Solving Flexible Multi-objective JSP Problem Using A Improved Genetic Algorithm

Meng Lan [1], Ting-rong Xu [2], Ling Peng [3]
College of computer science, Soochow university, Suzhou, 215006, China
Email:lan83827@yahoo.cn

Abstract—**Genetic algorithm is a combinatorial optimization problem solving in the field of search algorithm, because of its versatility and robustness, it has been widely used in various fields of science. However, there are some defects in traditional genetic algorithm. for its shortcomings, this paper proposed an improved genetic algorithm for multi-objective Flexible JSP (job shop scheduling) problem. The algorithm construct the initial solution based on judging similarity strategy and immune mechanisms, proposed a self-adaptation cross and mutation operator, and using simulated annealing algorithm strategy combined with immune mechanisms in the selection operator, the experiment proof shows that, the improved genetic algorithm can improve the performance.**

Index Terms—**Similarity; adaptive cross-variation; immune mechanism; simulated annealing; multi-objective flexible job shop scheduling**

I. INTRODUCTION

Genetic algorithms (GA), inspired by the biological theory of evolution is proposed by J. Holland in 1975, its self-organizing, adaptive, self-learning and group capacity to make it very suitable for the evolution in solving large-scale complex combinatorial optimization problem [1]. Genetic algorithm is a kind of local search method in essentially, Its main idea is, the algorithm generated a number of feasible solutions of the problem randomly (ie, chromosomes) in the solution space of a problem, The algorithm starts from these initial feasible solutions, and calculates the fitness level of each chromosome according to the objective function, through the crossover ,mutation, selection and other operations so that chromosome populations evolving from generation to generation and eventually converge to an “optimal solution.” Genetic algorithm is a general-purpose optimization algorithm, its coding and genetic manipulation of the technologies are relatively simple, suitable for solving combinatorial optimization problems. It has two significant characteristics: First, the global solution space of the search capability; second is the implicit parallelism in the search [1]. Although the genetic algorithm has been shown be able to converge to the global optimum under certain conditions, but these conditions are not met yet in the real world. And the traditional genetic algorithm has some drawbacks like its weak local search ability and convergence of the shortcomings too fast or too slow, but the algorithm is still an excellent algorithm, and with the development of computer technology, genetic algorithms become a research hotspot. the shortcomings of the traditional genetic algorithm has been improved by many excellent scholars and experts, and make it success in the area of machine learning, pattern recognition, image processing, optimizing control and so on.

In this paper, multi-objective flexible job-shop scheduling problem, design an improved genetic algorithm. The traditional Genetic algorithms are often overlooked a critical part, which can inpact the speed and quality of whole evolution, that is, the initial solutions(chromosomes)is generated randomly, the quality of these randomly generated initial solutions is often not high or too focused on the solution space of some area, even through the latter part of the continuous improvement of genetic operators, it fall into local minima easily, leading to the global optimal solution can not be found. for this shortcoming of Algorithm, this article introduced species similarity and immunological principles of the algorithm in the initial stages ,so it can produce some high-quality solutions in initial phase, to improve the convergence speed and global search capabilities.

II. IMMUNE GENETIC ALGORITHM THEORY

Immune algorithm is similar to the biological theory of natural immunity. Immune operator is divided into full immunity and target immunity, the two correspond to the Non-specificity immunity and characteristics of immune-specific immunity in life sciences. Among them, the full immunity is carried out in every aspect of each individual immunization operation; the target immunity will occurred immune response in some given individual's point. The former major acting on the initial stages of individual evolution, and in the process of evolution does not occur in the essential role, otherwise, it would likely lead to "assimilation" phenomenon, and the latter will be accompanied by the whole process of evolution,it was one of the basic immune algorithm operator.

