching capability, adaptive genetic algorithm (AGA) is also introduced in this paper, in which crossover and mutation probabilities are varied depending on the number of generations and the fitness value, respectively.

An attempt to apply ICGA to RPO is presented in this paper. The feasibility of the proposed algorithm for RPO is demonstrated and compared with IEEE 14-bus systems. The experimental results prove that the algorithm is reasonable and practicable.

This paper is organized as follows. Section 2 presents brief reviews on Simple Genetic Algorithm (SGA), and GCA, in Section 3, the ICGA method and the design of crossover and mutation probabilities are proposed respectively. In Section 4, a comparison among the ICGA, SGA and AGA by using typical test function is conducted. Then, the OPR model is mentioned in Section 5, and the results of the simulation for IEEE 14-bus systems are presented in Section 6. Finally a conclusion is presented in Section 7, and the end is references.

2. Genetic-Catastrophic Algorithm

GA, first proposed and investigated by John Holland in 1975 [16], is a robust probabilistic search and optimization techniques based on the natural selection and genetic production mechanism. Most of GA works are based on the Goldberg's simple genetic algorithm (SGA) framework [17]. Typically, the process of SGA follows this pattern [18]:

1) Initialization: Generate a first generation N_p with random parameters.

2) Evaluate all individuals of the generation N_p

3) Selection: selects those offspring individuals with a higher fitness value for the next generation N_s.

4) Crossover: crosses the selected best individuals together to get the new generation N_c.

5) Mutation: make random mutates of the N_c, and gets new generation N_m.

6) Evaluate the individuals of the new generation N_p, and then go back to 3), until certain criteria (such as a fixed number of generations. Or a time) are met.

The main difficulty of application of SGA in engineering problems is premature, which occurs due to loss of the population diversity. In order to avoid this problem and improve the convergence properties of SGA, GCA is presented on the based of SGA. In GCA, when premature is happened, catastrophic operator is employed to regain the population diversity.

The process of GCA follows this pattern [11].

1) Initialization

2) Evaluation

3) Selection, Crossover and Mutation

4) If premature convergence occurs, apply catastrophic operator, otherwise go to the step 5)

5) If the convergence criterion is satisfied, terminate the calculation. If not, go to step 2).

The catastrophic operator includes catastrophic condition and operation, catastrophic condition is to judge when to execute catastrophic operation. Generally, catastrophic operation includes two steps:

1) Remove a certain number (N_c) of individuals with low fitness value in current population

2) Regenerate N_c individuals via various methods and put into the current population to replace the removed ones.

And the flow chart is shown in **Figure 1**.

Obviously, by adding various new individuals to the current population, the diversity of population can greatly improve after employing catastrophic operator.

3. Improved Catastrophic Genetic Algorithm

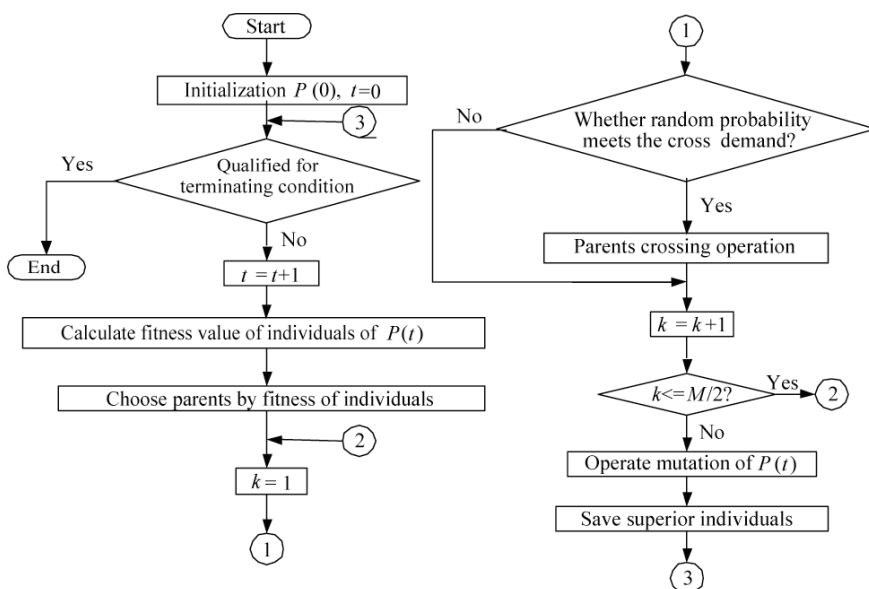Although GCA is an effective method to overcome pre-

Figure 1. Flow chart of SGA.

mature, the effect of catastrophic operator on GA's convergence properties is seldom researched. The following subsections will discuss this in more detail.

