Routing Flexibility in Job Shop Scheduling Problem - A Genetic Algorithm Approach

Suresh Holi[#1], B P Shivakumar*

[#] *Research Scholar, Department of Mechanical Engineering, JSS Academy of Technical Education, Bengaluru, affiliated to Visvesvaraya Technological University, Belagavi, INDIA*

**Department of Mechanical Engineering, JSS Academy of Technical Education, Bengaluru, INDIA*

[1]*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 the effect of routing flexibility on makespan performance measure. Two case studies of size five part types, five machines and ten part types, ten machines are taken into consideration. Results are generated for different routing flexibilities in a manufacturing scenario wherein setup times are comparable to operation processing times. It indicates that routing flexibility has some effect on makespan performance measure.**

***Keywords* -job shop scheduling; sequence dependent setup time; genetic algorithm; makespan; routing flexibility**.

I. INTRODUCTION

Scheduling in many manufacturing and service industries involves decision-making to allocate resources to tasks thereby optimizing the objectives and achieving the goals of the organization [1]. In the classical job shop scheduling problem 'n' jobs are to be processed on 'm' machines. For everyjob to be processed, the sequence of operations performed on a set of machines follow a particular order and each of the machine processes at most one operation at a time. In job shop scheduling, only sequencing of jobs on machines is done and there are no alternative machines for the operations. An extension of classical job shop problem, known as flexible job shop problem, allows operations to be processed on any amongst available machines to achieve better schedule [2] – [4]. The scheduling problem further gets complex with introduction of alternative machines as not only sequencing, also, job routes need to be decided.

In an ever changing demand for quick and efficient delivery, manufacturing systems have to overcome challenges for their survival and growth by adopting newer automation technologies and flexibility [5].The trend in global market place earlier fixed to cost, quality and service has made inroads to delivery, flexibility and innovation [6].The flexibility to perform wide variety of operations comes from multi-purpose machines with automatic tool and pallet changers. The term flexibility is complex, multi-dimensional and challenging to analyze. Many researchers have referred flexibility in their own way neither agreeing, nor disagreeing to the usage of the term. Sethi & Sethi [7] organize 11 types of flexibility, viz. machine, operation, material handling, process, product, routing, volume, expansion, program, production, and market flexibilities."Routing flexibility of a manufacturing system is its ability to produce a part by alternate routes through the system. Alternate routes refers to different machines, different operations, or different sequences of operations" [7]. This may be due to overlapping situation being faced or due to internal disturbances. Scheduling of jobs with flexible routing need to be robust and responsive as path of the job to be followed is unknown at the beginning. Further, the complexity increases with disturbances and alternate routings due to machine breakdown, variations in processing times, random arrival of jobs and so on [8]."Routing flexibility majorly contributes in flexible job shop manufacturing system providing better schedule due to efficient balance of machine loads, minimized system utilization and work-in-process inventory, improved productivity of machine shop and continuous production of the jobs despite the occurrence of unanticipated events such as machine breakdown, downtimes, rush orders, late receipt of machine tools and pre-emptive schedule" [9].

In the present work, an attempt is made to assess the effect of routing flexibility on the optimal performance measure of makespan.

II. LITERATURE SURVEY

Caprihan & Wadhwa [5] studied the influence of varying levels of routing flexibility on the performance of FMS adopting Taguchi's experimental design and concluded that increasing routing flexibility beyond a certain flexibility level deteriorates the optimal performance measure. Yu & Ram [8] proposed a response threshold model on bio-inspired multi-agent scheduling approach for scheduling dynamic job shop problems with sequence dependent setups and routing flexibility. The proposed model outperformed the auction-based model and dispatching rule-based approach.Rossi & Dini [10] proposed an ant colony optimisation-based software system to flexible job-shop scheduling with routing flexibility and separable setup times and tested on standard benchmark instances and found it to be very effective.