Fund：Suzhou Science and Technology Plan Project Fund .
Project ：Intelligence process control system development and application（110126）

Author[1]：Lan Meng，Male，Graduate student，Research direction is intelligence information system and system integration
Author[2]：Xu Ting-rong，Male, Associate professor，Master Tutor，Research interests include intelligent information systems and computer applications
Author[3]：Peng Ling，Female,Graduate student，Research directions is data mining

© 2010 ACADEMY PUBLISHER
doi:10.4304/jsw.5.10.1107-1113

Although the SGA (standard genetic algorithm) can improve the value of the chromosomes constantly through genetic operators, but the evolutionary procedure is randomly and accidentally, often resulting in the evolution is slow and even regress, because the SGA does not take full advantage of the characteristics of the problem information or empirical knowledge to guide the evolutionary process. The immune genetic algorithm is targeted at this problem has been improved, firstly ,it analyzing the issue(antigen) of extracting feature information (extracted vaccines), modify the chromosomes according to characteristic information, so the chromosomes can have a higher fitness value (vaccination). the set of all solutions produced by the program call antibody base on the vaccine; Finally, evaluate the modified chromosomes (immune selection), if its fitness value is higher than the parent generation, then let the new generation of offspring into the next generation of genetic evolution, or else, preserve the parent [4,10].

In the immunity algorithm, the vaccine correct choice has the very vital significance to the algorithm operating efficiency. It is the same as the coding of genetic algorithms, it is the based and security of the immune operator be able to effectively play a role in the algorithm. Must be explained that, select the pros and cons of vaccines to generate antibodies good or bad, will only affect the immune operator to play a role in the vaccine, and will not involve the convergence of the algorithm.

III. FLEXIBLE JOB SHOP SCHEDULING PROBLEM DESCRIPTION

Assumes that, there are n-parts$\{J_1, J_2, \cdots J_n\}$ has to go through m machines $\{M_1, M_2, \cdots M_m\}$ to process. A workpiece in a processing machine is called a "process." Workpiece processing sequence required the technical constraints, that is, the workpiece machining process, which is given in advance. Processing sequence is the first problem to solve. As each piece has its own unique processing routes to determine the processing order of the workpiece, then it belongs to job-shop (Job-Shop) of the scheduling problem [1], commonly used mathematical description is as follows:

$$\min \max_{1\le k\le m}\{\max_{1\le i\le m} c_{ik}\} \tag{1}$$

$$S.t.\quad c_{ik} - p_{ik} + M(1-a_{ihk}) \ge c_{ih}\ ,$$
$$i=1,2,..., n,\quad h, k=1,2,...,m$$
$$c_{ik} - p_{ik} + M(1-x_{ihk}) \ge p_{jk}\ ,$$
$$i, j=1,2,..., n,\quad k=1,2,...,m$$
$$c_{ik} \ge 0\ ,\ i=1,2,...,n,\quad k=1,2,...,m$$
$$x_{ihk} = 0,1\ ,\ i,j=1,2,...,n,\quad k=1,2,...,m \tag{2}$$

Formula(1) as the objective function, using minimize makespan; Formula(2) as the sequence of the workpiece processing order of the various processes and the sequence of various machines determined by constraint condition. c_{ik} is the completion time of workpiece i, p_{ik} is the processing time in machine k; M is a large enough positive number; a_{ihk}, x_{ihk} are instruct factor and instruct variable:

$$a_{ihk} = \begin{cases} 1, c_{ik} - p_{ik} > c_{ih} - p_{ih} \\ 0, c_{ik} - p_{ik} < c_{ih} - p_{ih} \end{cases} \tag{3}$$

$$x_{ijk} = \begin{cases} 1, c_{ik} - p_{ik} > c_{ih} - p_{ih} \\ 0, c_{ik} - p_{ik} < c_{ih} - p_{ih} \end{cases} \tag{4}$$

Flexible job-shop scheduling problem (Flexible job-shop scheduling problem, FJSP) is the expansion and extension of traditional job-shop scheduling problem and the a set of problem of many enterprises are facing in actual production procedure. In the traditional job-shop scheduling problems, the process of each workpiece can only be processed on a single machine. In the flexible job-shop scheduling problem, each process can be processed on multiple machines, and there are different processing time and processing costs in different machines. Flexible job-shop scheduling problem reduce the machine constraints, expand the search scope, and increase the difficulty of the problem [2].

