computing@tanet.edu.te.ua
www.tanet.edu.te.ua/computing

ISSN 1727-6209
International Scientific
Journal of Computing

A NEW HYBRID HEURISTIC TECHNIQUE FOR SOLVING JOB-SHOP SCHEDULING PROBLEM

Cheng-Fa Tsai, Feng-Cheng Lin

Department of Management Information Systems,
National Pingtung University of Science and Technology, Pingtung, Taiwan, 91201
Email: cftsai@mail.npust.edu.tw, URL:140.127.22.200/teach/james

Abstract: *This paper proposes a new and efficient hybrid heuristic scheme for solving job-shop scheduling problems (JSP). A new and efficient population initialization and local search concept, based on genetic algorithms, is introduced to search the solution space and to determine the global minimum solution to the JSP problem. Simulated results imply that the proposed novel JSP method (called the PLGA algorithm) outperforms several currently used approaches. This investigation also considers a real-life job-shop scheduling system design, which optimizes the performance of the job-shop scheduling system subject to a required service level. Simulation results demonstrate that the proposed method is very efficient and potentially useful in solving job-shop scheduling problems.*

Keywords: *JSP, genetic algorithms, local search*

1. INTRODUCTION

Most scheduling problems are NP-hard; the time required to solve the problem optimally, increases exponentially with the size of the problem. The job-shop scheduling problem (JSP) is one of the most extensively-studied problems in combinatorial optimization. The problem may be described as follows: n different jobs are to be scheduled on m different machines. Each job involves a set of operations, which are performed on the machines in a prespecified order. Each operation is specified by the required machine and the fixed processing time. A number of constraints apply to the jobs and machines [26], [34]: (a) a job does not visit the same machines twice; (b) no precedence constraints are imposed among the order of different jobs; (c) an operation cannot be interrupted; (d) each machine can process only one job at a time; (e) neither release times nor due dates are specified.

The problem is to determine the order in which the jobs should be completed on the machines to minimize the makespan, which is the time required to complete all jobs. This problem has important applications, and a number of heuristic algorithms have been proposed to determine relatively good solutions to the JSP in polynomial time. They include simulated annealing (SA)[20], [28], Tabu Search [6], [17], [23], ant system (AS) [5], neural network (NN)[30], genetic algorithm (GA)[1]-[3], [4], [7]-[11], [12]-[19], [21]-[22], [24]-[27], [29]-[34], and others. Simulated annealing is used to model crystallization in thermal physics. The ant system involves a set of cooperating agents called ants, which utilize communication indirectly, by a method mediated by a pheromone. GA involves the natural selection of chromosomes. GA is known as one of the most efficient algorithms for solving the TSP (traveling salesman problem) and JSP.

2. THE HYBRID OPTIMIZATION STRATEGY FOR JOB-SHOP SCHEDULING PROBLEM

The GA mechanism is not governed by the utilization of differential equations, and nor does it behave like a continuous function. However, the GA mechanism does have the unique ability to identify and optimize a solution for a complex system, where other mathematical oriented techniques may fail to compile the necessary design specifications. Because of its evolutionary nature, a standard GA may not be flexible enough for practical applications, and consultation with engineers is necessary whenever a GA is applied. This becomes increasingly apparent when the problem is complicated, and involves conflict and

