

A Hybrid Approach for Single Objective Job Shop Scheduling Problems

S.Gobinath¹, Prof.C.Arumugam², M.Chandrasekaran³

¹Research Scholar, Anna University Regional Centre, Coimbatore, India

²Coimbatore Institute Technology, Coimbatore, India

³Vels University, Chennai, India

nithnathdeep@yahoo.com

Abstract: Scheduling problems are usually solved using optimization techniques to get optimal or near optimal solutions because problems found in practical applications cannot be solved to optimality using reasonable resources in many cases. The n-job, m-machine Job shop scheduling (JSP) problem is one of the general production scheduling problems. In this paper, optimization of practical performance measure of makespan is considered. Hybrid approach is proposed to solve JSP problems. The hybrid approach is tested with 10 benchmark JSP problems in finding optimal makespan values. The results of hybrid approach are compared with Artificial Immune System (AIS), Tabu Search Shifting Bottleneck approach (TSSB) approach. The performance of hybrid approach is efficient in finding optimal solutions compared to that of other approaches reported in literature.

[S.Gobinath, Prof.C.Arumugam, M.Chandrasekaran. **A Hybrid Approach for Single Objective Job Shop Scheduling Problems.** *Life Sci J* 2013; 10(3): 163-166]. (ISSN: 1097-8135). <http://www.lifesciencesite.com> 26

Key words: Job Shop Scheduling, Hybrid Approach, Benchmark Problems

1. INTRODUCTION

The job shop problem is the most complicated and typical problem of all kinds of production scheduling problems, the allocation of resources over time to perform a collection of tasks (Alqahtani and Saba, 2013). Job shop scheduling can be stated as follows: given n jobs that have to be processed on m machines in a prescribed order under certain restrictive assumptions. The objective is to decide how to arrange the processing orders and starting times of operations sharing the same machine. Manufacturing systems with objectives require optimization criteria, such as stock size, due-date reliability and mean lead time.

The classical job-shop scheduling problem is one of the most difficult combinatorial optimization problems (Bruker, 1995). Issues concerning the content and scope of JSPs have been attracting much attention from researchers and practitioners. Mathematical and heuristic methods are the two major methods for resolving JSP. Optimization methods attempt to find the optimal solution through mathematical programming techniques or methods (Rehman and Saba, 2012b,c; Brucker et al, 1994). However, mathematical programming methods are time-consuming, and thus many researchers focus on developing heuristic algorithms. Heuristic algorithms in common use include shifting bottleneck (SB) (Rehman and Saba, 2012a), Tabu search (TS) (Saba and Altameem, 2013; Saba and Alqahtani, 2013), Simulated annealing (SA) (Saba et al., 2012; Krishan et al, 1995; Steinhofel et al, 1999), Genetic algorithm (GA) (Zhou et al, 2001) and Artificial Immune System

(AIS) (Rehman and Saba, 2012c). During the last decades a great deal of attention has been paid to solving these problems with many kinds of algorithms by considering single objective (Saba and Rehman, 2012a).

Additionally, research on job shop scheduling problems was concentrated primarily on the optimization of individual measures of system performance. While a single objective may be justified in certain situations Lee and Jung (1989), Murata, Ishibuchi, and Tanaka (1996) and Chandrasekaran et al (2006).

2. JOB SHOP SCHEDULING PROBLEM

Normally, the entire job-shop scheduling problem consists of two types of constraints: sequence constraint and resource constraint (Sulong et al., 2010; Saba and Rehman, 2012). The first type states that two operations of a job cannot be processed at the same time. The second type states that no more than one job can be handled on a machine at the same time. Job-shop scheduling can be viewed as an optimization problem, bounded by both sequence and resource constraints. For a job-shop scheduling problem, each job may consist of different number of operations, subjected to some precedence restrictions (Rehman and Saba, 2011). Commonly the processing orders of each job by all machines and the processing time of each operation are known and fixed. Once started operations cannot be interrupted. Assume job $i(i=1,2,\dots,n)$ requires processing by machine $k(k=1,2,\dots,m)$ exactly once in its operation sequence (thus, each job has m operations). Let p_{ik} is the processing time of job i on

machine k , X_{ik} is the starting time of job i on machine k , q_{ik} is the indicator which takes on a value of 1 if operation j of job i requires machine k , and zero otherwise. Y_{ihk} is the variable which takes on a value of 1 if job precedes job h on machine k , and zero otherwise. The objective function for the given Job Shop Scheduling is

$$\text{Minimize } Z = C_{\max}$$

Subject to

a) Sequence constraint

ie., for a given job i , the $(j+1)$ st operation may not start before the j th operation is completed.

b) Resource constraint

ie. Only one job will be processed in a machine.

