A Genetic Algorithm Based Approach to Job Shop Scheduling with Sequence Dependent Setup Times

Suresh Holi#, B P Shivakumar*
 # Research Scholar, Department of Mechanical Engineering, JSS Academy of Technical Education, Bengaluru, India
(Affiliated to Visvesvaraya Technological University, Belagavi, INDIA).
**Department of Mechanical Engineering, JSS Academy of Technical Education, Bengaluru, India*
 # Corresponding Author

***Abstract* — The paper presents a Genetic Algorithm (GA) approach to solve Job Shop Scheduling Problem (JSSP) with Sequence Dependent Setup Times (SDST) and assess effect of different combinations of crossover probability and mutation probability on makespan performance measure. Six case studies of varying sizes ranging from five parts, five machines to fifty parts, fifty machines are taken into consideration. Results for six case studies are generated for four different combination of crossover and mutation probabilities in a manufacturing scenario where setup times are equal to operation processing times. It indicates that the effect of crossover and mutation probability combination of 0.85 and 0.15 respectively results in optimal makespan.**

***Keywords* — genetic algorithm; job shop scheduling; sequence dependent setup times; makespan; crossover probability and mutation probability.**

I. INTRODUCTION

To remain in competition in ever changing markets, production scheduling activity plays a major role at the operational level in optimizing performance measures (Fuchigami & Rangel, 2018). Since scheduling is associated with making decisions of allocating resources to perform tasks overtime (Pinedo, 2016), it leads to efficiency and capacity utilisation, reduction in time to complete tasks, thereby increasing profitability for an organisation (Vinod & Sridharan, 2005).

Literature on different scheduling problems is abundantly available since last six decades in manufacturing and service companies for potential research from various perspectives.

The classical job shop consists of scheduling a set of ‘n’ jobs (part types) to be processed on a set of ‘m’ machines (Phanden & Jain, 2015). Each machine has a set of operations to be performed on each part in a particular order and each machine can process at most one operation at a time. Thus, (JSSP) deals with allocation of parts to various machines with the objective of minimizing the makespan, mean tardiness, number of tardy jobs, mean flow time or any other objective.

Each job (part type) has a certain processing time associated with it and additionally may require setup time on machines before next operation on the job. This may be due to the machines either being reconfigured or require cleaning between jobs. The setup times are said to be sequence dependent if duration of setup depends on completion of present job and immediate next job to be processed (Moghaddas R, 2008).

There has been appreciable interest among researchers in the recent years for considering sequence dependent setup times because business entities produce variety of goods using common resources wherein need for setup arises.

Job Shop Scheduling (JSS) was primarily treated by branch and bound method and other heuristic approaches based on priority rules. However, lately modern heuristics viz. Simulated Annealing, Tabu Search, Ant Colony Optimization, Particle Swarm Optimization, Fire-fly algorithm, Genetic Algorithm, Neural Network, and many other approaches are adopted to solve job shop scheduling problem producing high quality solution with reasonable computational effort (Wang & Zheng, 2002). Genetic Algorithm (GA) have been shown to be able to outperform conventional optimization techniques on difficult, discontinuous, multimodal, noisy functions.

In the present work, an attempt is made to assess the effect of crossover probability (pc) and mutation probability (pm) on the optimal performance measure of makespan.

II. LITERATURE SURVEY

The literature review of (Allahverdi et. al, 1999, 2008) scheduling with setup time considerations clearly indicates considering or neglecting setup as part of processing time can very severely affect the solutions quality. Also report that job shop with sequence dependent setup times (SDST) are much significant when operated with partial or full capacity in plant. The literature (Sharma & Jain, 2016) gives a comprehensive review on job shop scheduling with setup times and present the researchers with future areas to work upon. Job Shop Scheduling (JSS) problems are known to be most difficult NP hard combinatorial optimization problem, hence, heuristics are preferred to solve them with enhanced flexibility (Cheung & Zhou, 2001, Phanden et al, 2012). Genetic Algorithms are capable of tackling both discrete and continuous optimization problem (Naderi & Zandieh, 2009).

