An improved algorithm for flexible job shop scheduling

HAN Jin-dong[1]
School of Mechanical Engineering,Guilin University of Electronic Technology of China，Guilin 541004

ZHANG Ying-hong[2] *
School of Mechanical Engineering,Guilin University of Electronic Technology of China，Guilin 541004
E-mail zyh1433@sina.com

Abstract-In the traditional genetic algorithm, there are some defects such as precocious, poor stability, slow search speed etc.Summarize previous genetic algorithm, I proposed a Improved Genetic Algorithms , it combination of encoding, crossover probability, mutation probability, etc. and applied to flexible job shop scheduling.This optimization can accelerate convergence and improve search speed, and can effectively improve the stability of operations, effectively overcome premature, to find the optimal solution faster.The experimental results show this improvement more quickly than ever before to find the optimal solution of the genetic algorithm.

Key words—Improved Genetic Algorithm; Crossover probability; mutation probability; Flexible Job Shop Scheduling; Optimization

I. INTRODUCTION

Pipeline workshop now large-scale used limite the production steps products,the sequence of machining and the station of staff. Flexible job shop is different from the flow shop. It is a combination of flexibility, not used for large-scale production. There is no restriction on the machinepersonnel order strictly, Only processed products in accordance with the manufacturing process and assembly. This is more realistic production conditions, it is optimized for the study is also a hot spot today.

Flexible workshop machines and reduced personnel constraints, with great uncertainty.We need to maximize the production of machines and personnel in the labor intensity of the affordable range, which requires us to obtain the optimal solution product manufacturing minimum time, maximum yield and the like.At present methods can be used to search for the optimal solution of genetic algorithms, artificial immune algorithm, Memetic algorithms, particle algorithm, SFLA, bacterial foraging algorithm, ant colony algorithm and other algorithms.Genetic algorithm was first proposed by Professor Holland America. GA has a progressive optimization, guided random search, content parallel search, direct expression of the problem solution, robustness, versatility makes it the advantages of the more popular algorithms.

Improved genetic algorithm for current books and many papers. An improved adaptive genetic algorithm [1] ,Genetic Algorithm improvement strategies [2] etc. This paper will proposes a combination of such papers for flexible job shop scheduling optimization.

II. GENETIC ALGORITHM

Genetic algorithms are made by professor J.Holland in 1975. GA is the law of the evolution of the biosphere winning slightly elimination of the reference to a random search method, A kind of evolutionary algorithm. Computer artificial intelligence to solve a heuristic algorithm optimization. Initial Genetic algorithms obvious advantage but there is limited search capabilities for the new space, convergence to local optimal solution. Involving a large number of individual operation for a long time. For the problem of high dimension, it has a low processing speed.Because the genetic algorithm is a random algorithm, the need for multiple operation, the reliability is poor, can notstably obtained solution etc.We

need to improve on traditional genetic algorithm.

III. GENETIC ALGORITHM IMPROVEMENT STRATEGIES

Coding techniques and strategies

The main features are encoded closed, compactness, completeness, multiplicity, scalability, individual plasticity, modularity, redundancy and non-redundancy and complexity. For different applications Balakrishman had more comprehensive discussion of the characteristics of different encoding methods. Now commonly used coding methods can be divided into binary coding, coding and symbols floating point encoding three categories overall.

A. Binary code

Binary code is only 0 and 1 set of symbols. It has the advantages of simple encoding and decoding, crossover, mutation and simple. For some continuous function optimization search capabilities inadequate. Gray code can change this situation, it's formula is as follows.

Binary code conversion formula of gray code [2] :

$$\begin{aligned} g_m &= b_m \\ g_i &= b_{i+1} \oplus b_i, \quad i = m-1, \quad m-2...2,1 \end{aligned} \tag{1}$$

The gray code conversion formula of binary code:

$$\begin{aligned} b_m &= g_m \\ b_i &= b_{i+1} \oplus g_i, i = m-1, m-2,...2,1 \end{aligned} \tag{2}$$

Gray keeps the advantages of binary code, and enhance the ability of local searching, near optimal mutation does not generate new individual and maternal differences.

B. Floating point coding

For multi-dimensional, high-precision continuous function to find the optimal solution of the problem, there are some disadvantages of binary encoding. When binary encoding length is shorter, can not achieve the required accuracy. If the extended length encoding genetic algorithm is significantly expanded the search space, making the search time increased significantly.