3. PROPOSED HYBRID ALGORITHM FOR JOB SHOP SCHEDULING PROBLEM

In the proposed hybrid algorithm initial sequence is processed with AIS algorithm and finally results are refined with SFHM algorithm. The operative mechanisms of immune system are very efficient from a computational standpoint. The artificial immune system was built on the following two principles of the immune system. a) Clonal selection principle b) Affinity maturation principle

In sheep flocks heredity model algorithm special string structure, hierarchical genetic operations (crossover and mutation) are introduced. They are (1) sub-chromosome level genetic operation and (2) chromosome (global) level genetic operation. This hierarchical operation is referred to as "multi-stage genetic operation".

Generate a population of P antibodies (job sequences)

Stage 1(AIS Algorithm)

For each iteration

Select the sequence in the antibody population;

Find out the affinity of each antibody;

Cloning process (generate copies of the antibodies)

Steps in Mutation process (for each clone)

Find inverse mutation

Select the new sequence obtained from inverse mutation

Find the makespan of the new sequence

if (makespan (new sequence) == makespan (clone))

then if (tardiness(new sequence) < tardiness (clone))

clone = new sequence ;

else clone = clone;

if makespan (new sequence) < makespan (clone) then

Clone = new sequence

else

do pair wise interchange

select the new sequence

Find the makespan of the new sequence

if (makespan (new sequence) == makespan (clone))

then if (tardiness(new sequence) < tardiness (clone))

clone = new sequence

else clone = clone

If makespan (new sequence) < makespan (clone)

then

clone = new sequence;

else

clone = clone

antibody = clone

Eliminate worst %B number of antibodies in the population

Create new antibodies at the same number (%B of pop.)

change the eliminated ones with the new created ones while stopping criteria = false.

Stage 2: (SFHM Algorithm)

Use the population from AIS algorithm,

Select the parent

Sub chromosome level crossover

Set sub chromosome level crossover probability

If population probability is less than or equal to sub chromosome level probability

Perform sub chromosome level crossover

Else retain the old sequences

Sub chromosome level mutation

Set sub chromosome mutation probability

If population probability is less than or equal to sub chromosome mutation probability

