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Optimization and Application of Single-point Crossover and Multi-offspring Genetic Algorithm

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Abstract

Through researching the Single-point crossover and multi-offspring genetic algorithm, we find out the range of the offspring in the process of generation. It uses the shortest time and produces the least number of iterations. Then putting it into the agricultural harvest machinery system equipped with the model, we can get the best quantity in equipment. The application proves that the improved single-point crossover and multi-offspring genetic algorithm is better to solve nonlinear mixed integer programming problem.

Keywords: *Single-point crossover and multi-offspring genetic algorithm, Genetic algorithm, Equipped with harvest machine system model*

1. Introduction

Genetic Algorithm (GA) is based on the natural evolution of Darwin's theory named "survival of the fittest" and Mendel's genetic variation theory. It imitates the process of biological evolution, which includes the genetics and evolution, and it refer the statistical theory to form it[1].It makes the problems approach to the optimal solutions by means of selection, crossover and mutation operations. It is not only find out the extreme points, but also need to track the extreme points closely in the search space in terms of the time-varying problem. It requires the algorithm to adapt the changes in the environment of uncertain solution continuously [2]. Therefore, Wang Jiquan and others put forward the single-point crossover and multi-offspring genetic algorithm (SPGA), which is based on the theory of biological evolution [3]. Compared with the traditional genetic algorithm, it improved the number of offspring significantly. It is not only increase the possibility of outstanding individuals, but also make the competition more intensely, which promote the performance of the traditional genetic algorithm. So we try to find the best offspring number of the single point crossover genetic algorithm. There are two test functions used for testing. We get the range of offspring which have the shortest time and minimum number of iterations. Then it can be applied to the model with harvesting machine system which is nonlinear mixed integer programming problem. So it is proved that the single-point crossover and multi-offspring genetic algorithm is more suitable for solving this complex problem.

2. Optimizing Offspring Number of Single-point Crossover and Multi-offspring Genetic Algorithm

2.1Single-point Crossover and Multi-offspring Genetic Algorithm and Generation Method

Single-point crossover and multi-offspring genetic algorithm is a improved algorithm that two parent strings generate more than two offspring. It keeps the constant population size, the survival of fittest and elimination of poor individuals. In terms of traditional genetic algorithm, pair of parent strings generate a pair of offspring [4-5]. But

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in the process of biological evolution, the situation that the number of offspring generated by a pair of father less than or equal to two species is not exist in reality. Because the influence of disease, food and other factors which eventually lead to the specie extinct [6]. Single-point crossover and multi-offspring genetic algorithm can increase the number of individuals, intensify internal population competition and enhance viability of excellent individual of population. So the individuals with low viability will be eliminated and the species will develop gradually in the direction of adapting to living environment and produce more superior species [7].

The scheme of single-point crossover and multi-offspring genetic algorithm：

At first, the cases of two parent strings producing four offspring: If two parent individuals P1 and P2 are selected to participate in crossover [7-8]. Through selecting randomly from two different points of intersection, the P1 and P2 chromosome are divided into four sections, namely P1=D1E1,P1 =D3E3 ,P2=D2E2 ,P2=D4E4, in which D1 and D2, D3 and D4, E1 and E2, E3 and E4 have same gene numbers. The generating method of multi-offspring is: Produce two individuals of offspring C1 and C2 by exchanging position of E1 and E2, that is C1=D1E2，C2=D2E1 E3 and E4 exchange position to produce two individuals C3 and C4, that isC3=D3E4，C4=D4E3.Then the generation method of offspring of single point-crossover and multi-offspring genetic algorithm can be used Figure1 to represent.

Cross Point1			Cross Point1	
P1=D1	E1		C1=D1	E2
P2=D2	E2	Single Point Cross →	C2=D2	E1
Cross Point2			Cross Point2	
P1=D3	E3		C3 =D3	E4
P2=D4	E4		C4 =D4	E3

Figure1 Method of the single-point crossover and multi-offspring genetic algorithm

In Figure 1, Ci is the i-individual of offspring produced by crossover. From Figure1 we can see the individual number of offspring from the single point-crossover and multi-offspring genetic algorithm is twice as much as that of traditional genetic algorithm, that is after crossover 2 parent individuals generate 4 offspring individuals.

The situation of generating 6, 8, 10 offspring is same. We can see that the number of new individuals generated by single point-crossover and multi-offspring genetic algorithm will increase greatly, which can increase the possibility of producing more outstanding individuals, thus making the performance of single point-crossover and multi-offspring genetic algorithm better.

2.2Evolution strategies for single point-crossover and multi-offspring genetic algorithm

As shown in Figure 2.