Floating-point method is to use a float within a range of methods to express the gene.In the floating point coding must ensure that the crossover and mutation, the new entity is in this limits. The integer coding also belong to the floating-point coding. It has the advantages of high precision, convenient searching space, improve the complexity of the traditional genetic algorithm, improve the operation rate, easy to handle complex decision variable constraints.

C. Symbolic coding

Gene encoding symbol value by a number of non-meaning symbols, these symbols may be letters can also be digital. Such as {A，B，C，D，E，1,2,3}. The advantage is that the product of the number of blocks in line with meaningful, easy to use expertise in solving problems in the GA solution.

The probability of crossover and mutation strategies for improvement

The traditional method of genetic crossover and mutation probability is constant, so there early, slow convergence and other shortcomings.To cope with this situation generates an Adaptive Genetic Algorithm（AGA）。The main idea of this algorithm is using different crossover and mutation probability in the search of differentperiod. Based on the existing excellent genes, increase the adaptive mutation probability is low, so that the search out of local optimal solution.

This can speed up the convergence, improve the operation stability.

Genetic algorithm, the size of the rate-determining crossover generates new individual, the greater the crossover rate, the faster the speed of the new generation of individuals, the original pattern of the individual more susceptible to damage. Too small crossover will delay the generation of new individuals may appear premature. Mutation rate is a key operation out of a local, small mutation rate is not exhaustive generate new individuals may precocious, too GA mutation rate will lose its meaning becomes random search. Appropriate crossover and mutation rates are guaranteed a stable genetic algorithm solution. Traditional adaptive genetic algorithm crossover and mutation probability formula is as follows:

Crossover probability

$$P_c = \begin{cases} \dfrac{k_1(f_{\max} - f')}{f_{\max} - f_{avg}} & f' \geq f_{avg} \\ k_2, f' < f_{avg} \end{cases} \tag{3}$$

Mutation probability

$$P_m = \begin{cases} \dfrac{k_3(f_{\max} - f)}{f_{\max} - f_{avg}} & f \geq f_{avg} \\ k_4 \end{cases} \tag{4}$$

Type (i=1,2,3,4) is constant, $f_{\max}$ is the maximum fitness value, $f_{\min}$ is the the minimum fitness, f_{avg} is the average fitness value, f and f' are the current value of individual fitness.

Srinvas have proposed a genetic algorithm and improved method variance in terms of the cross, when an individual's fitness is below average fitness, it is found that it is vulnerable individuals, will have a great probability of being selected to participate in the crossover and mutation operations. If an individual fitness is greater than the population average fitness then it has a small chance to participate in crossover and mutation, and a high probability to be retained into the next generation.

The traditional AGA method is suitable for the environment to individual preservation, transformation is not suitable for the environment of individuals. When the search began, in f_{avg} below the individual will to the f_{avg} near, causing most of the individuals gathered in the right area of f_{avg}, thus resulting in search of stagnation and premature.In order to avoid this situation, we must maintain proper crossover and mutation frequency at f_{avg}, and in the nearoptimal solution also have small and not 0 crossover and mutation frequency. The improved crossover and mutation probability as shown in formula 5 and 6 [1] :

Crossover probability

$$P_c = \begin{cases} \dfrac{P_{c\max} - P_{c\min}}{1+\exp(A(\dfrac{2(f' - f_{avg})}{f_{\max} - f_{avg}} - 1))} + P_{c\min} & f' \geq f_{avg} \\ P_{c\min}, f' < f_{avg} \end{cases} \quad (5)$$

Mutation probability

$$P_c = \begin{cases} \dfrac{P_{m\max} - P_{m\min}}{1+\exp(A(\dfrac{2(f' - f_{avg})}{f_{\max} - f_{avg}} - 1))} + P_{m\min} & f' \geq f_{avg} \\ P_{m\min}, f' < f_{avg} \end{cases} \quad (6)$$

By equation (5), (6) shows that the individual crossover and mutation probability is based on the sigmoid function, between the maximum and average fitness fitness regulation. It is evident from Fig .1, when the majority of individual fitness improve, average fitness is also increasing, so most of the crossover and mutation frequency will be improved, to ensure that the search conducted. While the crossover and mutation frequency near the maximum fitness value is almost zero, they can retain the best individual genes. For the most part, as long as individuals make the most of the search will not appear on the evolution of stagnation and premature situation.