3.1. Effect of Catastrophic Operator on GA's Convergence Properties

3.1.1. Effect of Traditional Catastrophic Condition on GA's Convergence Properties

Catastrophic condition is to decide when to execute catastrophic operation, Traditional catastrophic condition is mainly based on the judge of premature convergence [11,15], this method has following disadvantages:

1) Cause disruption of convergence because successful convergence can still meet the catastrophic conditions.

2) Cause overly execution of catastrophic operation because the condition is easily meet, it will bring about the great increment of computing time.

3.1.2. Effect of Traditional Catastrophic Operation on GA's Convergence Properties

The key point of catastrophic operation contains two aspects: give an appropriate value for N_0 and decide how to generate new individuals, in traditional catastrophic operation, N_0 is a constant value and the new individuals are generated in these ways:

1) Sharply increasing mutation probability p_m.

2) Remove most of the individuals except the fittest one and randomly generate the new individuals.

These methods can critically affect the convergence performance of GA:

1) Increase the randomness of GA search because the new individuals are separated into the whole solution space.

2) Prolong the convergence time because there are many poor individuals in the new population, which can disrupt the previous superior individuals when they are selected to cross.

3) Disrupt the stability of GA at the late stage of evolution because N0 is a constant value through whole evolution process.

3.2. The Proposed Algorithm

In the previous subsection, it is saw that the traditional catastrophic operator can disrupt the GA's convergence properties, and increase the randomness of GA due to inappropriate design of catastrophic operator. In this subsection, the analysis of relationship between the evolution process and GA evolution process will be firstly given. Then, the design of proposed method is presented.

3.2.1. Analysis of Evolution Process and GA's Convergence Properties

In the whole GA evolution process, there are tradeoffs that occur in exploration and exploitation. At the early stage of evolution, to explore different solution space and avoid premature, more emphasis should be put on the exploration than exploitation. During the evolution, the population will gradually converge to an optimum solution. At the late stage of evolution, increase exploitation while decrease exploration will allow the GA to prevent the converged optimum solution from disrupting.

As to catastrophic operator, the number of new generated individuals (N_c) is the source of exploration, Setting N_c low allows the algorithm to exploit the superior individuals. Setting N_c high allows the algorithm to explore different solution space.

3.2.2. Design of the Proposed Method

Above analysis inspire us that the convergence properties of GA can be improved by varied N_c according to the number of generation. Therefore, N_c is given as:

$$N_c = Integer[\exp(-a \times t / T_{Gen}) \times N_0] \qquad (1)$$

Where $Integer$ [] is a rounding sign, t is current generation, a is controlled parameter, T_{Gen} is maximum generation, N_0 is maximum number of new generated individuals.

From the Equation (1), N_c is decreased by the number of generation, it means that the exploration is also decreased by the number of generation while the exploitation is on the opposite side. By this way, not only the search ability but also the convergence properties of GA can be enhanced,

The design of catastrophic condition and operation is in the following details:

1) Catastrophic condition:

If $residual(t/T) = 0$ && $t \leq T$, execute catastrophic operation, where T is the generation steps.

2) Catastrophic operation:

Catastrophic operation is performed by the following steps:

- Save the best individuals in current population
- Remove N_c individuals in current population
- Randomly generate N_c new individuals
- Add the new generated individuals to the current population.