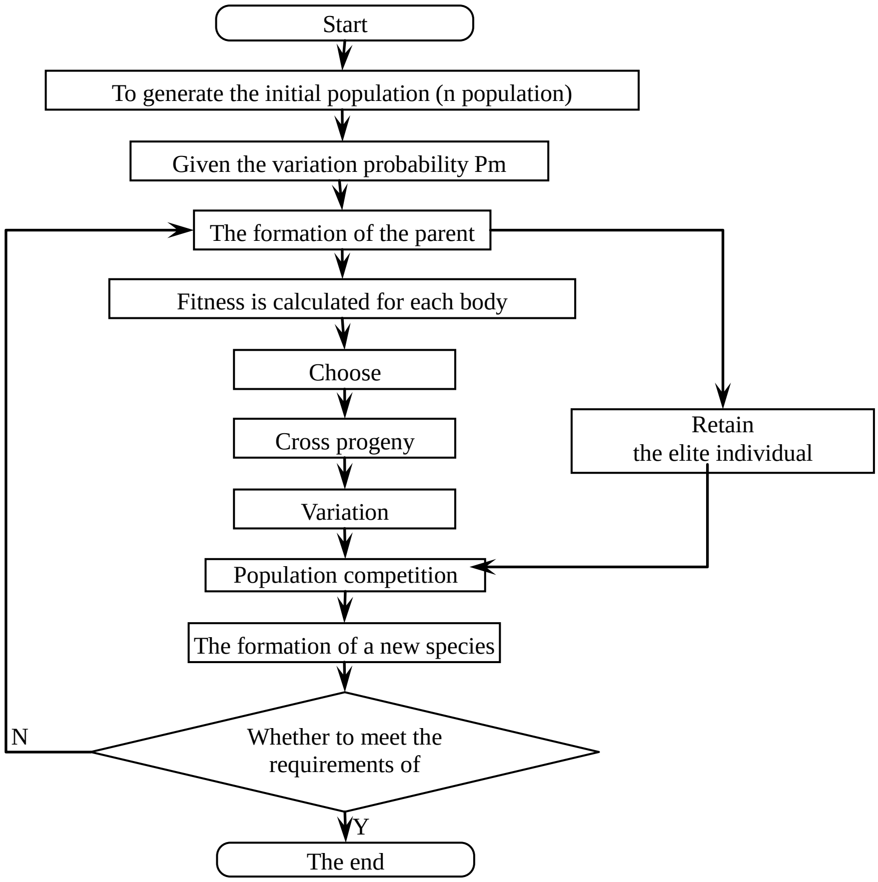

Figure 2. Evolutionary Strategy Frame of the Single Point-crossover and Multi-offspring Genetic Algorithm

2.3 Analysis of Single Point-crossover and Multi-offspring Genetic Algorithm Producing Offspring

The process of traditional genetic algorithm is the two parent strings produce two offspring, then calculating the fitness of each individual and carrying out selection, crossover and variation, and then replacing the worst individual after variation with a number of outstanding individuals of the parent strings to form offspring. This paper discusses n individuals produced by single point-crossover and multi-offspring genetic algorithm, then the variation, in which two parent strings produced 4,6,8,10,12,14,16 offspring(that is n= 4,6,8,10,12,14,16). The seven cases were respectively used in three test functions to research the optimal solution for offspring number.

3. The Numerical Simulation Test

In order to produce different offspring, these papers take the 2 test functions in literature [10]. Then calculate the eight kinds of situations (n=2-16). Test functions are as follows:

Test function1

$$f_2(x,y) = \left(\frac{3}{0.05 + x^2 + y^2}\right)^2 + (x^2 + y^2)^2 \qquad x, y \in [-5.12, 5.12]$$

Test function2

$$f_4 = \sin\left(\sum_{i=1}^{5} |x_i - 5|\right) \Big/ \sum_{i=1}^{5} |x_i - 5| \qquad 1 \le x_i \le 10$$

The function f_1 is Needle-in-haystack function, the maximum value of the function is 3600, the point of the maximum value is (0,0) . Four local maxima are symmetrically distributed on the point (5.12,5.12), (-5.12,-5.12),(5.12,-5.12),(-5.12,5.12), and local maximum value is 2748.1. The function f_2 is Sinc function and variable range is $1 \le x_i \le 10$. When $x_i = 5$, the global maximum value1 can be obtained from lecture [10].

