二階段模糊多目標混合式遺傳演算法零工式排程系統方法之研究

A Study of Two-Stage Fuzzy Multi-Objective Hybrid Genetic Algorithm Job Shop Scheduling System Approach

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中文摘要

本研究探討及提出一遺傳演算法(GA)/**禁忌搜尋**(TS)**混合求解方法，處理零工式排程問題 所考慮多目標函數同時包含多定量(時間及生產)與多定性(市場行銷)準則。現實課題，例如不確定性(模糊)方面、準則相對重要性與替代途程，在模糊集合理論、分析階層程序與動態機率分配的協助下，並於多重目標函數的架構裡予以解決。此外，亦提出一類神經網路應用於更新模糊期間。本** GA/TS **求解方法執行並經由一說明例子與計算結果予以闡述與支持。**

關鍵詞：零工式排程，遺傳演算法/禁忌搜尋，模糊集合，類神經網路，多重定性與定量目標

Abstract

In this research, a genetic algorithm (GA)/tabu search (TS) mixture solution approach is explored and proposed to address the job shop scheduling problems. Multiple objective functions considered include both multiple quantitative (time and production) and multiple qualitative (marketing) criteria. Realistic issues such as the uncertainty (fuzzy) aspect, relative importance of criteria and alternative process plans with the GA/TS approach are resolved with the aids of fuzzy set theory, analytic hierarchy process and dynamic probability distribution within the framework of the multiple objective functions. Furthermore, a neural network application to updating the fuzzy duration is proposed. Implementation of the GA/TS solution approach is demonstrated and supported by an illustrative example and computational results.

Keywords: Job shop scheduling; Genetic algorithm/tabu search; Fuzzy sets; Neural network; Multiple qualitative and quantitative objectives

1. Introduction

The job-shop scheduling problem (JSP) bears several significant objectives for production performance. In addition, its own difficulty to obtain a solution efficiently attracted an enormous number of researchers to study on this subject. Specifically, production scheduling has been studied from several aspects, including:

ª The uncertainty aspect (e.g. processing time of a job on a machine, due date);

ª The solution technique (various types of search techniques, e.g. tree, graph, genetic algorithms, tabu search, simulated annealing, neural networks, artificial intelligence, etc.);

ª The performance measure (objective) aspect (single vs. multiple criteria, relative importance of criteria);

This paper deals with all the above aspects in an integrated manner and is mainly concerned with the integrated multi-criterion approach to job-shop scheduling issues. Specifically, both time and production (or quantitative) and marketing (or qualitative) objectives (such as market consideration, etc.) are considered. To this purpose, the genetic algorithms (GAs) were adapted to handle these problems with the aids of such techniques as analytic hierarchy process (AHP) and tabu search (TS).

2. Fuzzy concepts & neural network application to revise fuzziness

We denote an operation j of a job J_i as O_{ij}. Define that an O_{ij} has a fuzzy processing time on a given machine by a triangular fuzzy number.

The due date of a job J_i is then defined as shown in Fig. 1.

2.1. *Fuzzy start and end times*

Possible fuzzy start time S_{ij} of an operation is evaluated according to [8]:

$$S_{ij} = (\max_{k\in U_{ij}} e_k^L,\ \max_{k\in U_{ij}} e_k^M,\ \max_{k\in U_{ij}} e_k^U) \qquad (1)$$

where U_{ij} denotes the set of operations that has influence on determining S_{ij} of O_{ij} and (e_k^L, e_k^M, e_k^U) are fuzzy end times of the operations in U_{ij}.

But (1) could also present a problem, where that the fuzziness of fuzzy times summed together gets fuzzier, the tolerance for the adjacent operations can become unsuitably large.

2.1.1. *Neural network to revise fuzzy time*

Back-propagation neural network (BPN) (e.g. [2]) may be considered. That is, in particular, the fuzziness of a possible start time of an operation may be updated according to the current machine statuses specified as e.g. 'good', 'fair' or 'poor'. The output is then a value of ~ for an ~-level cut of S_{ij} (Fig. 2). Satisfactory trained results have been applied in this study.