3.3. Design of Adaptive Crossover Probability Mutation Probability

The choice of p_c and p_m is known to significantly affect the performance of the GA, the p_c controls the rate at which solutions are subjected to crossover, the higher the

value of p_c the quicker are the new individuals introduced into the population, vice versa. When a population converges to a global optimal solution (or even a local optimal solution), p_c and p_m increase and may cause the disruption of the near-optimal solutions, therefore, it is hoped that p_c is given a high value to create more individuals at the early stage of evolution and maintaining a relatively low value for the purpose of protecting superior individuals and algorithm's stability at the late stage of evolution process, in this paper, p_c is gradually decreased depending on the number of generation in sigmoid function form:

$$P_c(t) = \frac{(P_{c\max} - P_{c\min})}{1 + \exp(\frac{-A \times (T_{Gen} - 2t)}{T_{Gen}})} + P_{c\min} \quad (2)$$

where $p_c(t)$ is crossover probability generation in t generation, P_{cmax} is maximum crossover probability, P_{cmax} is minimum crossover probability and A is assigned 9.903438.

Mutation operator is used to maintain genetic diversity from one generation of a population of chromosomes to the next, the choice of p_m is critical to GA performance, large values of p_m transform the GA into a purely random search algorithm, In this paper, p_m is varied adaptively depended on both the number generation and every fitness value of individual:

$$P_{mt} = \exp(\frac{f_{max} - f(X_i)}{f_{max}}) \times \frac{(P_{m\max} - P_{m\min})}{1 + \exp(\frac{-A \times (T_{Gen} - 2t)}{T_{Gen}})} + P_{m\min} \quad (3)$$

where $P_m(t)$ is mutation probability of individual X_i in t generation, P_{mmax} is maximum mutation probability, P_{mmax} is minimum mutation probability, A is assigned 9.903438.

4. Performance Measures

In this section, the experiments that are conducted to compare the performance of the ICGA, SGA and AGA [19] are discussed. In order to test these methods' convergent speed, the average number of generations that these GA methods require to generate a solution with a certain high fitness value and the average consumed times are taken into consideration. These can be obtained by performing the experiment repeatedly (in our case, 100 times). To measure the convergence probability of these methods, the number of instance (in 100 trials) for which the GAs have successfully converged to the given optimal solution is also employed.

4.1. Test Functions

In this research, the following multimodal functions with varying complexities are used [19]:

$$\begin{cases} f_1(x_1, x_2) = 100(x_1^2 - x_2)^2 - (1 - x_1)^2 \\ -2.048 \le x_i \le 2.048 \quad (i = 1, 2) \end{cases} \quad (4)$$

$$\begin{cases} f_2(x_1, x_2) = 0.5 + \frac{\sin^2 \sqrt{x_1^2 + x_2^2}}{[1.0 + 0.001(x_1^2 + x_2^2)]^2} \\ -100 \le x_i \le 100 \quad (i = 1, 2) \end{cases} \quad (5)$$

Function $f1$ is a two-dimension function and has only one minimum in its whole solution space. But it is an abnormal function and is not optimized easily. Its global minimum is $f1(1,1)) = 0$; Function $f2$ is a rapidly varying multimodal function with two variables, and is symmetric about the origin with the height of the barrier between innumerable adjacent minima increasing as the global optimal solution is approached. $f(0,0) = 0$ is its global minimum.

4.2. Experiment Results

In all our experiments, the population size for all functions is 64 and T_{Gen} is given 100, For the SGA, $P_c = 0.9$, $P_m = 0.1$, For the AGA, $k1 = k3 = 1$, $k2 = k4 = 0.5$, $P_{cmax} = 0.9$, $P_{cmin} = 0.5$, $P_{mma}x = 0.1$, $P_{mmin} = 0.01$. And for the ICGA, $P_{cmax} = 0.9$, $P_{cmin} = 0.5$, $P_{mma}x = 0.1$, $P_{mmin} = 0.01$, $a = 10$, $N0 = 59$. The algorithm will be stop when each GAs attaining a solution with an objective functional value of $f1$ ($f2$) equal to the threshold 0.0001, the experimental results are presented in **Table 1**:

As **Table 1**, both average generation and consumed time of ICGA are less than SGA and AGA, Others, the convergence times of ICGA is the best, it indicates that ICGA can effectively 'jump' from the local optimum.

5. Reactive Power Optimization Model

RPO is mainly implemented by setting generator bus voltages, VAR compensators and transformer taps. The core of the RPO problem is to determine the reasonable reactive power compensation point and the best compensation capacity, than it can minimize the real power losses and improve voltage profile. The models of reactive power optimization are described as follows:

5.1. Objective Function

$$P_{loss} = \sum_{i=1}^{N} V_j \sum_{j \in h} V_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \quad (6)$$

Table 1. Comparison of performance of SGA, AGA and ICGA.