Flexible job shop scheduling problem is not only to choose an optimal workiece scheduling order, but also to select machine for each workpiece processing, making the objective function to a minimum; In addition, processing of constraints needed to meet the following conditions:

(1) a machine can only process one piece of a process at the same time;
(2) The workpiece machining process can not be interrupted;
(3) the different processes of the workpiece have order;
(4) the process of the different workpiece, there is no priority;

IV. IMPROVED GENETIC ALGORITHM FOR JOB SHOP DESIGN

Genetic algorithm is a general-purpose random optimization algorithms, while the Job Shop problems is a special class of combinatorial optimization problems, in order to make GA to solve Job Shop issue better, on the one hand we can deal with the problem to adapt GA optimization, the other hand, GA can be processed to adapt the solution of Job Shop, more effective way is to deal with GA and Job Shop simultaneously to make them adapt to each other.

For the SGA (standard genetic algorithm) defect of slow convergence and fall into local minima easily[11], we hope that search algorithms can be carried out within a global search to avoid within a local search; the other hand, get some high-quality chromosome in the initial stage of the algorithm, so that future generations could inherit some good genes, and thus construct a higher fitness value of chromosomes to speed up the algorithm convergence speed.

© 2010 ACADEMY PUBLISHER

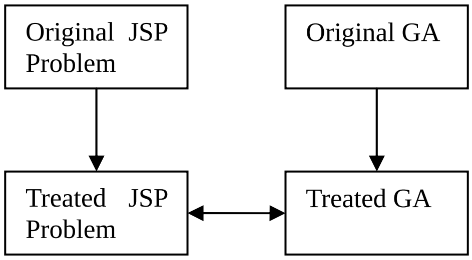


Figure 1. a optimization of GA and JSP

A. *Construct the initial solution*

While the randomness of the initial solution does not affect the limiting distribution in theory, but there are some fluctuations in the actual algorithm factors (such as cross-compilation operations on some approximation), so in order to maintain the population diversity and get some high-quality chromosome at the same time, the initial population is divided into two parts, for most of the chromosomes, first , judge the similarity between them [4,5,8], if their similarity higher than a certain threshold , then regeneration, to ensure that the initial distribution of chromosomes can be more evenly throughout the solution space, as shown:

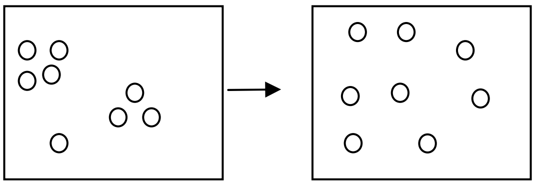


Figure 2. Dispersed distribution of chromosomes

The specific algorithm is as follows:

```
Num1=2*POPSIZE%3;
    for(i=0;i<Num1;i++){
        for(j=i+1;j<Num1;j++){
            if(diff(population[i],population[j])<f)
//f is the threshold，diff（x,y）is the similarity function；
                for(k=1;k<2* model.T_steps;k++){

population[k]=((int)(Math.random()*num_jobs))%(num_jobs)+1; …………
    //regeneration
    ………….
```

Similarity function using osine Formula: $\cos(A,B)=\dfrac{A\cdot B}{\|A\|\cdot\|B\|}$

For example: two chromosomes A(1,3,2,4) and B(2,3,1,4),using Consine formula : $\cos(A,B)\approx$ 0.96.

Select a part of the chromosomes using immunological theory, firstly , extract the vaccine through analyzing the problem. The algorithm extract vaccine through the use of characteristics of the demand information or a priori knowledge of the problem. The vaccine is not a mature or a complete individual, it only has the best individual gene loci on the possibility of partial characteristics. Choose this part of individuals, set up the individual for x1, x2, x3 ..... xn, vaccination vaccine by a priori knowledge, modify certain components of x by comparison, so as to produce a greater probability a higher fitness of the individual, and compare the old and new individual, if the individual to adapt to the emergence of new value is less than the old individual, the individual will retain the old one[4,10].