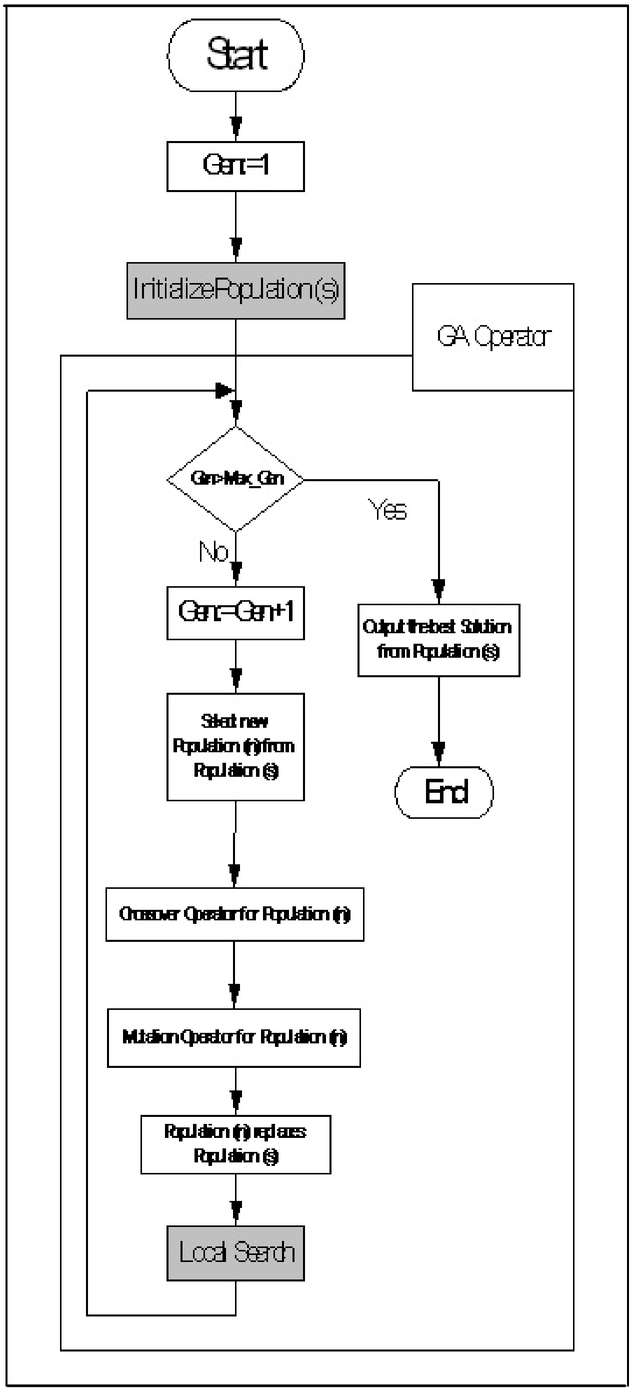

Fig. 1 - The outline of our proposed PLGA approach.

multi-tasking. Local search involves moving from a solution to another one in its neighborhood, by following many well-defined rules. The complementary strengths of GA and local search are such that a hybrid framework of GA and the local search can achieve more efficient optimization than GA alone and relax the dependence on parameters. This work presents some improvements in solving the job-shop problem obtained by taking a heuristic A method for combining other different search approaches is also provided. Fig. 1 shows the outline of our proposed PLGA approach, while Fig. 2 and 3 depict the algorithm of population initialization and local search, respectively. .

```
Procedure: population initialization
Begin
 Select the first job into the first position randomly;
 For i = 0 to code_size(n)    // n: the length of
      chromosome
  For j=0 to job_size(m)    // m: the number of jobs
   Insert job j that has not inserted into the
        chromosome temporarily;
   Evaluate the fitness value of this complete
        chromosome so far;
   Keep the fitness value in memory;
  End For
  Evaluate the best fitness value from the memory
     to get this job into position (i)
```

Fig. 2 - The algorithm of population initialization.

```
Procedure: local search
Begin
 Select one chromosome (s) from population
      randomly;
 Evaluate this chromosome (s);
  For i=0 to code_size-1
     For j=i+1 to code_size
  If (s [i]! =s [j]) // the value of position is not the
                          same;
       {
         Exchange the position of i and j
              temporarily;
         Evaluate the new chromosome (n);
         If (the new chromosome's (n) fitness value
                 is better than old chromosome's (s)
                 fitness value)
           {
             Keep the position of i and j in memory
                but do not exchange them presently;
             Update the old chromosome's (s) fitness
                value as the new chromosome's
                fitness value;
           }
         If (the new chromosome's (n) fitness value
                 is the same with old chromosome's
                 (s) fitness value)
         {Exchange the position of i and j
                 immediately;}
       }
     End For
  End For
 Exchange the position of i and j in memory;
End
```

Fig. 3 - The algorithm of local search.

The mechanisms of traditional genetic algorithms are similar as illustrated in the following steps:

Step1: Initial a population of chromosomes (solutions)

Step2: Evaluate the fitness of all chromosomes

Step3: Select fitter chromosome for reproduction
Step4: Perform crossover operator on a pair chromosome
Step5: Perform mutation operator on a chromosome
Step6: If a stopping criterion is satisfied, then stop and output the best chromosome (solution); if not, got to Step2

* Stopping criterion is mean maximum number of generations exceeded or convergence achieved.