Function	Average Generations			Convergence Times			Consumed Time		
$f1$	SGA 91	AGA 61	ICGA 41	SGA 82	AGA 92	ICGA 97	SGA 0.47	AGA0.36	ICGA 0.28
$f2$	48	35	28.9	71	91	99	0.39	0.32	0.22

where P_{loss} is net loss for meritorious indicators, N is the number assemble of transmission lines in the network, V_i is the voltage value at bus i, V_j is the voltage value at bus j, δ_{ij} is the phase-angle difference of the voltage value between bus i and j, G_{ij} and B_{ij} are admittance matrix elements in the real and imaginary parts.

5.2. Constraints

$$\begin{cases} P_i = V_i \sum_{j=1}^{N} V_j (G_{ij} \cos d_{ij} + B_{ij} \sin d_{ij}) \\ Q_i = V_i \sum_{j=1}^{N} V_j (G_{ij} \sin d_{ij} - B_{ij} \cos d_{ij}) \end{cases} \quad (7)$$

where P_i, Q_i, V_i is active power, reactive power and voltage of node i respectively.

Variable equation:

Power system safe operation must be made within the scope. Select capacitive reactive power compensation capacity C_i, adjustable transformer tap position T_j and generator terminal voltage V_{gk} as the control variables. And select and Node voltage amplitude Vi as state variables reactive power generators Q_{gj}.

$$\begin{cases} C_{i\min} < C_i < C_{i\max} \\ T_{j\min} < T_j < T_{j\max} \\ V_{gk\min} < V_{gk} < V_{gk\max} \end{cases} \quad (8)$$

The unequal constraint (9) is the unequal constraint of the control variable vector, where T_{jmin}, T_{imax} is adjustable load transformer tap position of the upper and lower limit. C_{imin}, C_{imax} is capacitive reactive power compensation capacity of the upper and lower limit; V_{gkmin}, V_{gkmax} is generator terminal voltage the upper and lower limits.

$$\begin{cases} V_{i\min} < V_i < V_{i\max} \\ Q_{gj\min} < Q_{gj} < Q_{gj\max} \end{cases} \quad (9)$$

The unequal constraint (10) is the unequal constraint of dependent variable vector, where V_{imin}, V_{imax} are the node voltage amplitude of the upper and lower limit. Q_{gjmin}, Q_{gjmax} are the limits of generators reactive power. The control variables are self-constrained and dependent variables are constrained by adding them as penalty terms to the objective function (Equation (1)). So the objective function is changed to:

$$\min P_{loss} + \lambda_V \Sigma (\frac{\Delta V_i}{V_{i\max} - V_{i\min}})^2 + \lambda_Q \Sigma (\frac{\Delta Q_{gi}}{Q_{gi\max} - Q_{gi\min}})^2 \quad (10)$$

where λ_V and λ_Q are penalty factors; ΔV_i and ΔQ_{gi} are the violations of load-bus voltages and generators reactive power, respectively, defined as:

$$\Delta V_i = \begin{cases} V_{i\min} - V_i & V_i < V_{i\min} \\ 0 & V_{i\min} \leq V_i \leq V_{i\max} \\ V_i - V_{i\max} & V_i < V_{i\max} \end{cases} \quad (11)$$

$$\Delta Q_{gi} = \begin{cases} Q_{gi\min} - Q_{gi} & Q_{gi} < Q_{gi\min} \\ 0 & Q_{gi\min} \leq Q_{gi} \leq Q_{gi\max} \\ Q_{gi} - Q_{gii\max} & Q_{gi} < Q_{gi\max} \end{cases} \quad (12)$$

6. Numerical Results

The study is implemented using Matlab and tested on an IEEE 14-bus system, which includes three transformers, two generators and three compensation points. The step size of reactive power compensation and transformer tap ratios is 0.05 pu and 0.0125 pu respectively. Capacity ceiling of Reactive compensation device is 0.5 pu, and the step is 0.01 pu. The control variables are showed as: $Y = [U_{G1} \ U_{G2} \ Q_{G3} \ Q_{G6} \ Q_{G8} \ T_{47} \ T_{49} \ T_{56}]$. Details of this system and parameters are given in [20]. The number of generation is 30 and other parameters are following: $T_{Gen} = 30$, $N_0 = 29$, $\lambda_V = 15$, $\lambda_Q = 1.5$. The best optimization results of SGA, ICGA and GCA are given in **Table 2**, which are obtained from different kinds of algorithm respectively performing 30 times.

