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Parameterization of Genetic Algorithm for Job Shop Scheduling

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ABSTRACT

The present paper explains the effect of GA (Genetic Algorithm) parameters such as population size, crossover rate, mutation rate using DOE (Design of Experiments) on GA performance when determined on a real world job shop scheduling problem. The objective of DOE is to experimentally seek good parameter values that give a cause effect relationships between the GA factors and the GA's response. When the significant factors were found their levels were decided using Taguchi's signal to noise(S/N) ratios technique. A software module was developed that generated optimum schedule using GA algorithm and the results were compared with purely random search after which the design of experiments were performed. Although numerous solution methods like branch and bound method exist for solving this problem, the present work uses genetic algorithm as it does not get normally struck in local minima as compared to other traditional scientific techniques. Weighted completion time is the optimization criterion here that gives consideration to relative importance of different products thus providing better services to the customers.

Keywords: Job Shop Scheduling Problem (JSSP), Genetic Algorithm (GA), Signal-to-noise(S/N), Design of experiments (DOE), Analysis Of Variance (ANOVA), Weighted completion time (WCT).

Introduction

In a general job shop there are a set of m machines and n jobs to be scheduled. Each job requires some operations that are to be processed in a particular sequence. Jobs may not require processing on all the machines and they may require some machines more than once. Also there may be multiple copies of the same machine that can process the jobs. Scheduling allocates time intervals on one or more machines to each of one or more jobs. The required inputs are the list of the operations of each job, the amount of time of each operation, and list of any precedence constraint that explains which operation need to precede other operation.

Basically three different classes of solution methods exist for job shop scheduling problems. Integer-Linear Programming methods guarantee that optimal solution to the problem would be found but have computational complexity, which often results into high running time, especially with large problems. On the other hand, Heuristic Methods use set of the rules in order to determine optimum schedule for the problem but they sometimes get struck in local maxima or minima. Evolutionary methods seldom find the optimal solution, but usually generate an acceptable solution faster. One of the widely used evolutionary methods is Genetic Algorithm (GA) [1]. The algorithms solve a problem using the evolution principle. In this search process a new solution is generated using genetic operators known as selection, crossover and mutation. This is repeated until some condition like number of populations or improvement of the best solution is satisfied.

Our intention in this research is to find out the effect of parameters such as population size, crossover rate, mutation rate on GA performance [2] for above job shop problem using design of experiments. Also the objective is to find those parameters whose interaction among them has an effect on the performance of the GA. This will help in selecting the parameters at such levels so that their effects do not counter each other. We also intend to find the level of relevant factors using Taguchi's signal-to-noise (S/N) ratios technique.

1.1 ***Job Shop Scheduling Problem (JSSP):***

The job-shop scheduling problem (JSSP) can be described as a set of n jobs denoted by J_j where j =1.....n which have to be processed on a set of m machines denoted by M_k where k=1,...m. Operation of j_{th} job on the k_{th} machine will be denoted by O_{jk} with the processing time p_{jk}. Each job should be processed through the machines in a particular order There is a processing order of each job on each machine known as technological constraint.We assume that setup times are included in the specification of the total processing time. The times required for all operations are called make span. In this paper our objective is to minimize makespan.

Implementation of genetic algorithm for generalized job shop scheduling starts with Generating a sequence of operations called the Assignment Sequence using some technique [3] and then the sequence is assigned to resources to get feasible solutions to the first generation. This is known as initial population. Objective function value of each individual is calculated as fitness value. Minimizing weighted completion time [4],[7] is the optimization criteria here that give consideration to relative importance of different products.

Min W = $\sum_{i=0}^{N}(P_i * C_i)$ Where C_i = completion time of i^{th} product, N = No. of products,

P_i = priority of i_{th} product

In selection, for a certain percentage of population, the top elite individuals are selected from the previous generation. From the rest of the population, tournamenting is applied in which any two individuals are randomly picked up from the previous generation and the better individual is retained. The other individual is returned back into the pool of unselected individuals in the population. For crossover two individuals are randomly picked up from the population and are combined in certain ways to produce daughter solutions. We have examined the effect of two different types of crossover methods on the effectiveness of the program. They are one point crossover and two point crossover. The adjacent-two-job change mutation operator has been implemented in this project. An operation here is chosen randomly from the given sequence of operations, excluding the last operation. All the immediate successors of this operation are examined to see if the next operation in the assignment sequence is an immediate successor or not. If the next operation is not an immediate successor of the selected operation, then the two operations are interchanged. Calculate objective function value of each individual again. If the termination criteria (number of population here) is met solution is achieved else again search for the solution by applying selection, crossover and mutation [8].