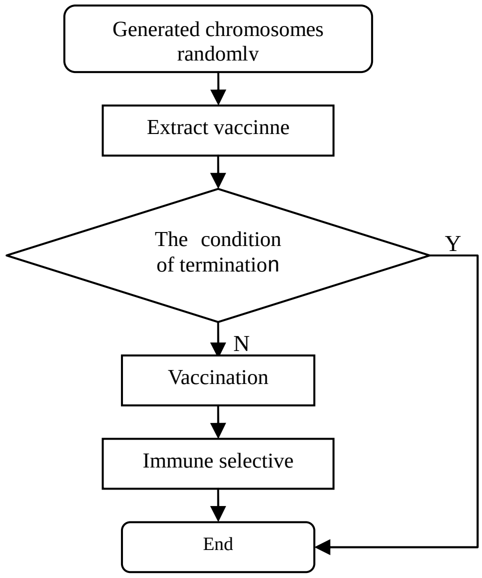
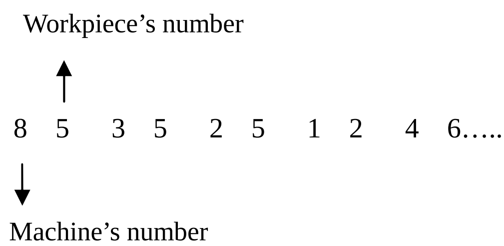


Figure 3. Immune genetic algorithm flowchart

The immune algorithm scatters the distribution of chromosome through the similarity computation and the modification of chromosome n the entire solution space, and produces some high grade chromosomes through the immunity genetic algorithm, not only guarantee population's quality and also guarantee its multiplicity, sharpened the genetic algorithm search ability greatly.

B. *Encoding*

The algorithm uses a real number coding in the paper. The length of chromosome is the twice of the sum of the process for all the workpieces. The odd bits in chromosome represents processing machine, while even bits stand for workpiece number. The ith appearences of the same workpiece number in the chromosome represents the ith processes of the workpiece.



The advantage of this coding is that,it can decode easily, and so can improve the execution speed.

© 2010 ACADEMY PUBLISHER

C. Self-adapting crossover and mutation

a) Several concepts for probability of self-adapting crossover and mutation

In the GA, the limited space of all the individuals is Ω ,the entire solution space of all the populations corresponding is P, once the number and length of a given chromosome is identified, then $|\Omega|$,which is the number of dimensions of Ω is limited, and $|P|^N$, the number of dimensions of P is also limited. As the status of each generation in the algorithm only related with crossover, mutation and selection operation, but not related with algebra, so GA algorithm can be viewed as a finite state homogeneous Markov chain. The cross-state transition matrix decided by crossover operation is labeled by $C=(c_{ij})_{|P|\times|P|}$,and c_{ij} is defined as the probability of cross-post from the state i to state j. while mutation operators determine the status of the transfer matrix $M=(m_{ij})_{|P|\times|P|}$, m_{ij} is defined as the probability of mutation from the state i to state j. and selection operation determine the status of the transfer matrix $S=(s_{ij})_{|P|\times|P|}$, s_{ij} is defined as the probability of selection from the state i to state j. The GA algorithm can be expressed as the following *Markov* chain:

$$P_k = CMSP_{k+1}$$

P_k is the state of the kth generation. C is the cross-state transition matrix, M is mutation transfer matrix and S is selection transfer matrix.

b) Design of adaptive crossover and mutation probability.

The important condition of Genetic algorithm convergence is to ensure that the optimal individual not to be destroyed or less destroyed, called the elitist strategy or a strategy for ensuring quality [6,7,9,12,14], in order to achieve this goal, we hope to give a lower crossover probability and mutation probability to chromosome with high adaptive value while higher crossover probability and mutation probability to chromosome with low adaptive value, so that in the evolutionary process the crossover can be eliminated as quickly as possible. Meanwhile, the adaptive crossover and mutation probability should be applied throughout the evolutionary process, At the start of the algorithm requires a relatively high probability of crossover and mutation in order to maintain population diversity, otherwise, in the initial stage, a number of individual with high adaptive value is difficult to cross with other individuals to exchange information. and genes of these outstanding individuals are difficult to be inherited and so resulted in premature convergence. In the final part of the algorithm requires a lower probability of crossover and mutation in order to expedite the convergence speed. In this paper we design crossover probability as follows:

$$p_i=\begin{cases}\eta^{-k}p_c, f_i>f_a\\ \eta^{-k}p_c(f_{\max}-f_i)/(f_{\max}-f_a), f_i<f_a\end{cases}$$

η is an adjustable constant, and between 1 and 1.02.and, if the algorithm converges too fast, then take a smaller number to slow down the speed of evolution, otherwise, take a bigger number to speed up the speed of evolution. K is the number of evolution. f_i is the value of individual fitness and f_a is the value of average fitness for the group. $f_{\max}$ is the highest adaptive value of the group. p_c is the crossover probability.