As **Table 2**, the initial generator reactive power Q_{G2} and load voltages $V_{D3} \sim V_{D14}$ are outside their limits, after optimization by the three methods, all the state variables are regulated back into their limits, besides, P_{loss} is decreased to 0.1375 by ICGA while that of 0.1378 by GCA and 0.1385 by SGA, thus, ICGA may find better outcome than the rest kinds of methods.

Table 3 shows the comparison of the best, worst, average and standard deviation values for different methods. Due to probabilistic characteristic of evolutionary algorithms, results reported here correspond to average from 30 trials.

Table 2. Variables of IEEE 14-bus system.

Var.	Lower limit	Upper limit	Initial Value	SGA Results	GCA Results	ICGA Results
U_{G1}	0.95	1.05	1.000	1.05	1.05	1.05
U_{G2}	0.95	1.05	1.000	1.0339	1.0307	1.0371
T_{47}	0.90	1.10	0.975	1.05	0.9875	0.9875
T_{49}	0.90	1.10	1.000	1.000	1.075	1.075
T_{56}	0.90	1.10	0.925	1.000	1.000	1.000
Q_{G3}	0.00	0.40	0	0.31	0.37	0.32
Q_{G6}	−0.06	0.24	0	0.23	0.24	0.24
Q_{G8}	−0.06	0.24	0	0.15	0.24	0.24
Q_{G1}	−0.50	1.50	−0.295	−0.1231	−0.0816	−0.2098
Q_{G2}	−0.50	1.00	1.515	0.5077	0.3146	0.4939
U_{D3}	0.95	1.05	0.9111	0.9983	1.0048	1.0051
U_{D4}	0.95	1.05	0.9228	0.9961	1.0014	1.0049
U_{D5}	0.95	1.05	0.9295	1.0041	1.0074	1.0109
U_{D6}	0.95	1.05	0.9245	1.0037	1.0084	1.0119
U_{D7}	0.95	1.05	0.9077	1.0178	1.0071	1.0103
U_{D8}	0.95	1.05	0.9077	1.0427	1.0474	1.0499
U_{D9}	0.95	1.05	0.8891	0.9903	0.9934	0.9967
U_{D10}	0.95	1.05	0.8865	0.9848	0.9881	0.9915
U_{D11}	0.95	1.05	0.9011	0.9905	0.9945	0.9979
U_{D12}	0.95	1.05	0.9080	0.988	0.9926	0.9961
U_{D13}	0.95	1.05	0.8989	0.983	0.9875	0.9911
U_{D14}	0.95	1.05	0.8719	0.9679	0.9716	0.9751
P_{loss}			0.1746	0.1385	0.1378	0.1375

Table 3. Comparison of best, worst, average and standard deviation values for SGA, GCA and ICGA.

	Best Ploss/pu	Worst Ploss/pu	Average Ploss/pu	Stardard Deviation
SGA	0.1385	0.1500	0.1423	0.0030
GCA	0.1780	0.1464	0.1405	0.0019
ICGA	0.1375	0.1394	0.1380	4.88E-04

As **Table 3**, the results found by the ICGA are apparently better than those obtained by SGA and GCA. Because standard deviation clearly reflects degree of scatter about simulation results, the result illustrates that ICGA has preferable convergence stability.

7. Conclusions

Although Catastrophe Genetic Algorithms is an effective method to enhance GA's global search ability, it comes up with the problem of instability. To solve this conflict, this paper presents the ICGA. In this method, new catastrophic operator is proposed and new adaptive crossover and mutation probability is designed. And the comparison with test functions shows that not only the stability of ICGA is greatly improved, but also the convergent speed and global searching capability. The proposed ICGA is applied to reactive power optimization of power system. The simulation results of the IEEE 14-bus system indicate that ICGA can be able to undertake global search with a fast convergence rate and a feature of pref-

erable convergence stability. It is proved to be efficient and practical during the reactive power optimization.

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