An Adaptive Immune Genetic Algorithm and Its Application

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Abstract. To avoid premature and guarantee the diversity of the population, an adaptive immune genetic algorithm(AIGA) is proposed to solve these problems. In this method, the AIGA flow structure is presented via combining the immune regulating mechanism and the genetic algorithm. Experimental results showed that the proposed AIGA can rise above efficiently such difficulties of SGA as precocious convergence and poor local search ability and provide well the global converging ability to enhance both global convergency and convergence rate, thus solving effectively the flexible job-shop scheduling problem (FJSP).

Keywords: flexible job-shop scheduling problem, immune genetic algorithm, immune operator, adaptive strategyvaccine.

1 Introduction

IGA (Immune Genetic Algorithm) is a improved algorithm based on biology immune mechanism, which is the combination of immune principle and SGA (Simple Genetic Algorithm) [1]. Immune algorithm is an effective global optimization algorithm, which adds the immune operations. And in some degree restrains the degradation in the optimizing progress and the late evolution stage. So, introducing the immune operator into GA can increase the algorithm overall performance. In the meantime it can restrains the unit degradation in the optimizing process by using the information characteristics, and increase the algorithm global convergence [2].

This article puts forward the improved IGA, which can not only add immune operators and also apply self-adaption strategy to overlap and variation operation, namely Adaptive Immunity Genetic Algorithm. By applying the algorithm to the flexible job-shop schedule example, the result shows the algorithm is effective and feasible [3].

2 The Model

The FJSP description is: N different processing sequence workpiece are finished on M machines .Each workpiece is processed by the same machine more than one time,

Y. Wu (Ed.): International Conference on WTCS 2009, AISC 116, pp. 373–380.
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and each process can't be enable to interrupt .We use U to denote each piece J contains nj processes, and each process order can't be enable to change. O_{ij} denotes J workpiece i process, which can be processed on any machine with processing capacity. $p_{i,j,k}$ denotes the time needed in process O_{ij} dealt by machine M. Let T denotes as follows:

$T = \left\{ p_{i,j,k} \middle| 1 \le j \le N; 1 \le i \le n_j; 1 \le k \le M \right\}$, N denotes workpieces, M denotes machines. Please see the table 1,which is a processing time of FJSP.

Table 1. Processing time of FJSP

		M_1	M_2	M_3	M_4
J_1	$O_{1,1}$	1	3	4	1
	$O_{2,1}$	2	6	2	1
	$O_{3,1}$	3	5	3	7
J_2	$O_{1,2}$	4	1	1	4
	$O_{2,2}$	2	3	8	3
	$O_{3,2}$	7	1	2	2
J_3	$O_{1,3}$	8	5	3	5
	$O_{2,3}$	3	5	8	1

In the FJSP, the assumptions as follow should be satisfied:

Every machine should be available at t=0,and every job may be started at t=0;

In given time one process can only be adopted by one time, another process can be scheduled after finishing the process, this is called source restriction;

Every job process only can be machined as scheduled and this is called precedence constraints.

The FJSP optimization goal reached in this paper is to find a most optimized schedule scheme satisfied the described precedence constraints and source restriction to make the makespan shortest.

3 Job-Shop Scheduling of Adaptive Immune Genetic Algorithm

Inspired by the immune system, an self-adaptive immune genetic algorithm was put forward, which can keep the original selection, crossover and mutation genetic operators. Premising the characteristics, change the crossover in different stages of genetic evolution, keep the excellent individual with genetic code, promote the optimal solution [4] .

1) Antigens recognition

Antigens recognition is to input the optimal designed objective function as an antigen immune genetic calculation. For the FJSP, the optimal designed index may be the performance indicator of the finished time, such as the maximum completion time; may be performance indicator of delivery: the maximum delay time; may be the performance indicator: the average stock for processing work packages [5-6]. This article adopt the maximum completion time as the FJSP optimal index.