IV. CASE STUDY

A size of 1000×1000 workshop, Automatic feed materials using robots, robot initial position (0,0). When a station only raw material production to meet demand in the future time t_1, then issue a request to send materials. From the period of time after the receipt of the first request, the system received a number of requests. Then began directing the robot to send raw materials, raw materials required to meet all the needs in the shortest time t_2 ,and $t \geq t_1 + t_2$.

Suppose there are 10 stations emit delivery request to the requesting station numbered sequentially accept raw station coordinates are:

TABLE I Receives raw station plot

NO.	*Coordinate*	*NO.*	*Coordinate*	*NO.*	*Coordinate*	*NO.*	*Coordinate*
1	50,50	2	50,450	3	690,450	4	690,50
5	100,120	6	100,380	7	640,380	8	640,120
9	30,150	10	30,350	11	710,350	12	710,150
13	160,70	14	580,430	15	160,150	16	160,350
17	580,350	18	580,150	19	230,250	20	300,130
21	440,130	22	510,250	23	440,370	24	300,370
25	250,180	26	490,320				

Robot station needs to carry all the raw materials in order delivery. When receiving raw materials to be

distributed in the two-dimensional position, the path of the robot can be described as a departure from the first delivery point, the omission does not repeatedly go through all the delivery points, and finally return to the starting point.At this point the goal of optimizing the shortest path for the robot to walk. Reference traveling salesman problem (TSP), an optimization model to minimize the walking path as the goal:

$$\min L = \min \sum_{i=1}^{n} D_i \tag{7}$$

$$D_i = \begin{cases} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2} \, (i = 1、2、3 \ldots 9) \\ \sqrt{(x_i - x_1)^2 + (y_i - y_1)^2} \, (i = 10) \end{cases} \tag{8}$$

Genetic algorithm steps are as follows:

1) set the population size, the number of iterations, the probability of crossover and mutation, initializationcondition;

2) on population coding using floating-point coding, generation of initial population;

3) calculate the fitness of each individual of the population;

4) For individuals mutation and crossover operation produces a new individual populations;

5) Determine whether the end condition is met, such as the return is not satisfied in step (3).