Moon et al. [11] formulated a mixed-integer LP model and proposed genetic algorithm approach with alternative routings for scheduling job shop problems. The results show that GA performs better than heuristic algorithms. Özgüven et al. [12] proposed two mixed-integer linear programming models for flexible job shop scheduling problems encompassing routing and sequencing along with process plan sub-problem and compared results on a variety of test problems. Oddi et al. [13] proposed iterative flattening search (IFS) for effectively solving SDST-FJSSP and exhibited that the new slack-based relaxation strategy showed enhanced performance than the random selection one.

Defersha & Chen [14] developed a mixed-integer programming model for a flexible job shop with sequence-dependent setup times and demonstrated that the proposed parallel genetic algorithm solved the model efficiently. Sharma & Jain [9] in their simulation-based experimental study of flexible job shop manufacturing system show that routing flexibility and sequencing rules have noteworthy impact on system performance and starts deteriorating beyond a certain level of route flexibility.

Fantahun and Mingyuan [15] presented a mathematical model for job shop scheduling problem with sequence-dependent setup times by incorporating alternative routings. The computational results of the proposed parallel genetic algorithm provided enhanced performance than the simple genetic algorithm. Joseph and Sridharan [16] focused on a simulation-based experimental study of the effects of routing flexibility, sequencing flexibility and part sequencing rules on the flow time and tardiness of parts of a flexible manufacturing system and concluded that system performance improves by incorporating routing flexibility, sequencing flexibility or both, but, reduces at higher flexibility levels.

Chang [17] proposed mathematical models for routing flexibility measurement that incorporates routing efficiency, routing versatility, and routing variety. The methodology developed for measurement used are data envelopment analysis (DEA) and entropy approach. Chan et al.[18] proposed an adaptive genetic algorithm for distributed scheduling problems in multi-factory and multi-product environment. They introduced a new crossover mechanism named dominated gene crossover to enhance the performance of genetic search and eliminating the problem of determining the optimal crossover rate.

III. PROBLEM FORMULATION

Literature survey tells us that job shop scheduling problem has been attempted by various researchers with different approaches, but, there is limited research employing routing flexibility for optimization of job shop scheduling with sequence dependent setup times for a given performance measure. Hence, the present work is an attempt to assess the effect of routing flexibility on makespan performance measure for a job shop scheduling problem with sequence dependent setup times.

The following assumptions are made in the present work [19] – [22].

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

IV. METHODOLOGY ADOPTED

The present work adopts a Genetic Algorithm (GA) based methodology to find an optimal schedule for job shop problem with routing flexibility.

Genetic algorithm starts 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. [23], [24]. The Table I below indicates the GA parameters considered in the present work.

TABLE I

GA PARAMETERS CONSIDERED IN THE PRESENT WORK

Sl. No.	GA Parameter	Value
1	Population size	10
2	Tournament Size	2
3	Crossover probability	0.85
4	Mutation probability	0.15
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 attempts to assess the effect routing flexibility on the optimal makespan performance measure. The problem size considered is 5 machines, 5 part types and10 machines, 10 part types with fixed number of operations. Further the manufacturing scenario, viz. operation setup time is comparable to operation processing time is considered in the problem. Thus two case studies are carried out to assess the effect of routing flexibility on the optimal makespan performance measure.

TABLE II

RANGE OF PARAMETERS CONSIDEREDIN THE PRESENT WORK

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

For the two case studies considered, input is randomly generated in the range as shown in Table II and adopted methodology is utilised to find the optimal makespan. Further, for both case studies, ten simulation runs are carried out and the run that yields the maximum fitness value is taken as optimal makespan. Figures 1&2 indicate the convergence curves for case study 1 without routing flexibility (RF0) and highest routing flexibility (RF4) respectively. Figures 3& 4 indicate the convergence curves for case study 2 without routing flexibility (RF0) and highest routing flexibility (RF9) respectively.

Table 3 indicates the results generated for optimal makespan values for two problem sizes (i.e., 5 machines, 5 part types and 10 machines, 10 part types) and for crossover and mutation probability combination of 0.85 and 0.15 respectively when operation setup times are comparable to operation processing times.