Crossing method using partially mapping cross, first, randomly select two crossover points, exchange the fragments of parent individual between two cross-points,for the genes remaining, if they does not conflict with the fragments changed ,they will be kept, otherwise, determine the genes through the partially mapping, until there are non-conflict genes in individule, and obtain the individual offspring finally. For example, there are two parent individuals $p_1=[264|7358|91]$, $p_2=[452|1876|93]$, if the cross-point is 3,7, then the fragment exchange. For the remaining genes, since Digital 2 does not conflicts with fragment (1876) ,keep digital 2, for digital 6, there is a conflict,and its mapping gene 8 are still conflicts, but for the digital 3 which is the mapping gene of digital 8, there is no conflict, it will be filled in the corresponding location of the child individual. Followed by analogy, we get the child individual $c_1=[234|1876|95]$, we can also get the other child individual $c_2=[412|7358|96]$ similarly. This operator meet the fundamental nature of the holland's Schema Theorem in a certain extent, the child individuals inherit an effective model of the parent individuals.

At the same time,we add a small-scale competitive merit-based operation in a small scope In the crossover operation, if a pair of parent chromosomes A, B, cross-post them n times, resulting in 2n offspring individuals, choose the highest fitness value of individual offspring to join the offspring queue, repeat the above operations, until generate the specified number of offspring of individuals. At the same time, after adding small-scale competitive merit-based operation, the algorithm can avoid the "inbreeding", such as chromosomes X, Y generated the x, y by the cross operation, in the next round of genetic operation, x, y may be selected as the new parents to run cross operations, the algorithm convergence rate can be speeded up.

c). Design of adaptive crossover operation

Mutation operator is just similar to the cross operator. The mutation operator design as follow:

© 2010 ACADEMY PUBLISHER

$$p_{mi}=\begin{cases}\theta^{-k}p_m,\ f_i>f_a\\ \theta^{-k}p_m(f_{\max}-f_i)/(f_{\max}-f_a),\ f_i<f_a\end{cases}$$

θ is an adjustable constant, and between 1 and 1.02.and, if the algorithm converges too fast, then take a smaller number to slow down the speed of evolution, otherwise, take a bigger number to speed up the speed of evolution. k is the number of evolution. f_i is the value of individual fitness and f_a is the value of average fitness for the group. $f_{\max}$ is the highest adaptive value of the group. p_m is the crossover probability.

D. Selection operator

Simulated annealing algorithm is an algorithm that simulated annealing process of crystals. that is suitable to solve multi-variable combinatorial optimization problems. The principle of this algorithm is:at the beginning of the algorithm, given an initial state solution and a large enough initial temperature, followed by the initial solution to generate a new solution compared with the objective function, if the objective function is less than the to accept the new solution to the current solution, otherwise, with probability $\exp(\frac{-\Delta}{T})$ to accept the new solution, and gradually iterated until the temperature reaches a constant temperature after the end of algorithm. Its characterized is that it can accept an inferior solution by a certain probability. In theory,it has been proved that, this algorithm can converge with probability 1 to the global optimal solution as long as the simulation process thorough enough. But in fact, it is difficult to simulate the annealing process was thorough enough, especially for large-scale problems, which requires very long computing time[16].

GA(genetic algorithm) and SA (Simulated annealing algorithm)are the optimization algorithm based on the the probability distribution mechanism, difference is that, SA act with serial optimize structure, and SA can effectively avoid falling into local minima and ultimately tends to the global optimization by giving an ever-changing and ultimately tends to 0 the probability of sudden rebound. And the GA use a parallel structure , it search the optimal solution through the groups evolved mechanism,. They are highly complementary to each other both in structure and mechanism.