3. COMPUTATIONAL RESULTS

In order to test the performances of our hybrid optimization strategy, some benchmark instances with different scale are selected and examined. These instances also are widely utilized in literatures [8], [13], [27] and are available from an anonymous ftp site ftp://mscmga.ms.ic.ac.uk/pub/jobshop1.txt. The experiments were conducted on a Pentium Ⅳ -1.7G with 2G RAM using C++ running on windows 2000 operating system. Meanwhile, we set Pc (crossover rate) and Pm (mutation rate) as shown in Table 2, Table 3, and Table 4, and each instance is randomly run 30 times for each algorithm. Table 1 indicates several different strategies for our proposed PLGA approach. Notably, MGA_1 uses random initialization and elitist strategy [26]; MGA_2 uses Population Initialization, elitist strategy [26]; MGA_3 uses random initialization, elitist strategy [26], and Local Search; while MGA_4 uses 50% random initialization+50% Population Initialization, Local Search, and elitist strategy [26]. Fig. 4 reveals structure of our PLGA system, while Fig. 5 shows the viewer of our system for job-shop scheduling (an instance of optimum for 10 x10 FT). Moreover, Table 5 and Table 6 indicate simulation results of GA [33], GA+MGA_1, GA+MGA_2, GA+MGA_3, and GA+MGA_4 for 10x10FT (optimal: 930) and 20x5FT (optimal: 1165), respectively. In Table 5 and Table 6, the proposed methods (four different strategies) can obtain better solutions than GA [33] does for 10x10FT and 20x5FT. Table 7 and Table 8 depict comparisons of the best performance between our GA (PLGA; MGA_4) and some literature results [18], [19], respectively. Such a result already demonstrated its effectiveness in finding good solutions. To the best of our knowledge and simulation results [1]-[34], our proposed approach clearly outperforms the already existing algorithms in most of job-shop scheduling problem. Due to the limitation of paper length, we cannot list all comparisons of performance with the already existing methods. In sum, the results reveal that the proposed algorithm is, indeed, a good method for solving the job-shop scheduling problem.

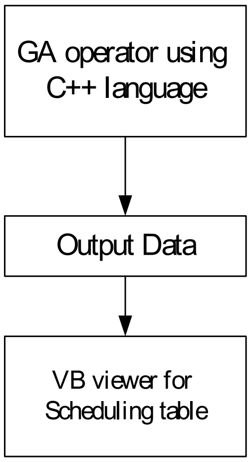

Fig. 4 - Structure of our PLGA system.

(an instance of optimum for 10 x10 FT).

Table 1. Several different strategies

MGA_1	random initialization, elitist strategy [26]
MGA_2	Population Initialization, elitist strategy [26]
MGA_3	random initialization, elitist strategy [26], Local Search
MGA_4	50% random initialization+50% Population Initialization, Local Search, elitist strategy [26]

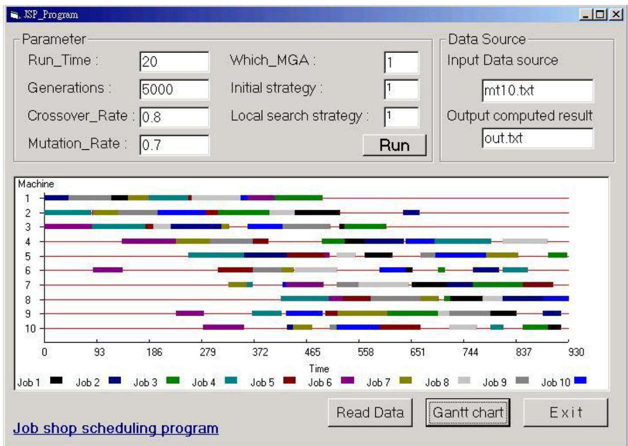

Fig. 5 - The viewer of our system for job-shop scheduling.