VI. CONCLUSION

The present work considers a genetic algorithm based approach for job shop scheduling problem with sequence dependent setup time to assess the effect of routing flexibility. Two case studies of size 5 part types, 5 machines and 10 part types, 10 machines are considered. The crossover and mutation probability for the case studies considered are 0.85 & 0.15.Results are generated by varying routing flexibility from zero to four, i.e. RF0 to RF4, for case study 1 and from zero to nine, i.e. RF0 to RF9, for case study 2. It is clearly evident from results (Table 3) that the system performance increases in case of RF1 & RF2. However, in case of RF2 the increase in system performance is comparatively less than RF1. As routing flexibility is increased from RF2 to RF4, the system performance measure starts deteriorating. Thus, the optimal level of flexibility for the case study 1 is one.

In case study 2, it is observable from results (Table III) that as routing flexibility increases the system performance increases. Though the system performance improves for all routing flexibilities, the system performance is maximum when routing flexibility is 2.

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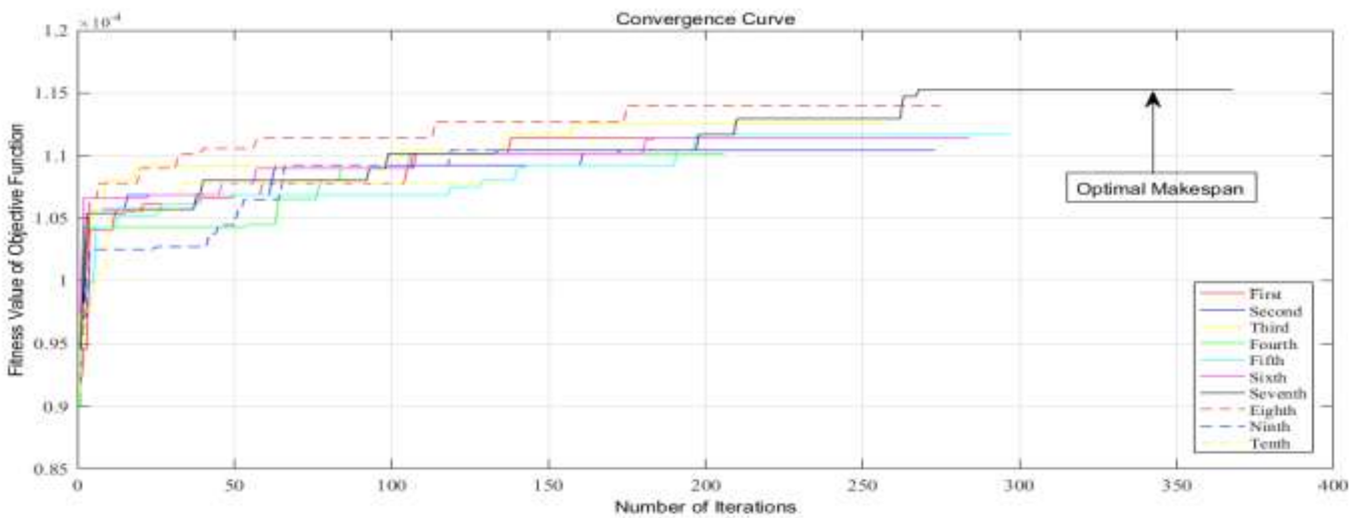

Fig. 1 – Convergence curve for case study 1 without routing flexibility(RF0)