Perform sub chromosome level mutation

Else retain the same sequences

Select two sequences from population

Chromosome level crossover

Set crossover probability

If population probability is less than or equal to crossover probability

Perform chromosome level crossover

Else retain the same sequences

Chromosome level mutation

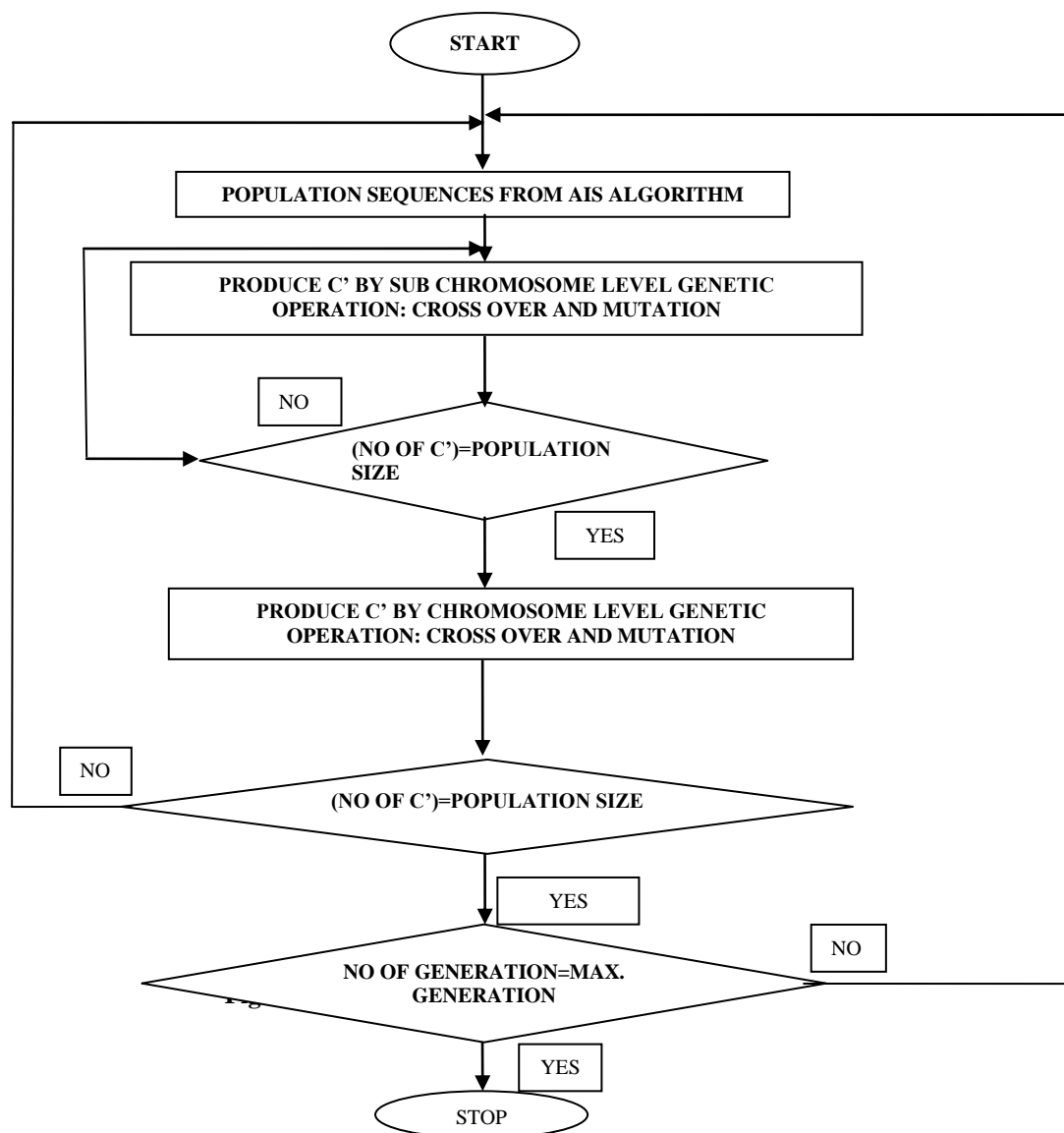
Set mutation probability

If population probability is less than or equal to mutation probability

Perform chromosome level mutation

Else retain the same sequences

End if terminal condition satisfied



4. RESULTS AND DISCUSSION

The proposed hybrid algorithm has been tested for 10 problem instances of various sizes collected in the following classes:

TABLE 1. Results of ten job shop scheduling problems

Problem	n	m	Hybrid	AIS	TSSB
ORB1	10	10	1059	1062	1064
ORB2	10	10	888	891	890
ORB3	10	10	1005	1005	1013
ORB4	10	10	1005	1005	1013
LA05	10	5	593	593	593
LA06	15	5	926	926	926
TA05	20	20	1213	1215	1229
TA15	20	15	1298	1348	1360
TA23	20	20	1477	1556	1573
TA51	50	15	2759	2760	2760

In Table 1, the solutions for job shop problems obtained from hybrid are compared with AIS, TSSB procedure. Hybrid gives optimum value than AIS and TSSB procedure.

5. CONCLUSION

In this paper, the proposed hybrid approach has been used for solving job shop scheduling problem with the objective of makespan minimization. The hybrid approach uses simple but effective techniques for calculating cloning process, applying mutations a receptor editing procedure and SFHM Algorithm. The algorithm has been tested on 10 benchmark problem instances. The findings were compared with Artificial Immune System, Tabu Search Shifting Bottleneck procedure. The proposed hybrid approach found better results in most of the problems.