2.Problem Description

Problem considered consists of total 31 operations on 14 products. All products have same release time. Products have inter-product precedence relationship. Sequence of operations on each of the 14 products has been given. Priority of each product is different. Processing times of each product are given. In total there are 10 resources.

Table1- Job shop showing products and machines occupied along with their processing times and sequence

Job No.	Job Description	Operation1	Operation2	Operation3	Opeartion4
P1	Base plate	GSP(15)	Bh(8)	-	-
P2	Top plate	GSP(15)	Bh(8)	-	-
P3	RetainerBlock	Ml(6)	GrC(4)	-	-
P4	Setting Block	GrS(10)	-	-	-
P5	Pillar	GrC(3)	-	-	-
P6	Pillar	GrC(3)	-	-	-
P7	Die Plate	Ml(12)	Gr(4)	JGr(4)	Bh(8)
P8	Shank	Ml(1)	-	-	-
P9	Aux. Bush	Tu(6)	GrC(6)	-	-
P10	Aux. Bush	Tu(6)	GrC(6)	-	-
P11	Die Insert	GrC(3)	-	-	-
P12	Locator	Tu(1)	CNC(8)	GrS(3)	JGr(1)
P13	Strippingblock	CNC(8)	Gr(2)	GrS(4)	JGr(2)
P14	Strippingblock	CNC(8)	Gr(2)	GrS(4)	JGr(2)

Inter product precedence relationships

- GrC(P3) – Bh(P1)
- GrC(P11) – Bh(P1)
- Ml(P8) – Bh(P2)
- GrC(P10) – Bh(P1)
- GrC(P6) – Bh(P1)
- GrS(P4) – Bh(P1)
- JGr(P14) – Bh(P2)

3. Model Development and Experimentation

The results of the optimum schedule were generated after 40th generation with various parameter values for the above problem using genetic algorithm. Our objective here is to experimentally seek good parameter values that give a *cause–effect relationships* between the *GA factors* and the *GA's response*. All the main factors have been examined at only two levels and a partial factorial design has been used. This would also allow investigation into effect of interaction among factors. The levels chosen for each of the factors are as follows:

Table 2 - GA Factors and levels

Factors Code	Factors	Level 1	Level 2
A	Population size	10	20
B	Crossover Probability	50%	80%
C	Mutation Probability	5%	20%
D	Type of crossover	1 point crossover	2 point crossover

The experiment was conducted in the standard DOE format in 'trials'. In each trial the factors are set at two different levels (level 1 or level 2) with two replications. L8 Orthogonal array [5] was selected for the present experimentation. Each row in the array shows the settings for trial and each column in the array may be assigned to a factor. Some column values show the interaction of the columns at each of the x axis and the y axis.

Table 3 - L-8 Array with assignment of columns

Exp/TrialNo.	a	b	axb cxd	c	axc bxd	bxc axd	d	WCT Observation1	WCT Observation1
	1	2	3	4	5	6	7		
1	1	1	1	1	1	1	1	7	14
2	1	1	1	2	2	2	2	12	10
3	1	2	2	1	1	2	2	8	13
4	1	2	2	2	2	1	1	7	9
5	2	1	2	1	2	1	2	19	14
6	2	1	2	2	1	2	1	17	15
7	2	2	1	1	2	2	1	12	13
8	2	2	1	2	1	1	2	11	6

The experiments were conducted by varying the factors strictly according to the L8 Orthogonal array. The experimental data was obtained when each GA run of each trial was run for 40 generations assuming GA would get sufficiently close to the true unknown optimum solution. The analysis (ANOVA (analysis of variance) analysis) was done using the best value achieved of objective function in the last (40th) generation.