Several researchers have attempted to solve JSSP with sequence dependent setup times with the objective of minimizing performance measures makespan, mean tardiness, mean flow time, etc. However, literature survey on impact of crossover probability and mutation probability on performance measures is quite limited. Long Xu and Wenbin Hu (2012) compared the efficiencies of 36 combination of genetic operators and studied the effect of crossover and mutation probability on performance using genetic algorithm for JSSP with operation-based representation scheme and concluded that one point crossover operator and shift mutation operator outperforms the other combinations for the sample JSSP instances of the OR-Library. Varnamkhasti et al (2012) in their proposed fuzzy genetic algorithm for solving knapsack problem show that the crossover operator and selection technique based on population diversity using fuzzy logic controllers is effective in finding better and comparable solutions.

Hong et al (2002) proposed dynamic genetic algorithm that simultaneously uses more than one crossover and mutation operators to generate offspring for solving an arbitrary problem which saves time and performs better than algorithms with a single crossover and single mutation operator. Tay & Wobowo (2004) in their proposed new chromosomes representation to solve flexible job shop scheduling problem produces a schedule with shorter makespan. From their experiment, suitable crossover and mutation operators were found to be 0.85 and 0.006 to 0.0017 respectively. Azzouz et al (2016) in their investigations on flexible job shop scheduling with sequence dependent setup times using genetic algorithm with crossover and mutation probability of 0.8 & 0.2 showed superiority of solution quality for benchmark instances with makespan and bi-criteria objective function as performance measures.

Naderi et al (2009) developed hybridised genetic algorithm incorporating restart phase and local search for solving job shop scheduling problem with sequence dependent setup times with the objective of minimizing makespan and found their approach to be highly effective. Sadeghieh (2006) studied effect of parameter values on GA performance to optimise production schedules using a range of crossover (0.10, 0.20, 0.60, 0.8, 0.90) and mutation (0.001, 0.005, 0.01, 0.02) probabilities. The performance measure, makespan, is insensitive to all population sizes and mutation rates for selected crossover rate and performance degrades either side of a range of good mutation values. Jia et al (2007) proposed GA integrated with GC (Gantt chart) for distributed scheduling problems by applying gene crossover once and gene mutation twice for the process plans and operation schedules to improve the computational performance.

Defersha & Chen (2010) proposed a comprehensive mixed integer linear program (MILP) and parallel genetic algorithm (PGA) for a flexible job shop scheduling problem incorporating sequence dependent setup time, machine release dates and time lag requirements with objective function, makespan. They tested their model for medium and large size problems with promising and encouraging results compared to sequential genetic algorithm (SGA). Roshanaei et al. (2010) formulated mixed integer linear programming model for job shop scheduling (JSS) with sequence dependent setup times (SDST) and adapted metaheuristic electromagnetism-like algorithm (EMA) for minimizing the makespan for small and large sized problems with superiority.

III. PROBLEM FORMULATION

Literature survey reveals that job shop scheduling problem has been attempted by various researchers with different approaches, but, there is limited research to identify the optimal values of crossover and mutation probabilities for optimization of job shop scheduling with sequence dependent setup time problem in batch mode for a given performance measure. Hence, in the present work, an attempt is made to assess the effect of various crossover and mutation probabilities combination on makespan performance measure for a job shop scheduling problem with sequence dependent setup times.

The present work makes the following assumptions in line with previous studies (French, S 1982, Mattfeld, 2013, Moghaddas R. et al. 2008, Bagheri A. et al. 2011).

1. "All jobs and machines are available for processing at time zero.
2. Each machine is continuously available for production, i.e., no breakdown of machines.
3. At any given time, the machine can process only one operation of a job and pre-emption is not allowed.
4. A started operation cannot be interrupted.
5. The operation processing times for all jobs are known in advance and constant.
6. The setup times of jobs on each machine are sequence dependent and are known.
7. There is no restriction on queue length for any machine.
8. The machines are not identical and perform different operations.
9. An operation cannot start processing until its precedence operation has finished its processing." [5].

IV. METHODOLOGY ADOPTED

The present work adopts Genetic Algorithm (GA) based approach in finding an optimal schedule for job shop with sequence dependent setup times.