2) Population initialization

According to the characteristics of problem solving, produce the antibody group. The reasonable design of antibody encoding mechanism has a great impact on IGA quality and benefit. The chromosomes legitimacy , feasibility , effectiveness and the integrity of the solution space representation must be considered when immune coding .This article adopts expression method based on the process, namely to assign the same sign to all the part, and then to explain according to the appearance order in the give chromosomes. If three parts, each workpiece have three procedure, chromosome "122313132 ", the first" 1 "denotes the first piece first procedure, the second "1" denotes the first workpiece the second process, the rest may be deduced by analogy [7].

3) Immune choice

a) Affinity evaluation valued operator.

Affinity denotes the combination intensity between immune cells and antigen, similar with IG fitness. Affinity evaluation valued operator usually is a function aff(x). The input for the function is antibody unit, and the output is the evaluated result. The affinity evaluation is related to the concrete problem, for the different optimal problems it is should define affinity evaluation function according to the characteristic of the problem under the premise of understanding the problem's substance. The article's affinity is defined as the max finished time [8].

b) Antibody concentration evaluation operator

Antibody concentration den(x) denotes the antibody population diversity good or bad. The antibodies concentration is high ,which means the similar units exit in large, so the search for optimization is focused on a sector in the available interzone, it goes against to the global optimization. So the optimal algorithm should restrain the high concentration units and keep the individual diversity. Antibody concentration is usually defined as:

$$den\left(ab_i\right) = \frac{1}{N}\sum_{j=0}^{N-1} aff\left(ab_i, ab_j\right) \tag{1}$$

Thereinto, N denotes population scale; ab_i denotes population i antibody; $aff(ab_i,ab_j)$ denotes the affinity between antibody i and antibody j.

$$aff\left(ab_i, ab_j\right) = \frac{1}{1 + H_{i,j}(2)} \tag{2}$$

Thereinto $H_{i,j}(2)$ denotes the average information entropy of the antibody group comprised of antibody ab_i and antibody $ab_{j.}$, which is defined as :

$$H_{i,j}(2) = \frac{1}{L}\sum_{k=0}^{L-1} H_{i,j,k}(2) \tag{3}$$

Thereinto L denotes the code length, $H_{i,j,k}(N)$ denotes the information entropy on the k gene of the antibody group comprised of antibody ab_i and antibody $ab_{j.}$, which is defined as :

$$H_{i,j,k}(2)=\sum_{n=0}^{S-1}-p_{n,k}\log p_{n,k} \tag{4}$$

In this formula S the allele quantity for every dimension in the discrete codes , such as binary system S=2, $p_{n,k}$ denotes the probability of the K dimension n allelic in the antibody group comprised of antibody ab_i and antibody ab_j.[9] .

c) Motivation efficiency calculation operator
Antibody motivation efficiency sim(x) is the final evaluation for the antibody quality , which should be considered the antibody affinity and antibody concentration. Usually high affinity low concentration antibodies will get more motivation efficiency [4]. The calculation of motivation efficiency usually can be got by using the evaluation for the antibody affinity and antibody concentration by simple mathematics, such as:

$$sim(ab_i)=aff(ab_i)\bullet e^{-a\bullet den(ab_i)} \tag{5}$$

And $sim(ab_i)$ denotes antibody ab_i motivation efficiency ; a and b is calculating parameter.

d) Immune optional operator
Immune optional operator Ts is based on antibody motivation efficiency to make sure which antibodies are chosen to clone operation. The higher motivation efficiency antibodies have better quality and easier to be chosen to clone operation, which can go on local search in more valuable search zone in search space. Immune optional operator are defined as:

$$T_s(ab_i)=\begin{cases}1, & sim(ab_i)\geq T\\ 0, & sim(ab_i)<T\end{cases} \tag{6}$$

Thereinto I denotes motivation efficiency threshold.