Table 2. Crossover rates and mutation rates for FT benchmark problems

	6x6 FT & 10x10 FT			20x5 FT		
	GA	SyGA 1	SyGA 2	GA	SyGA 1	SyGA 2
Pc	0.6	0.8	0.8	0.6	1	0.6
Pm	0.3	0.7	0.9	1	0.8	0.7

Table 3. Crossover rates and mutation rates for LA benchmark problems

SyGA1	LA01. LA06. LA11. LA16. LA21	SyGA1	LA26. LA31. LA36.
Pc	0.8	Pc	1
Pm	0.7	Pm	0.8

Table 4. Crossover rates and mutation rates for ORB benchmark problems

SyGA1	ORB01. ORB04
Pc	0.8
Pm	0.7

Table 5. Results for 10x10FT (optimal: 930)

	GA [33]	GA +MGA_1	GA +MGA_2	GA +MGA_3	GA +MGA_4
Best	966	950	941	**930**	937
Average	993	979.8	970.05	**952.4**	955.65
Std div	19.45	15.6629	15.3742	10.3842	**9.75098**
	SyGA_1 [33]	SYGA_1 +MGA_1	SyGA_1 +MGA_2	SyGA_1 +MGA_3	SyGA_1+ MGA_4
Best	937	937	945	935	**930**
Average	965.85	969.3	961.2	**953.5**	954.9
Std div	15.85	15.8748	**6.75589**	12.2496	12.6876
	SyGA_2 [33]	SyGA_2 +MGA_1	SyGA_2 +MGA_2	SyGA_2 +MGA_3	SyGA_2 +MGA_4
Best	930	937	941	**930**	937
Average	965.5	961.8	961.45	**948.8**	952.95
Std div	17.09	14.6309	**8.23647**	12.9883	11.0047

Table 6. Results for 20x5FT (optimal: 1165)

	GA [33]	GA+MGA_1	GA +MGA_2	GA +MGA_3	GA +MGA_4
Best	1210	1197	**1173**	1179	1178
Average	1251.1	1226.45	1212.2	1191.7	**1191.35**
Std div	24.21	14.2366	16.3405	11.8726	**8.8755**
	SyGA_1 [33]	SyGA_1+MGA_1	SyGA_1+MGA_2	SyGA_1+MGA_3	SyGA_1+MGA_4
Best	1189	1203	1176	1178	**1175**

Average	1214.9	1226.8	1202.8	1195.7	**1192.8**
Std div	15.51	16.1916	15.9427	**13.654**	13.7596
	SyGA_2 [33]	SyGA_2+MGA_1	SyGA_2+ MGA_2	SyGA_2+MGA_3	SyGA_2+MGA_4
Best	1178	1193	1177	1178	**1173**
Average	1233.75	1223.35	1199.6	1197.05	**1190.3**
Std div	23.24	21.4114	13.382	**10.7971**	11.6533

Table 7. Comparisons of the best performance between our GA (PLGA) and some literature results [18]

Problem	Job,Machine	Best known	PLGA	GA [18] best	SA [28] best	TS [6] best	GA [11] best	SB [4] best
MT06	6,6	55	55	55	55	55	55	55
LA01	10,5	666	666	666	666	666	666	666
LA06	15,5	926	926	926	926	926	926	926
LA11	20,5	1222	1222	1222	1222	1222	1222	1222
MT10	10,10	930	930	930	930	935	945	930
MT20	20,5	1165	1173	1165	1165	1165	1178	1178
LA16	10,10	945	945	945	956	945	979	978
LA21	15,10	1046	1051	1058	1063	1048	1097	1084
LA26	20,10	1218	1218	1218	1218	1218	1231	1224
LA31	30,10	1784	1784	1784	1784	1784	1784	1784
LA36	15,15	1268	1279	1292	1293	1278	1305	1305

Table 8. Comparisons of the best performance between our GA (PLGA) with MGA, SA, GA from [19]

Problem	Job, Machine	Best known	PLGA	MGA best	SA best	GA best
MT06	6,6	55	55	55	55	55
MT10	10,10	930	930	930	939	997
MT20	20,5	1165	1173	1165	1227	1247
LA01	10,5	666	666	666	666	666
LA06	15,5	926	926	926	926	926
LA11	20,5	1222	1222	1222	1222	1222
LA16	10,10	945	945	945	979	979
LA21	15,10	1046	1051	1058	1083	1156
LA26	20,10	1218	1218	1218	1253	1328
LA31	30,10	1784	1784	1784	1784	1836
LA36	15,15	1268	1279	1291	1321	1384

4. CONCLUSIONS

The simulation results observed in this paper show that our proposed PLGA algorithm can be applied to obtain the optimal solution or near optimal solution for the job-shop scheduling problem.