References

- [1] Bruker P. (1995). Scheduling Algorithms 2nd Edn, Springer-Verlag, Berlin.
- [2] Rehman, A. and Saba, T. (2012b). Off-line Cursive Script Recognition: Current Advances, Comparisons and Remaining Problems. *Artificial Intelligence Review* Springer, vol. 37(4), pp:261-268.
- [3] Sulong, G. Saba, T. and Rehman, A. (2010). Dynamic Programming Based Hybrid Strategy for Offline Cursive Script Recognition. 2nd IEEE International Conference on Computer and Engineering, vol. 2, pp. 580-584.
- [4] Rehman, A. and Saba, T. (2012c) Neural Network for Document Image Preprocessing, *Artificial Intelligence Review*, DOI:10.1007/s10462-012-9337-z.
- [5] Krishan K., Ganeshan K., Ram DJ. (1995). Distributed simulated annealing algorithm for job shop scheduling, *IEEE Transactions* 25(9), 1102–1109.
- [6] Saba, T. and Altameem, A. (2013) Analysis of Vision based Systems to Detect Real Time Goal Events in Soccer Videos, *Applied Artificial Intelligence*, vol. 27(7), pp. 656-667.
- [7] Saba, T. and Alqahtani, F.A. (2013) Semantic Analysis Based Forms Information Retrieval and Classification, *3 D Research*, vol. 4(4).
- [8] Rehman, A. and Saba, T. (2012a). Evaluation of Artificial Intelligent Techniques to Secure Information in Enterprises. *Artificial Intelligence Review*, DOI 10.1007/s10462-012-9372-9.
- [9] Saba, T. Rehman, A. and Elarbi-Boudihir, M. (2011). Methods and Strategies on off-line Cursive Touched Characters Segmentation: A Directional Review, *Artificial Intelligence Review*, Springer, DOI 10.1007/s10462-011-9271-5. pp:45-54.
- [10] Saba, T. Alzorani, S. Rehman, A. (2012) Expert system for offline clinical guidelines and treatment, *Life Science Journal*, 2012; vol. 9(4):pp. 2639 -2658.
- [11] Saba, T. and Rehman, A. (2012). Effects of Artificially Intelligent Tools on Pattern Recognition, *International Journal of Machine Learning and Cybernetics*, vol. 4(2), pp. 155-162.
- [12] Saba, T. and Rehman, A. 2012a, *Machine Learning and Script Recognition*, Lambert Academic Publisher, ISBN-10: 3659111708, pp.110-120.
- [13] Steinhöfel K., Albrecht A., and Wong CK, (1999). Two simulated annealing-based heuristics for the job shop scheduling problem, *European Journal of Operational Research* 118(5), 524–548.
- [14] Rehman, A. and Saba, T. (2011). Performance Analysis of Segmentation Approach for Cursive Handwritten Word Recognition on Benchmark Database”. *Digital Signal Processing*, vol. 21(3), pp. 486-490.
- [15] Zhou H., Feng Y., and Han L. (2001). The hybrid heuristic genetic algorithm for job shop scheduling, *Computers and Industrial Engineering* 40(5), 191–200.
- [16] Mattfeld D.C. (1996). *Evolutionary Search and the Job Shop*, Physica-Verlag.
- [17] Ono I., Yamamura M., and Kobayashi S. (1996). A genetic algorithm for job-shop scheduling problems using job-based order crossover, In *Proceedings of ICEC '96*, 547-552.
- [18] Bagchi T. P. (1999). *Multi objective scheduling by Genetic Algorithms*, Kluwer Academic Publishers.
- [19] Deb K. (2001). *Multi-Objective Optimization Using Evolutionary Algorithms*, John Wiley & Sons.
- [20] Daniels DL. (1994). Incorporating performance information into multi objective scheduling, *European Journal Operational Research* 77, 272–286.
- [21] Lee SM., Jung HJ, (1989). A multi-objective production-planning model in a flexible manufacturing environment, *International Journal of Production Research* 27(11), 1981–1992.
- [22] Murata T., Hisao I., Tanaka H, (1996). Multi-objective genetic algorithm and its applications to flow shop scheduling, *Computers and Industrial Engineering* 30(6), 957–968.
- [23] Chandrasekaran M., Asokan P., Kumanan S., Balamurugan T. (2006). Sheep Flocks Heredity Model Algorithm for solving job shop scheduling problems, *International journal of Applied Management Technology* Vol 4(1), 79-100.
- [24] Garen J. (2002). Multi objective Job-Shop Scheduling with Genetic Algorithms Using a New Representation and Standard Uniform Crossover, *MOMH Workshop*, Paris.
- [25] F. A. Alqahtani and Saba, T. (2013). Impact of Social Networks on Customer Relation Management (CRM) in Prospectus of Business Environment, *Journal of American Sciences*, vol. 9(7), pp480-486.

7/11/2013