4) Clone operation
Clone operator Tc denotes duplicating the antibody units chosen by immune choice operator. Clone operator is defined as:

$$T_c(ab_i)=clone(ab_i) \tag{7}$$

In this formula $clone(ab_i)$ denotes the assemblage comprised of m_i clones the same with ab_i ; m_i antibody cloning quantity.

5) Self-adaptive crossover and variation
a) Population average information entropy

$$H(N)=\frac{1}{L}\sum_{k=0}^{L-1}H_j(N) \tag{8}$$

$H_j(N)$ denotes gene j information entropy:

$$H_j(N)=\sum_{n=0}^{S-1}-p_{i,j}\log_2^{p_{i,j}} \tag{9}$$

$p_{i,j}$ denotes the probability that i signal appearance on loca, namely :

$p_{i,j}$ = (the total quantity i signals on j) /N

b) Population similarity

$$A(N) = \frac{1}{1+H(N)} \tag{10}$$

A(N) represent the whole population similarity, $A(N) \in (0,1)$,The larger $A(N)$ is , the similarity of the population higher, vice versa. When $A(N)=1$, each antibody in the population is totally the same.

c) Self-adaptive strategy
Crossover probability p_c and variation probability p_m is the two important parameters in IGA, no matter huge or small ,which will effect the algorithm convergency rate directly. It is difficult to find an optimum suitable for every problem to the different optimal problem. Self-adaptive strategy is able to make the p_c and p_m change voluntarily following the population diversity. When the population unit fitness tends to the same or tends to local optimum, p_c and p_m increase. When the fitness tends to dispersion p_c and p_m decrease. p_c and p_m adjusts by the following formula.

$$p_c = e^{2(A(N)-1)} \tag{11}$$

$$p_m = 0.1e^{2(A(N)-1)} \tag{12}$$

6) Vaccine extraction
Supposed each generation keeps K_b fitness optimal antibodies, the latest K (current generation included) generation totally keeps antibody group comprise of $K*K_b$ optimal antibodies, every gene loci of each antibody has $k_1, k_2, \cdots, k_s$ five selectable signs. The probability that i is k_i is $p_{i,j} = \frac{1}{K*K_b}\sum_{j=1}^{K*K_b} a_j$,when $g(i)=k_j$, $a_j = 1$, if not , $a_j = 0$. $g(i)$ is the i allele sign in the population. The allele maximum probability (namely $p_i, i=1,2,\cdots,L$) k_j is taken as the allele vaccine section, thereby to extract the vaccine $H = (h_1, h_2, \cdots, h_L)$.

7) Vaccine inoculation
Selecting the antibodies needed inoculation from the father generation, to get the new immune units which are replaced by one or more gene segment according to the roulette, thus forming the more excellent group. The gene segment selection way is as following: from section 3.6, vaccines are denotes $H = (h_1, h_2, \cdots, h_L)$, supposed $q_i = \frac{p_i}{\sum_{j=1}^{L} p_j} (i=1,2,\cdots,L)$, correspond with h_i, the p_i is same with section 3.6.

According to principle of gambling wheel, q_i partitioned the whole disk. The probability that every vaccine is chosen depends on q_i.

8) Clone restrained operator

Clone restrained operator choose the units operated following the mentioned above, restrain the low affinity units, retain the high affinity units, form the new antibody group. In the cloning process, the original antibodies and clone antibodies, by crossover variation and vaccination,then form a temporary antibodies group X_{ti} , cloning restrained operation will keep the highest affinity units, restrains other antibodies. Cloning restrained operator may be defined as the following:

$$T_r\left(X_{ti}\right) = ab_i^* \tag{13}$$

ab_i denote the highest affinity antibodies in the gather X_{ti} , aff(ab_i)=max{aff(ab_k, $ab_k \in X_{ti}$}. Because of cloning, the original antibodies in variation operator operation is excellent units, and cloning restrained operator temporary antibodies group includes the father original antibodies, so the artificial IA operator implicates optimal units reservation scheme [8].