5. REFERENCES

[1] Cheng-Fa Tsai, Chun-Wei Tsai, and Chin-Chang Tseng. New and efficient ant-based heuristic method for solving the traveling salesman problem, *Expert Systems* (accepted, will appear in vol. 20, no. 4, 2003).

[2] Cheng-Fa Tsai, Chun-Wei Tsai, and Ching-Chang Tseng. ACOMAC: An Efficient Method for Solving Traveling Salesman

Problem. *2002 IEEE International Joint Conference on Neural Network (IJCNN 2002)*, pp. 1540-1545, Honolulu, Hawaii, USA.

[3] Cheng-Fa Tsai, Chun-Wei Tsai, and Chi-Ping Chen. A Multiple-Searching Approach to Genetic Algorithms for Solving Large Traveling Salesman Problem. *6th Intern. Conf. on Computer Science and Informatics*, pp. 362-366, Durham, NC, USA.

[4] J. Adams, E. Balas, D. Zawack. The shifting bottleneck procedures for job shop scheduling. *Management Science*, vol. 34, pp. 391-401, 1988.

[5] A. Colorni, M. Dorigo, V. Maniezzo, M. Trubian. Ant system for Job-shop Scheduling. *JORBEL - Belgian Journal of Operations Research, Statistics and Computer Science*, 34(1), pp. 39-53, 1994.

[6] Dell's Amico M, M. Turbian. Applying tabu search to the job shop scheduling problem. *Annual Operations Research*, 40, pp. 231-252, 1993.

[7] L. Davis. Applying adaptive algorithms to epistatic domains. *In Proc. of the Inter. Joint Conf. on Artificial Intelligence*, pp. 162-164, 1985.

[8] D. Applegate, W. Cook. A computational study of the job-shop scheduling instance. *ORSA Journal on Computing 3*, pp. 149-156, 1991.

[9] E. Taillard. Benchmarks for basic scheduling problems. *European Journal of operational Research*, 64, pp.278-285, 1993.

[10] E. Falkenauer, S. Bouffoix. A genetic algorithm for job shop. *Proc. of the 1991 IEEE international Conference on Robotics and Automation*, 1991.

[11] F. Croce, R. Tadei, G. Volta. A genetic algorithm for the job shop problem. *Computers & Operations Research*, pp. 15-24, 1995.

[12] Guoyong SHI, Hitoshi IIMA, and Nobuo SANNOMIYA. A new Encoding Scheme for Solving Job Shop Problems by Genetic Algorithm. *Proc. of the 35th Conference on Decision and Control Kobe*, Japan, pp. 4395-4400, 1996.

[13] H. Fisher and G. Thompson. Probabilistic Learning Combinations of Local Hob-Shop Scheduling Rules. *In Industrial Scheduling,* J. Muth and G. Thompson eds.,Prentice-Hall, pp. 1225-1251, 1963.

[14] Hong Zhou, Yuncheng Feng, Limin Han. The hybrid heuristic genetic algorithm for job shop scheduling. *Computer & Industrial Engineering*, pp. 191-200, 2001.

[15] Kyung-Mi Lee and Takeshi Yamakawa. A genetic Algorithm for General Machine Scheduling Problems. *2nd International Conference on Knowledge-based Intelligent Electronic Systems*, pp. 60-66, 1998.

[16] S. Kobayashi, I One, M. Yamamura. An efficient genetic algorithm for job shop scheduling problems. *Proc. of the sixth International Conference on Genetic Algorithms. San Francisco*, CA: Morgan Kaufmann Publishers, pp. 506-511, 1995.

[17] Koji Morikawa, Takeshi Furuhashi, Yoshiki Uchikawa. Single Populated Genetic Algorithm and its Application to Job-shop Scheduling. *Proc. of Industrial Electronics, Control, Instrumentation, and Automation on Power Electronics and Motion Control*, pp. 1014-1019, 1992.

[18] L. Wang, D.-Z. Zheng. An effective hybrid optimization strategy for job-shop scheduling problems. Computers & Operations Research 28, pp. 585-596, 2001.