3.1Determine the Optimal Range of Offspring

Each test function has some uncertain factors in calculating and programming, so making the population size is 400, the maximum number of iterations is 200, crossover probability $p_c = 0.6$ and mutation probability $p_m = 0.01$. Then selected the same computer version of MATLAB7.0 statistical software for the 2 test functions and count 5000 times. We got the more representative conclusion, and the test results are shown in table 2.Comparing the test time and iteration initialization function, it can be seen the range of 4 to 8 have the shortest time and the least number of iterations. Therefore, the range of 4 to the 8 is the best range of single point-crossover and multi-offspring genetic algorithm.

Table 2. Test Result

Function		GA	SPGA						
		2n	4n	6n	8n	10n	12n	14n	16n
f_1	Average time /s	1.698	0.6436	1.241	1.680	3.1993	3.4532	4.3219	6.892
	Average number of iterations/time	325.64	152.09	220.87	263.12	306.58	489.75	587.90	902,32
f_2	Average time /s	3.9579	1.4319	1.2972	1.1257	1.5125	2.0642	2.9836	3.8052
	Average number of iterations/time	728.763	324.92	150.67	102.96	206.21	463.32	583.02	689.47

3.2 Comparative Analysis between GA and SPGA

In order to prove that the improved single-point crossover and multi-offspring genetic algorithm converges faster and better. Comparing the single-point crossover and multi-offspring genetic algorithm (SPGA, n=6) with traditional genetic algorithm (GA), it used in the same computer version of MATLAB7.0 software. Analysing the 2 test functions mentioned above, the maximum number of iterations is 400, the crossover probability is $p_c = 0.6$ and mutation probability is $p_m = 0.01$. And the results as shown in Table 3, Figure 3 and Figure 4.

Table 3. The Optimization Results of Extremum Problems of f_1 and f_2 (10 Times Experiment)

Algorithms	$f_1(x, y)$				
	Optimum	Average	The first optimal number of iterations	Numbers of success	corresponding curve
$SPGA_6$	3600	3600	171	10	1
GA	3600	2912	361	3	4

Algorithms	f_2				
	Optimum	Average	The first optimal number of iterations	Numbers of success	corresponding curve
$SPGA_6$	1	0.9782	37	9	3
GA	1	0.9196	41	6	4

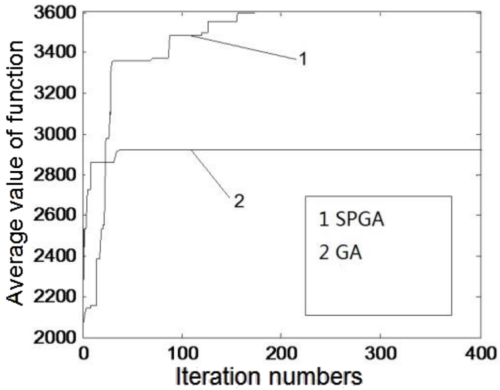

Figure 3. $f_1(x, y)$ **Function Optimization Results**

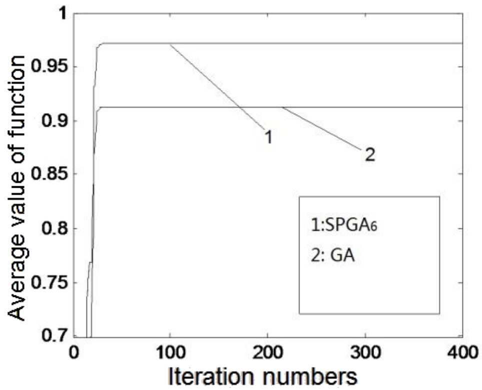

Figure 4. f_2 **Function Optimization Results**

It can be seen from Table 3, Figures 3 to 4 that the improved algorithms of this paper not only have a faster search speed, but also have a strong global search capability on the optimization problems.

4. The Application in Harvesting Machine Systems Equiping Model

A genetic algorithm has good global search capability, but contrasting with traditional genetic algorithm, Single-point crossover and more offspring genetic algorithm has the higher operation speed and the fewer iterations. Secondly, due to the number of units of the various power machines and working machines that equip with agricultural machinery system are integers, in order to get the maximum cost savings，the number of days to complete the job can be the decimal. It can be seen that harvesting machine model is a complex system with nonlinear mixed integer programming. In previous studies, because of the difficulty of getting the optimal solution in nonlinear mixed integer programming problem，this paper attempts to use improved single point of cross more offspring genetic algorithm to search the solution of optimization problems.