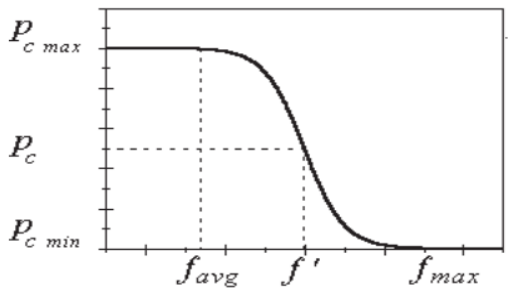

Figure 1. Adaptive crossover probability curve

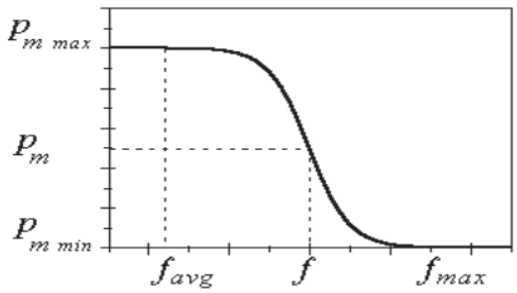

Figure 2. Adaptive mutation probability curve

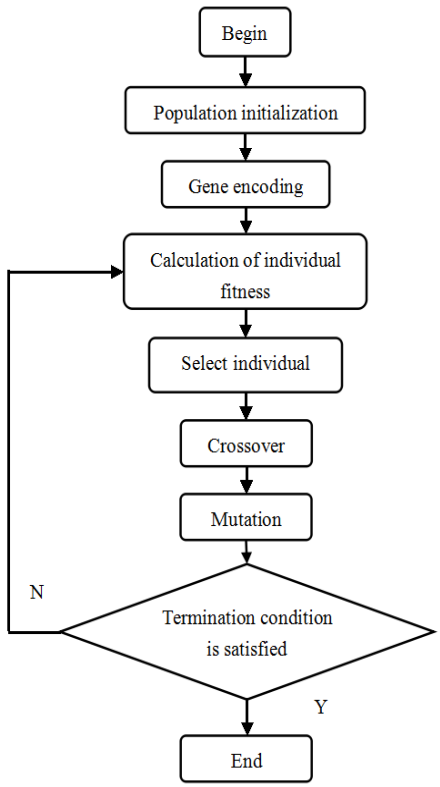

Figure 3. Genetic algorithm flowchart

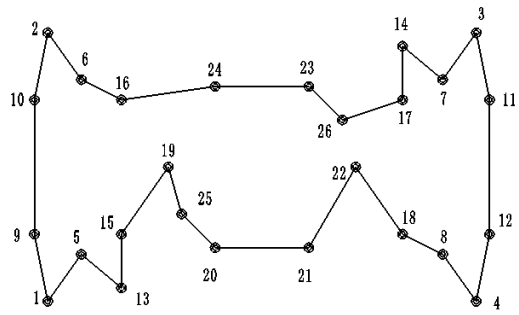

Figure.4. Improved Genetic Algorithm route map

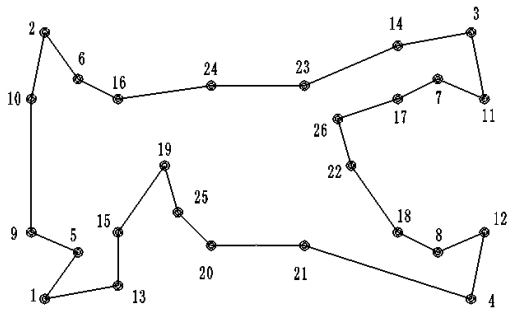

Figure.5. Genetic Algorithm route map

TABLE II Comparison of traditional genetic algorithm and improved genetic algorithm

Name	*Number of initial population*	*Crossover probability*	*Mutation probability*	*Maximum iteration algebra*	*Optimal solution (mm)*
Genetic Algorithm	100	0.8	0.1	50	3325
Improved Genetic Algorithm	100	Equation (5)	Equation (6)	50	2716

V. CONCLUSION

Genetic algorithm for solving complex optimization problems provide a new way, but the traditional genetic algorithm premature convergence speed and slow search speed and other defects. In this paper, all kinds of previous genetic algorithm improvements, given a combination of adaptive crossover, mutation probability of improved genetic algorithm and applied to flexible job shop scheduling. This method can largely compensate for the shortcomings of traditional genetic algorithms, improve reliability, convergence speed and search speed.

ACKNOWLEDGEMENTS

This research is supported by the Guangxi key laboratory of Manufacturing System and Advanced Manufacturing Technology under Grant No. 10-046-07_005， Guilin Key Technologies R & D Program under Grant No.20120118-4

REFERENCES

[1] Jin jing. An improved adaptive genetic algorithm[J]. Computer engineering and applications, 2005:64-69.

[2] Zhao Zhenyong Improved genetic algorithm and Strategy Research[J].Computer application, 2006-12:189-191.

[3] Li-Li Yao, SHI Hai-bo. Mixing line shop scheduling based on genetic algorithm for solvingmulti-objective[J]. Application Research of Computers, 2011-09:3264-3267.

[4] Xie Hao, Bao Sheng Ying, Yuan Bo.The genetic algorithm path flexible job shop scheduling optimization based on [J]. Journal of Wuhan University of Science and Technology, 2012-12:465-468.

[5] Zhang Guohui, Gao Liang, Li Peigen. An improved genetic algorithm for solving flexible job shop scheduling problem[J]. Chinese Journal of mechanical engineering, 2009-07:145-151.

[6] Qi Xiaoning, Wang YJ, Jia Jing.Shop scheduling based on genetic algorithm optimization for manufacturing green[J].Modular Machine Tool & Automatic Manufacturing Technique, 2012-10:16-18.

[7] Ling Ling, Wang Qingqing, Hu yuin. Holes machining path optimization based on Improved Genetic Algorithm[J]. Journal of Huazhong University of Science and Technology, 2009-08:88-91.

[8] L. De Giovanni,F. Pezzella.An Improved Genetic Algorithm for the Distributed and Flexible Job-shop Scheduling problem[J].European Journal of Operational Research ,200 (2010) 395−408.

[9] Jianchao Tang,Guoji Zhang,Binbin Lin, Bixi Zhang.A Hybrid Algorithm for Flexible Job-Shop Scheduling Problem[J],Procedia Engineering 15(2011) 3678−3683.

[10] Wang ling, Job shop scheduling with genetic algorithm[M],Beijing Tsinghua University press 2003