[19] L. Wang and D.-Z. Zheng. A Modified Genetic Algorithm for Job Shop Scheduling. *The International Journal of Advanced Manfacturing Technology by Springer-Verlag*, vol. 20, pp. 72-76, 2002.

[20] M. Kolonko. Some new results on simulated annealing applied to the job shop scheduling problem. *European Journal of Operational Research*, pp. 123-136, 1999.

[21] M. Gen and R. Cheng. *Genetic Algorithms and Engineering Design*. John Wiley&Sons, New York, 1997.

[22] M. Pinedo. Scheduling: theory, algorithm, and systemd. *Prentice-Hall*, Englewood Cliffs, NJ, 1995.

[23] E. Nowicki, C. Smutnicki. A Fast Taboo Search Algorithm for the Job Shop Problem. *Management Science,* vol. 42, pp. 797-813, 1996.

[24] K. Oey, S.J. Mason. Scheduling batch processing machines in complex job shops. *Conference Proceedings of the winter on Simulation*, vol. 2, pp. 1200-1207, 2001.

[25] I One, M. Yamamura, S. Kobayashi. A genetic algorithms for job-based order crossover. *Proc. of the Third IEEE Conference on Evolutionary Computation. Japan*, pp. 547-52, 1996.

[26] R. Cheng, Mitsuo Gen and Yasuhiro Tsujimura. A tutorial Survey of job-shop scheduling problem using genetic algorithm-I. Reprentation. *Computer ind. Engng* vol. 30, no. 4, pp. 983-997, 1996.

[27] S. Lawrence. Resource constrained project scheduling: an experimental investigation of heuristic scheduling techniques. *Graduate School of Industrial Administration*, Pittsburgh, Carnegie-Mellon University, 1984.

[28] Van Laarhoven PJM, Aarts EHL, and Lenstra JK. Job shop scheduling by simulated annealing. *Operations Research*, 40, pp.113-125, 1992.

[29] Xiu Li, Wenhuang Liu, Shouju Ren, and Xuerui Wang. A solution of job-shop scheduling

problems based on genetic algorithms. *IEEE International Conference on Systems, Man, and Cybernetics*, vol. 3, pp. 1823 -1828, 2001.

[30] Yoon-Pin Simon Foo and Yoshiyasu Takefuji. Stochastic Neural Networks for Solving job-shop scheduling part 1. Problem representation. *IEEE International Conference on Neural Networks*, vol. 2, pp. 275 -282, 1988.

[31] Y. Tsujimura, M. Gen and Y. Mafune. Relations between Evaluation Functions and Schedule-structures in GA-based Job-Shop Scheduling. *Technical Report of IEICE in Japanese*, AI99-13, pp. 17-24, 1999.

[32] Y. Tsujimura, M. Gen and R. Cheng .Improved Genetic Algorithms for Solving Job-shop Scheduling Problem. Engineering Design and Automation, vol. 3, no. 2, pp. 133-144, 1997.

[33] Y. Tsujimura, Y. Mafune and M. Gen. Effects of Symbiotic Evolution in Genetic Algorithms for Job-Shop Scheduling. *Proc. of the 34th Hawaii International Conference on System Sciences*, 2001.

[34] Y. Tsujimura, T. Sugimoto, Y Mafune and M. Gen. A Genetic Algorithm for Job-shop Scheduling by Means of Symbiosis Mechanism. *Proc. of the 3rd Australia-Japan Joint Workshop on Intelligent and Evolutionary Systems*, Canberra, Australia, pp. 228-231, 1999

Cheng-Fa Tsai, *an IEEE member, an associate professor of the Management Information Systems Department at the National Pingtung University of Science and Technology (NPUST), Pingtung, Taiwan. His research interests are in the areas of data mining, data communication networks, database systems, intelligent system, intelligent mobile agent, and wireless networks, with emphasis on efficient intelligent systems implementation and rapid prototyping. He has published over 80 papers in the above fields.*

Feng-Cheng Lin *received his BS degree from Ming Chuan University (Taipei, Taiwan) in 2000 and Master degree from National Pingtung University of Science and Technology (Pingtung, Taiwan) in 2002. Currently, he is a PhD student of National Chi Nan University in Department of Computer Science and Information Engineering (Taiwan) since 2002. His research interests are in the areas of scheduling, algorithm and the optimization of combinatorial problems.*