So we introduce the strategy of simulated annealing algorithm to selection operator. if the parent p_1, p_2 generated c_1, c_2, after using crossover and mutation operator progency, after the calculation of the fitness, if $f_{c_i}>f_{p_i}$, i=1,2, then use c_i to replace p_i, otherwise, reserve p_i at the probability $\min\left[1,\exp(\frac{-\Delta}{T})\right]$ for the annealing algorithm. T is the initial temperature and gradually decreased over time, and eventually reach a constant value [3,6,10,11,15].

E. Selection of the objective function

Considering of the actual production process, a complex of various factors may impact production processes, there may be differences among different processing machines in their performance[17], this algorithm add two parameters ,which are processing efficiency and processing costs, to enhance the practicality of the algorithm. And in the selection of the objective function, the algorithm select the maximum completion time (makespan) and processing cost (cost) constitutes a linear function as the objective function:

$$f=\alpha\cdot C_{\max}+\beta\cdot \cos t$$

α and β are the weight of processing costs and maximum completion time respectily. The specific values can be adjusted accordingly, based on the actual situation.

F. Steps of improved genetic algorithm

(1)Input the parameter needed for the algorithm;

(2)Generate initial population of p_{size} chromosomes randomly, p_{size} is the population size;

(3) Compute the similarity between every two chromosomes, if the similarity is greater than a set threshold, then re-generate a new chromosome, so that chromosomes evenly distributed throughout the solution space;

(4) Select a part of chromosomes, generated by the immune system as part of a higher individual fitness;

(5) Evaluate the fitness value of each chromosome;

(6) Identify the best individual and the worst one and set them as global variables, and calculate the average fitness value;

(7) Carry out self-adaptive crossover and mutation operations;

(8) Introduce immune mechanisms and simulated annealing strategy to select operation;

(9) Determine whether to terminate the conditions met, if meet the conditions, then output the optimal solution. Otherwise, switch to (5) .

V. EXPERIMENT

A. Experiment parameter and data

In order to demonstrate the effectiveness of the improved GA algorithm, we test on a group of 10×8 test data, and compared with SGA (standard genetic algorithm), IGA (immune genetic algorithm) and SAGA (simulated annealing genetic algorithm) and select the maximum completion time (Makespan) and processing costs as the objective function. The initial mutation probability P_m = 0.1, crossover probability P_c = 0.9, similarity threshold f = 0.4,coefficient of annealing rate is 0.9, population is 300, and evolution algebra is 100. Algorithm using java language, the JVM (java virtual machine) platforms, as cross-platform nature of java language, allowing algorithms can run on any operating platform.