4.1 The Building of Harvesting Machine Systems Equipment Model

The objective function takes the minimize of machine's operating cost in per unit area of operation and the sum of timeliness loss as the goal, the main parameters which can be divided into four parts, including power machine's fixed costs C_F, operating machinery's fixed costs CI、unit operation's variable costs CV and timeliness loss T_L[11].

$$f_{\min} = \left(C_F + C_I + C_V + T_L\right) / S \qquad (1)$$

4.2 The Building of Constraint Equations

1) Work area constraint. In any work, the sum of various unit's complete workload should greater than or equal to this work's requirement workload.

$$\sum_{j=1}^{J} W_{ij} X_{ij} \geq \lambda_i S \qquad (2)$$

In formula (2), W_{ij} -the productivity of finishing work i by power unit j (hm2/class); X_{ij} - The number of classes for finishing work i by power unit j; S- total workload

2) Power machinery equipment constraint. Within any farming stage, the sum of power machinery that assigned to the every work cannot exceed this power machinery's total.

$$\sum_{i=1}^{n} X_{jik} \leq X_j \left(k = 1,2.......I_m; j = 1,2...j\right) \qquad (3)$$

In formula (3), X_{jik} -the number of j power machinery required to be provided in farming stage k; X_j -the number of power machinery required to be provided for completing annual workload.

3) Work machinery equipment constraint. Within any farming stage, the sum of work machinery that assigned to the every work can not exceed the sum of work machinery that equipped for this work.

$$\sum_{i=1}^{n} X_{ijk} \leq X_q \left(j = 1,2,...J; k = 1,2,...I_m\right) \qquad (4)$$

In formula (4), X_j -the number of power machinery j required to be provided for completing annual workload(j=1,2,,,J); X_{ijk} -the number of unit required to be provided for finishing work i in stage k by power machinery j(i=1,2,,,n; k=1,2...m); X_q -the number of farm tool q for finishing work.

4.3 Harvesting Machine Systems Equipment Model

The model of total cultivated area S=3580.5hm2, Where λ1=25%, λ2=14%, λ3=61%. Basic operations such as table 2.Combining the characteristics of the model, we use the model of the improved single point-crossover and multi-offspring genetic algorithm. Choosing the optimal performance of the algorithm (n=6), the maximum number of iterations is 400, the crossover probability is $p_c = 0.6$ and mutation probability is $p_m = 0.01$.It is used in the same computer version of MATLAB7.0 software. The basic situation of operation as shown in Table 3.

Table 3. Basic Operation Table

Job Project	Job type	Farming Stage	Stage Days	Shift work	Weather coefficient	Productivity （hm^2/class）
Harvesting wheat	200 Harvester X_1	1	6	1	0.7	27.658
picking wheat	1075HarvesterX_2	2	6	1	0.7	25.99
	9660HarvesterX_3	2	6	1	0.7	47.21
combining wheat	1075HarvesterX_4	3	3	1	0.7	25.82
	9660HarvesterX_6	3	3	1	0.7	48.32
combining	1075HarvesterX_8	4	16	2	0.8	26.425
	9660HarvesterX_7	4	16	2	0.8	49.43
	9660HarvesterX_9	5	6	2	0.9	31.643

X_{10}, X_{11}, X_{12} and X_{13} which are operating days in the operation can be the decimal, but the number of machine is integer. Compared the improved single-point crossover and multi-offspring genetic algorithm with traditional genetic algorithm, they are calculated on the MATLAB7.0 software in the same computer. The results obtained in Table 4 below.

Table 4. Comparison and Analysis Table

Variables	GA	SPGA	The actual equipment
The total number of 200 Harvester	4	4	2
The total number of 1075 Harvester	5	3	11
The total number of 9660 Harvester	3	2	0
The total cost of operation（Wan Yuan RMB）	73.855	51.935	66.365

It can be seen from Table 4 that single-point crossover and multi-offspring genetic algorithm (SPGA6) is better than the traditional genetic algorithm .Because the SPGA6 is less 2 sets of equipment and save 21.88 Wan Yuan, which shows that the improved genetic algorithm (SPGA6) is better to resolve the nonlinear mixed integer programming problem. Compared with the optimization results and actual production, it can be seen that the assembly work saved 14.43 Wan Yuan which indicated that the improved genetic algorithm has an important guiding significance for the actual production.

5. Conclusion

The study find out the more offspring number of single-point crossover and multi-offspring genetic algorithm is not making the speed faster, the time shorter and the more possibility. According to the different situations of offspring, we found that the number of offspring from 4 to 8 has the high operation speed, less iterative times and the shortest time getting the best individual. Then improving the Single-point crossover and multi-offspring genetic algorithm which is generated by the control in the 4 to the 8 generation, and it is applied to the harvesting machine equipped with the system model. Compared with the traditional genetic algorithm, it is the better for resolve nonlinear mixed integer programming problem.

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