Genetic algorithm begins with job based representation in which an initial set of random solutions called population is generated. Each individual in the population called 'chromosome' represents a solution to the problem and is encoded as a sequence of numbers. The performance evaluation of each chromosome gives some measure of fitness via a fitness function. The tournament selection and selection pressure decides which set of chromosome should undergo crossover and mutation, since better chromosome are selected to drive search in good region of search space. Two point crossover with different crossover probabilities is used to get new and better strings by exchanging information among strings from the mating pool. Swap mutation with different mutation probabilities generate an offspring solution by randomly modifying the parents feature and helps maintain a reasonable level of population diversity and a mechanism to escape from local optima. Due to crossover, some illegal off-springs generated compels repairing to resolve the illegitimate off-spring after mutation. Elitism, helps in retaining some of the best individuals of previous generations, as some of them may get lost, if not selected or destroyed by crossover or mutation. A restart scheme is exercised if no improvement is found in the fitness value for 10 successive iterations. The GA terminates further exploration in the search space if the fitness value does not change for 100 iterations. (Deb, K, 1999, Busetti, F, 2007).

TABLE 1

GA PARAMETERS CONSIDERED IN THE PRESENT WORK

Sl. No.	GA Parameter	Value
1	Population size	10
2	Tournament Size	2
3	Crossover probability	0.80, 0.85, 0.9, 0.95
4	Mutation probability	0.20, 0.15, 0.1, 0.05
5	Elitism rate	0.9
6	Crossover type	Two point crossover
7	Mutation type	Swap mutation
8	Restart criterion	If fitness value remains constant for 10 iterations
9	Termination criterion	If fitness value remains constant for 100 iterations

V. RESULTS AND DISCUSSIONS

The present work makes an attempt to assess the effect of crossover probability (p_c) and mutation probability (p_m) on the optimal makespan performance measure. Six problem sizes ranging from 5 machines, 10 part types to 50 machines, 50 part types with fixed number of operations. Further the manufacturing scenario viz. operation setup time is equal to operation processing time is considered in the problem. Table 1 presents the range of parameters considered in the present work. The following six problem sizes [5x10, 10x10, 15x15, 15x20, 20x30, 50x50] are taken into consideration to assess the effect of crossover probability and mutation probability on the optimal system performance.

TABLE 2
RANGE OF PARAMETERS CONSIDERED IN THE PRESENT WORK

Number of Machines	: [5 – 50]
Number of Part Types	: [5 – 50]
Production Quantity of each Part Type	: [10 – 50]
Operation Processing Time	: [1 – 99]
Operation Setup Time	: [0 – 99]
Crossover & Mutation Probability Combination	: [0.8,0.2], [0.85,0.15], [0.9,0.1], [0.95,0.05]

For each case study, input is randomly generated in the range as shown in Table 1 and adopted methodology is utilised to find the optimal makespan. Further, for each case study, ten simulation runs are carried out and the run that yields the maximum fitness value is taken as optimal makespan. Fig. 1 & 2 indicate the convergence curve for two case studies (5 machines, 10 part types and 20 machines, 30 part types) for crossover and mutation probability of 0.85 and 0.15 respectively.

Table 3 indicates the results generated for optimal makespan values of different problem sizes and four combination of crossover and mutation probabilities when operations setup times are equal to operation processing times. The Table 4 indicates percentage variation for each case study calculated by considering difference between highest and lowest values for different combinations of crossover probability (p_c) and mutation probability (p_m) in manufacturing scenario when setup times are equal to operation processing times.