© 2010 ACADEMY PUBLISHER

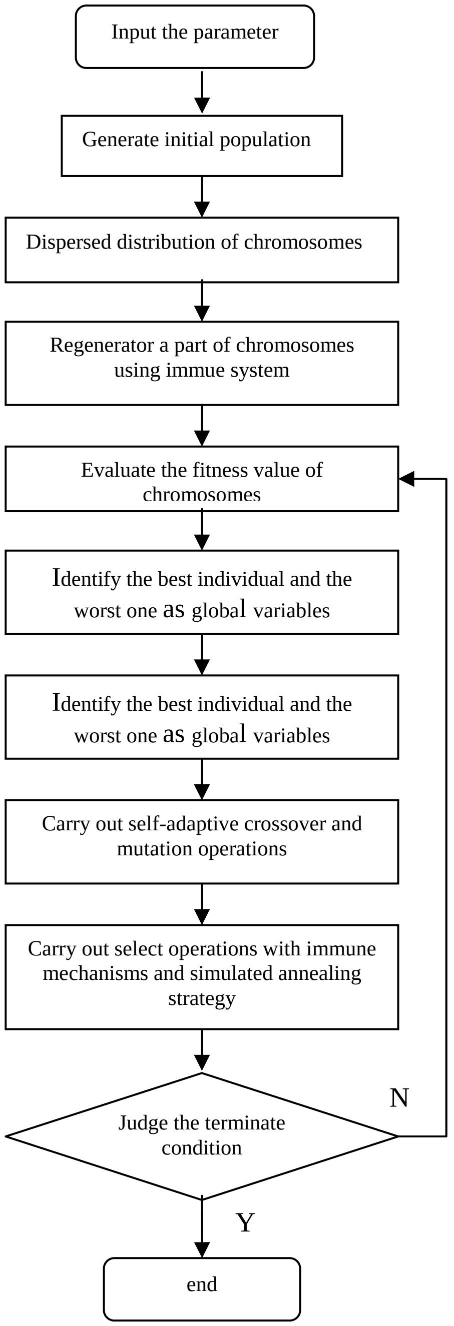


Figure 4. Algorithm flow chart

TABLE 1. Processing data

	Process1(time)	*Process2*	*Process3*
Workpiece1	*4*	*2*	*3*
Workpiece2	*5*	*1*	*8*
Workpiece3	*10*	*6*	*3*
Workpiece4	*3*	*4*	*5*
Workpiece5	*2*	*1*	*3*
Workpiece6	*1*	*4*	*5*
Workpiece7	*4*	*3*	*4*
Workpiece8	*9*	*2*	*7*
Workpiece9	*7*	*8*	*2*
Workpiece10	*8*	*2*	*7*

TABLE 2. Performance of Machine Processing

	Processing efficiency	*Processing costs*
Machine1	0.8	1
Machine2	0.7	2
Machine3	0.8	3
Machine4	0.8	2
Machine5	1.0	1
Machine6	0.8	2
Machine7	0.8	2
Machine8	1.0	1

Here, the weights of Processing cost and the maximum completion time are α = 0.4 and β = 6.0 respectively.

B. Experiment result

We can abtain these result following after running SGA,IGA,GASA and IGASA respectively about 100 times:

TABLE 3. Operational Results

	SGA	IGA	GASA	IGASA
Optimum	240.71	238.85	238.45	232.23
Average	322.96	323.56	318.12	310.18
End Generation	41	52	55	65

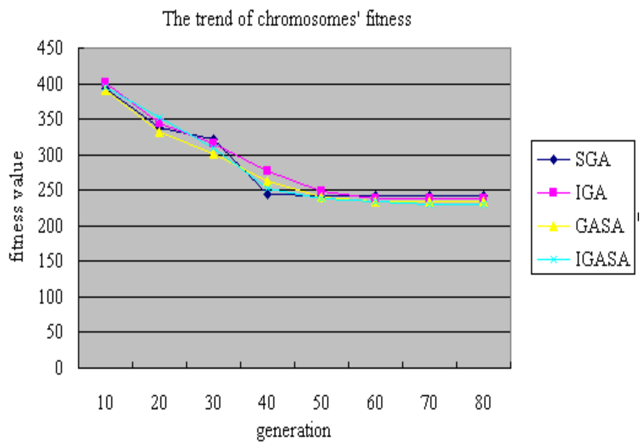


Figure 5. Comparison of SGA,IGA,GASA and IGASA

As table 3 and figure 5 shows, we can see that in the comparison with other algorithms, the optimal value computed by our improved genetic algorithm is better than other algorithms. And the initial value of populations is better than others due to adding immue algorithm and judging similarity of different chromosomes. While adding the adaptive crossover and mutation probability and simulated annealing strategies, enabling the improved genetic algorithm can better search and can also be more effective to prevent "premature" phenomenon. The following table shows one of the optimal scheduling results:

© 2010 ACADEMY PUBLISHER

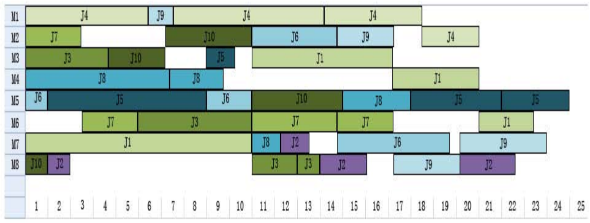


Figure 6. Optimal scheduling of a 10x8

VI. CONCLUTION

Flexible job-shop scheduling is more complicated np-hard problem, but also is a class of problem,which is the most pressing need to be solved in the actual production.