9) Population refresh operator

Population refresh operator T_d refresh the low motivation units, cancel this antibodies from antibodies group and generate the new antibodies randomly ,which is useful for the antibody diversity and searching for the new feasible solution space. Population refresh operator is defined as the following:

$$T_d\left(X_n\right) = X_n^* \tag{14}$$

X_n is the low motivation antibody gather, X_n^* is the new antibody gather randomly, and gather X_n^* and gather X_n has the same scale.

4 Simulation

Because many factors will be considered in the actual production process, scheduling problem is also very complex, so in different production system, JSP exist some differences. Taking a manufacturing processing workshops as the example, simplify the production data , design a simulation with 7 workpiece, 6 processes , a total of 11 machines to complete assignment. The specific workpiece, processes, machinery and processing information are in table 2, 3, and 4 following. In table 2, 1 denotes the processes that can be completed by machines and 0 denotes not.

Table 2. Working procedure-machine relationship

	Turning M1	Turning M2	Boring M3	Milling M4	Milling M5	MC M6	MC M7	MC M8	Grinding M9	Grinding M10	Planning M11
Turning	1	1	0	0	0	1	1	1	0	0	0
Milling	0	0	0	1	1	1	1	1	0	0	0
Planning	0	0	0	0	0	0	0	0	0	0	1
Grinding	0	0	0	0	0	0	0	0	1	1	0
Drilling	0	0	0	0	0	1	1	1	0	0	0
Boring	0	0	1	0	0	0	0	0	0	0	0

Table 3. Workpieces procedure information

	working procedure					
Work-pieces	1	2	3	4	5	6
J1	Turning	Milling	Planning	Boring	Drilling	Grinding
J2	Milling	Grinding	Boring	Drilling	Turning	Planning
J3	Boring	Drilling	Turning	Planning	Grinding	Milling
J4	Grinding	Planning	Drilling	Turning	Milling	Boring
J5	Planning	Turning	Grinding	Milling	Boring	Drilling
J6	Turning	Boring	Milling	Grinding	Drilling	Planning
J7	Drilling	Boring	Grinding	Milling	Planning	Turning

Table 4. Working procedure over time

		J1	J2	J3	J4	J5	J6	J7
Turning	M1	4	6	4	7	9	3	3
	M2	3	5	3	8	8	5	2
	M6	4	7	7	5	7	7	4
	M7	5	6	6	6	6	8	5
	M8	5	5	5	4	5	8	4
Milling	M4	3	5	8	4	3	9	4
	M5	2	6	7	3	5	10	6
	M6	5	9	4	5	7	8	7
	M7	4	8	6	6	5	8	6
	M8	6	7	5	5	5	6	8
Planning	M11	4	5	3	7	3	4	5
Grinding	M9	7	3	4	8	6	8	6
	M10	6	5	4	7	4	6	4
Drilling	M6	4	6	5	4	9	3	5
	M7	6	4	4	6	7	4	6
	M8	5	7	6	5	8	3	5
Boring	M3	5	3	3	6	4	6	7

Table 5. Simulation parameters for three algorithms

Algorithms	population quantity	crossover probability	variation probability	vaccination probability	Cloning size	generations
GA	200	0.9	0.1			300
IGA	200	0.9	0.1	0.2		300
AIGA	200	0.9	0.1	0.2	30	300

This article adopt the GA, IGA and AIGA to dispatch the example separately , the parameters for each algorithm is just as table 5. From the result, the SA-IGA property introduced in this article is better than GA and IGA. SA-IGA not only can keep the population diversity, accelerate the evolution speed, but also avoid the early convergent phenomenon in the evolution process.

5 Conclusion

This article analyzes the GA principle and convergence and puts forward the GA improved strategy introduces immune operator and self-adaptive strategy, forms the SA-IGA and applied it to the FJSP. Immune operator can prevent degeneration phenomenon in the population units re-crossover and re-variation process, self-adaptive strategy keeps the population diversity and algorithm convergence [10]. The result shows AIGA can resolve the FJSP quickly and effectively.

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