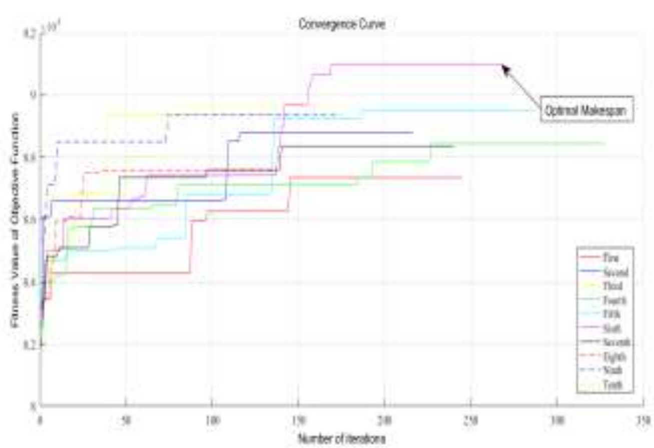

Fig. 1 Convergence Curve for Case Study 1 with Performance Measure as Makespan

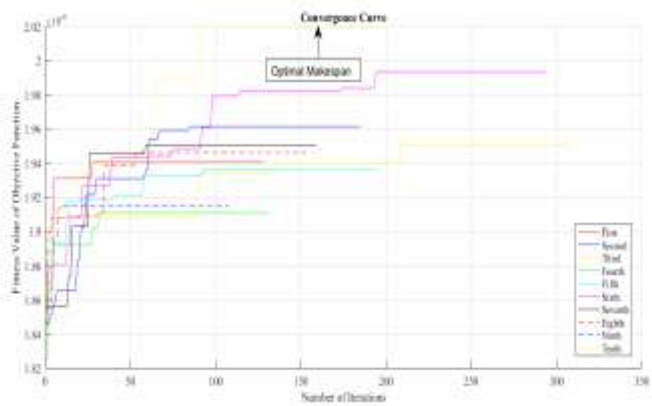

Fig. 2 Convergence Curve for Case Study 5 with Performance Measure as Makespan

TABLE 3

OPTIMAL MAKESPAN VALUES FOR CONSIDERED CASE STUDIES

Legend: m – Number of machines, n – Number of part types (jobs)

Problem Size m*n	Setup Times ≈ Processing Times			
	p_c =0.8, p_m =0.2	p_c =0.85, p_m =0.15	p_c =0.9, p_m =0.1	p_c =0.95, p_m =0.05
5*10	10987	10874	11173	**10807**
10*10	3638	**3605**	3717	3669
15*15	3289	**3234**	3269	3294
15*20	**4756**	4760	4789	4770
20*30	5032	**4953**	5035	5081
50*50	**2155**	2170	2161	2161

TABLE 4

PERCENTAGE VARIATION IN OPTIMAL MAKESPAN FOR CONSIDERED CASE STUDIES

Problem Size m*n	Setup Times ≈ Processing Times			
	p_c = 0.8, p_m = 0.2	p_c = 0.85, p_m = 0.15	p_c = 0.9, p_m = 0.1	p_c = 0.95, p_m = 0.05
5*10	1.66	0.62	3.30	0
10*10	0.91	**0**	3.10	1.77
15*15	1.70	**0**	1.08	1.85
15*20	0	0.08	0.69	0.29
20*30	1.59	**0**	1.65	2.58
50*50	0	0.69	0.28	0.28

Legend: m – Number of machines, n – Number of part types (jobs)

In manufacturing scenario considered, i.e., when setup times are equal to operation processing times, the percentage variation in makespan values for different crossover and mutation probabilities ranges between 0 to 3.3 % which is quiet insignificant. Hence, any value of p_c and p_m may be selected for performance measure.

Of six case studies considered, it can be seen that the makespan values for three cases (50 %) with p_c and p_m of 0.85 and 0.15 resulted in optimal values. It is also observable that in two other cases of p_c and p_m of 0.8 and 0.2 (33.33 %) also resulted in optimal makespan and in only one case (16.66%) with p_c and p_m of 0.95 & 0.05, the optimal makespan resulted in lower value.

VI. CONCLUSION

The present work considers a genetic algorithm based approach for job shop scheduling problem with sequence dependent setup time. The approach considers tournament selection, two point crossover and swap mutation with different combination of crossover and mutation probabilities, restart scheme and termination criterion. The present work assesses the effect of crossover and mutation probability combination on makespan performance measure. Four different combination of crossover and mutation probability viz. (0.8 & 0.2, 0.85 & 0.15, 0.9 & 0.1, and 0.95 & 0.05) are taken into consideration. Six case studies were considered to assess the effect of crossover and mutation probability combination. From results it can safely be concluded that crossover and mutation probability combination of 0.85 & 0.15 yields optimal makespan in most of case studies.

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