In this paper, after the research of the problem of multi-objective flexible JSP problem, according to poor local search ability, easy to "premature" and other defects of the traditional genetic algorithm, we proposed a new improved genetic algorithm by optimizing the initial population firstly through judging the similarity of each other, and in the computing process, introduce the immune system and simulated annealing strategy, and to add adaptive mutation and crossover probability in the genetic operators.

At last, the paper has done a lot of experiments to compare with other mixed algorithm. Experiments show that the algorithm improved the performance in a certain extent. And is also better than other mixed algorithms.

REFERENCES

[1] Grefenstette, J.J. Optimization of Control Parameters for Genetic Algorithms[J].. Systems, Man and Cybernetics, IEEE Transactions on,Jan. 1996,16(1): 122-128

[2] John wiley. Genetic algorithms and Engineering Design.Canada,1997

[3] F. Herrera, M. Lozano and J.L. Verdegay. Tackling Real-Coded Genetic Algorithms: Operators and Tools for Behavioural Analysis[J].Artificial Intelligence Review,1998,12(4): 265-319

[4] Kanpur Genetic Algorithms Laboratory. Multi-objective Genetic Algorithms: Problem Difficulties and Construction of Test Problems [J].Massachusetts Institute of Technology, 1999，7(3):205-230

[5] ONO ISAO, SATO HIROSHI, KOBAYASHI SHIGENOBU. A Real-Coded Genetic Algorithm for Function Optimization Using the Unimodal Normal Distribution Crossover [J]. Journal of Japanese Society for Artificial Intelligence,1999,14(6):1146-1155

[6] Il-Kwon J, Ju-Jang L. Adaptive Simulated Annealing Genetic Algorithm for System Identification [J]. Engineering Applications of Artificial Intelligence, 2001,9(6):523-532

[7] Kanpur Genetic AlgorithmsLaboratory .Self-Adaptive Genetic Algorithms with Simulated Binary Crossover [J]. Massachusetts Institute of Technology, 2001,9(2):197-221

[8] Gionis A,Indyk P,Motwani R.Similarity search in high dimensions via hashing.In:Atkinson MP,Orlowska ME,Valduriez P,Zdonik SB,Brodie ML,eds.Proc.of the 25th Int\'l Conf.on Very Large Databases.San Francisco:ACM Press,1999.518-529.

[9] Roberto Frias. A Hybrid Genetic Algorithm for the Job Shop Scheduling Problem[J]. AT&T Labs Research Technical Report TD-5EAL6J, September 2002

[10] Affenzeller M, Wagner. S.SASEGASA: an evolutionary algorithm for retarding premature convergence by self-adaptive selection pressure steering[C]//LNCS 2686 the 7th International Work Conference on Artificial and Natural Neural Networks (IWANN2003), Menorca,Balearic Islands,Spain,2003:438-445

[11] Park L J, Park C H. Robert.Genetic algorithm for job-shop scheduling problems based on two representational schemes[J]. Electronic Letters,1995,31(23):2051-2053

[12] Srinivas M. Adaptive probabilities of crossover anmutation in genetic algorithms [J]. IEEE Trans on Systems , Man and Cybernetics , 1994 , 4(24): 656-667

[13] Halena R L.Job-shop scheduling:computational study of local search and large-step optimization methods[J].European Journal of Operational Research,1995,83(1):347-364

[14] M Srinivas, L M Patnaik. Adaptive Probabiltiesof Crossover and Mutation in Genetic Algorithm [J]. IEEE Trans on SMC, April,1994,24 (4)

[15] S Kirkpatrick, CD Gelatt, Jr. M PVecchi. Optimization by Simulated Annealing[J]. Science, 1983,220:671～689.

[16] Grefenstette J J. Incorporating problem specific knowledge into genetic algorithm[C]. Genetic Algorithm and Simulated Annealing. Pitman , 1987: 42-60

[17] Gold berg D E,Richardson J. Genetic algorithms with sharing for multimodal function optimization[C]//Proc. 2nd Int. Conf. Genetic Algorithms and Their Applications. Hillsdale: Lawrence Erlbaum,1987:41-49.

© 2010 ACADEMY PUBLISHER