Table 4- ANOVA Table

Factor	SS	v	V	F	$F_{\alpha=.05,v1,v2}$	Decision
A	45.56	1	45.56	9.51	5.32	Significant
B	52.56	1	52.56	10.97	5.32	Significant
C	10.56	1	10.56	2.204	5.32	N.S
D	0.063	1	0.063	0.013	5.32	N.S
AXB	18.06	1	18.06	3.77	5.32	N.S
AXC	1.563	1	1.563	0.326	5.32	N.S
BXC	10.56	1	10.56	2.204	5.32	N.S
CXD	18.06	1	18.06	3.77	5.32	N.S
BXD	1.563	1	1.563	0.326	5.32	N.S
AXD	10.56	1	10.56	2.204	5.32	N.S
Error	38.33	8	4.79			
T	205.75	15				

As per above parameterization experiments the significant factors/interactions are

(i) Population Size (ii) Crossover probability

4. Analysis of experimental results

The goal of the experiment is to increase the factors that work in favour of performance within the chosen controllable factors and reduce the noise factors that work in against the performance from environmental (uncontrollable) factors and thus make the system unfavourable to noise and thus decrease the variation of measurable characteristics.

To measure the performance measures characteristics, Taguchi's signal-to-noise ratios known as S/N ratio have been used. After finding relevant factors, the level of each of them is to be decided using this technique. Here smaller-the-better performance measure is used as criteria, thus maximizing the S/N ratio [6] for a factor is equivalent to minimizing the objective function (weighed completion time).

For smaller-the-better type performance measure:

S/N ratio for WCT $=-10log_{10}(1/n \sum y_i^2)$

For n observations of values y_i in each trial.

The effect of a control factor at a defined level can be evaluated using the experimental data. The average S/N ratio for each factor at each level is average of S/N ratio for all experiment where level of that factor is either of two levels.

Thus the optimal level for each factor can be determined as the level that has largest value of S/N ratio. The calculations and results according to our experimental data are shown as under:

Exp No	1	2	3	4	5	6	7	8
S/NRatio	-20.88	-20.86	-20.66	-18.13	-24.45	-24.09	-21.95	-18.95

Table 5-Avg. S/N Ratio for each factor at each level

Significant Factors	Level 1	Level 2
Population Size	-20.14	-22.36
Crossover Probability	-22.57	-19.92

It can be concluded that the optimal level of population size is 1 and that of crossover probability is 2.

Another experiment was conducted to compare the effectiveness of the GA developed with purely random search. A random sample of WCT values of size n is selected, and the sample mean (X bar) and sample variance ($s^{2)}$ are calculated. The sampling distribution of the quantity is $(\overline{X} - \mu)/(s/\sqrt{n})$ which is known as a t-distribution with (n-1) degrees of freedom.

A sample size should be 30 or more to allow a close approximation of a normal distribution.

A 100(1- α)% two sided confidence interval for the population mean μ is given by,

$$\vec{X} - t_{\propto/2, n-1}\, {}^{s}/_{\sqrt{n}} \leq \vec{X} + t_{\propto/2, n-1}\, {}^{s}/_{\sqrt{n}}$$

Where $t_{\alpha/2,\ n-1}$ represents the axis point of the t-distribution where the right tail area is $\alpha/2$ and the number of degrees of freedom is (n - 1).

A random sample of 30 readings of WCT are taken and with a confidence level of 95%, the interval obtained is

$11 \leq \mu \leq 14$.

5. Results and Discussion

The work on this paper started with the desire to solve a real life Job Shop problem using optimizing methods. One such problem was identified and mathematically formulated. A case of a job shop scheduling problem was studied and the optimum schedule was generated after 40 generations. The research study demonstrated that choosing suitable genetic operators and parameters like mutation rate, crossover rate and population size of genetic algorithm are an important criteria to get better optimal results. The effect of all the main factors of GA on GA's performance have been examined using DOE and the significant factors were found to be Population Size and Crossover probability. Their levels were then decided using Taguchi's signal to noise(S/N) ratios technique and hence an optimum value of schedule is found.

A comparison of genetic algorithm was made with purely random search where interval estimation of population of objective function value was done assuming the sampling distribution of the above quantity follows a t-distribution. On comparing the results with genetic search it is seen that some values obtained in various generations in genetic search are lower than the lower confidence interval above. Hence it is understood that genetic search produced better results than 3σ limit of random search distribution of objective function.

Appendix:Notations for machines/operations

GSP	Special purpose machine
Bh	assembly
Ml	Milling
GrC	Centerless grinding
Gr	Grinding
GrS	Surface grinding
Tu	Turning
JGr	Jig Grinding
CNC	Computer Numerical control

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