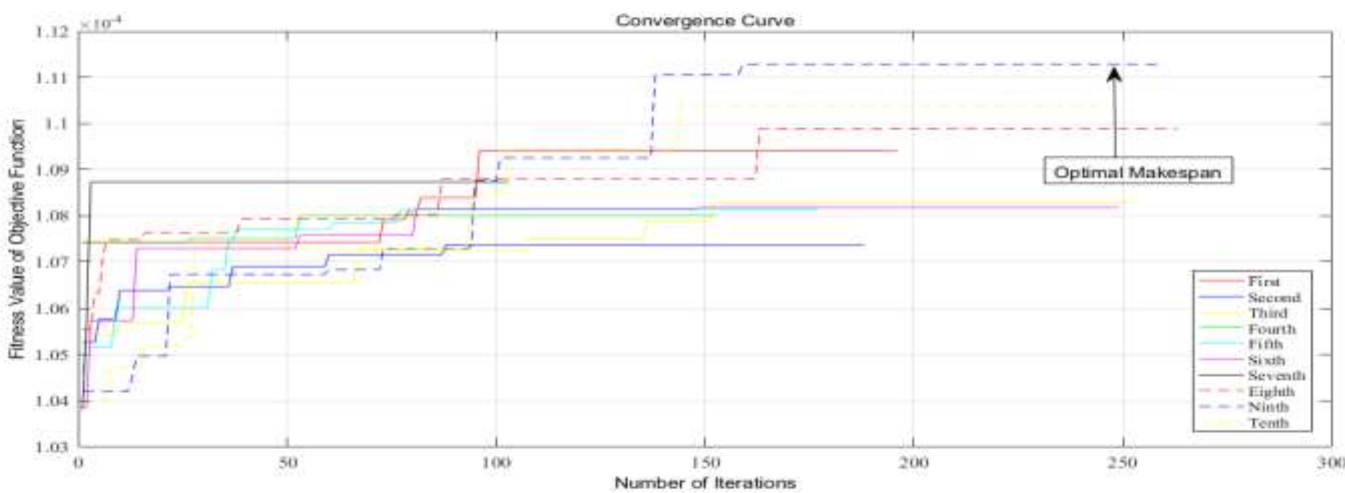

Fig. 2 – Convergence curve for case study 1 with highest routing flexibility (RF4)

TABLE III
OPTIMAL MAKESPAN VALUES WITH ROUTING FLEXIBILITYFOR BOTH CASE STUDIES

Problem Size	RF0	RF1	RF2	RF3	RF4	RF5	RF6	RF7	RF8	RF9
5*5	8673	8053	8369	9018	8985					
10*10	12404	8737	7778	7921	8186	8309	8360	8394	8329	8303

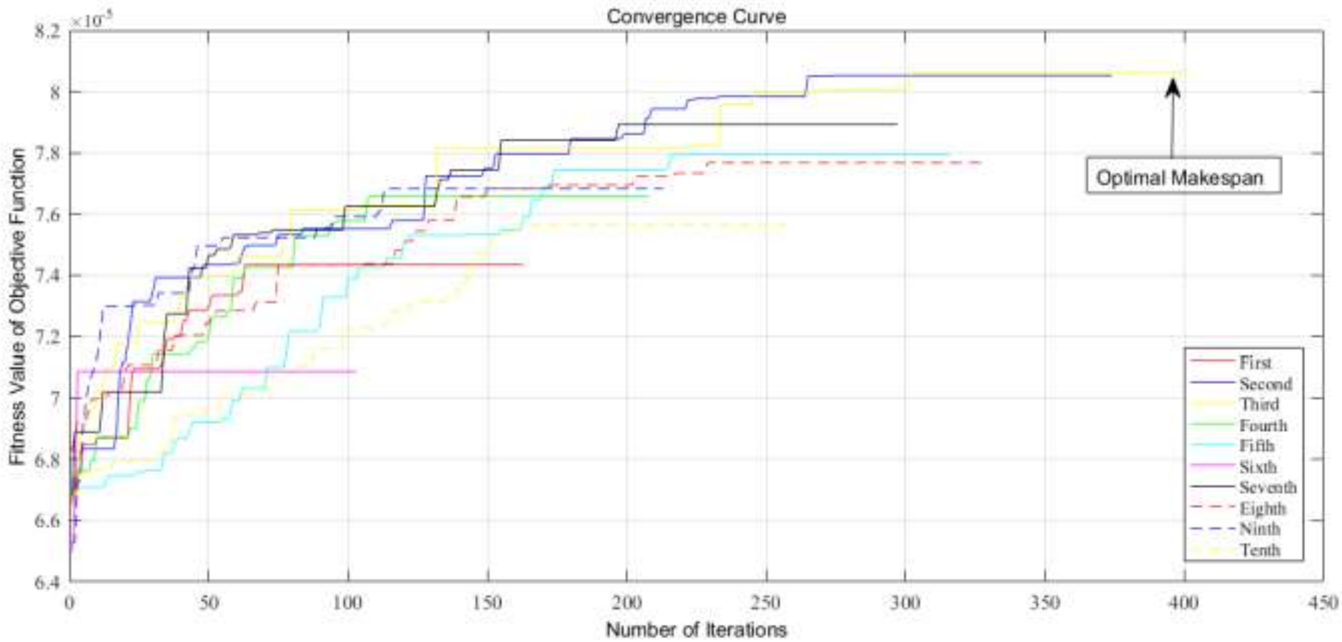

Fig. 3 – Convergence curve for case study 2 without routing flexibility (RF0)

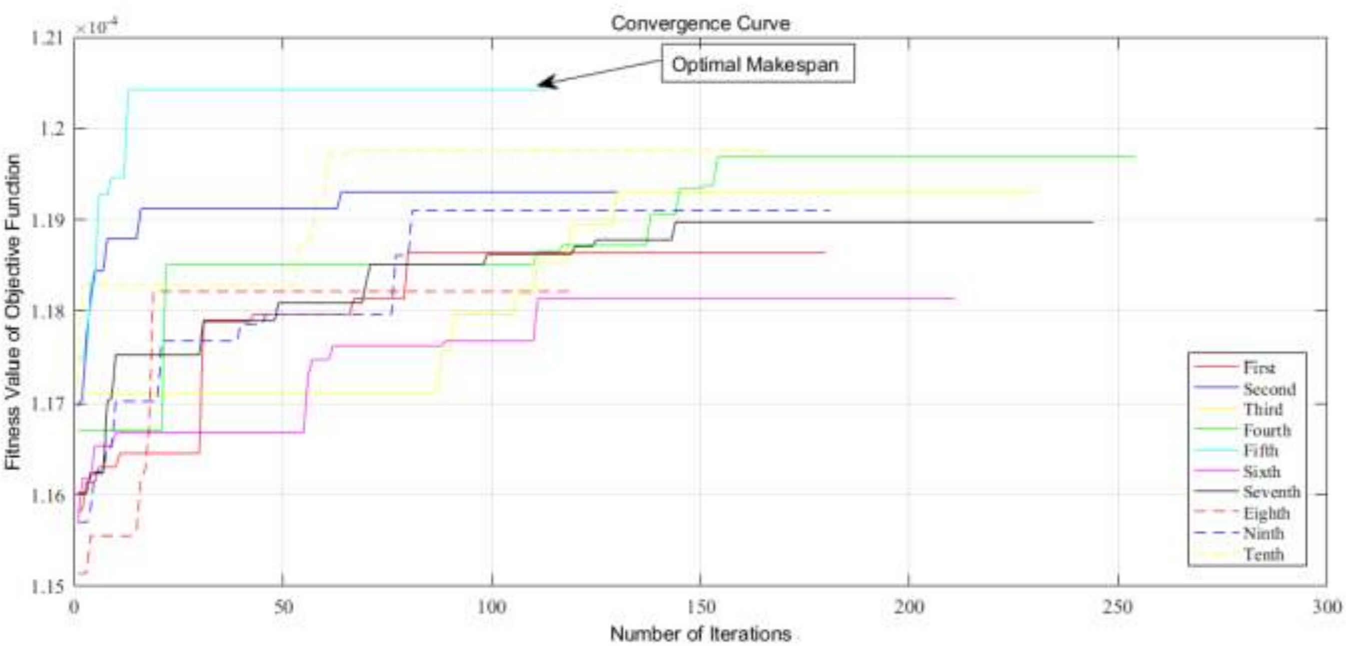

Fig. 4 – Convergence curve for case study 2 with highest routing flexibility (RF9)