2.2. *Comparison of fuzzy numbers*

In this study, the overall-existence-ranking index (OERI) [3] was adopted. For a triangular fuzzy number, in the simple pure weighting case,

$$OM(P_{ij}) = \left(p_{ij}^{L} + 4p_{ij}^{M} + p_{ij}^{U}\right)\big/6 \qquad (2)$$

3. Problem formulation

3.1. *The qualitatively evaluated job-sequence*

The consideration of qualitative objectives, however, represents some difficulties (e.g. judgement and quantification) and may be considered a multi-criteria decision-making problem (e.g. [7]). The AHP methodology [12] appears to provide a powerful and simple method for handling these issues. A simple AHP may be found in [7] and easily adapted for the multiple qualitative criteria for JSPs, which may result in herein called a "qualitatively evaluated job-sequence".

As the soft constraint of the GA/TS algorithm, specifically job sequences generated by GA/TS may be compared with the qualitatively evaluated job-sequence. If variance occurs, a penalty value may be imposed upon the genetically generated job sequence. The penalty function is detailed in Section 4.1.3.

3.2. *Quantitative objectives*

A number of quantitative criteria [10] has been suggested in the literature. Frequently utilized, three criteria may be modeled here for demonstration.

3.2.1. *Model 1: minimization of makespan* (F_1)

$$F_1 = OM(MS)_{\min}\big/OM(MS_p) \qquad (3)$$

where $OM(MS)_{\min}$ represents the defuzzified smallest makespan found up to a given point of time. $F_1 \in (0, 1]$.

3.2.2. *Model 2: due-date satisfaction* (F_2)

We propose a model similar to [8] as: let $C_i=(c_i^L, c_i^M, c_i^U)$ denote the completion time of J_i with membership $\mu_i^C(t)$. The degree of due date satisfaction of J_i can be defined as

$$F_2 = \int_{c_i^L}^{c_i^U}[\mu_i^D(t) \wedge \mu_i^C(t)]dt \Big/ \int_{c_i^L}^{c_i^U}\mu_i^C(t)dt \qquad (4)$$

3.2.3. *Model 3: machine utilization* (F_3)

To calculate the machine utilization (MU), the process time of each of the operations scheduled on a machine can be summed and then divided by the completion time of the last operation on the machine using fuzzy arithmetic. Further, use the OERI to defuzzify the machines' utilization, and the mean utilization is calculated.

4. Multi-criteria GA/TS approach

Fig. 3 depicts the framework of the GA/TS approach (for short, MC-GA/TS). The following subsections discuss its components.

4.1. *GAs for multi-objective JSPs*

In this section, the GAs, terminology and design issues are discussed for developing a GA for the JSPs.

4.1.1. *Chromosome representation*

In this study, a modified operation-based method for this purpose that it is suited for differing numbers of operations of jobs is proposed and used (Fig. 4).

However, a chromosome thus produced may consist of genes, which indicate the sequence of operations and that does not meet the jobs' process routes. In this case, exchange of the violating genes gives an easy remedy.

4.1.2. *Evaluation or fitness function*

As multiple criteria are concerned in this study, a fitness function may be constituted by these two groups of objectives.

$$F = w_1\left(\sum_{k=1}^{3}\omega_k F_k\right) + w_2(1 - L) \qquad (5)$$

where w_1, w_2 and ω_k denote the weights of the quantitative and qualitative groups and objectives F_k, $w_1 + w_2 = 1$, $\sum\omega_k = 1$, and L represents the penalty function.

The penalty L may be computed as follows.

[Penalty function algorithm]

Step 1. Compute the overall sequence of the jobs in a chromosome as that: first compute the average genes of these jobs, AVG_i.

$$AVG_i = \sum_{g_k \in J_i} g_k \big/ n_i \qquad (6)$$

where n_i denotes the number of operations of J_i.

Step 2. Sequence the jobs according to AVG_i. Denote it as $[gs_i]_{1\times n}$, i=1,…, n, where gs_i represents the ordinal number of sequence of J_i.

Step 3. Calculate the penalty function value L: let $[qs_i]_{1\times n}$, i=1,…,n, represent the qualitatively evaluated job-sequence where again the value of qs_i denotes the ordinal number of sequence of J_i.

$$L = \sum_{i=1}^{n}(gs_i - qs_i)^2 \big/ L_{\max} \qquad (7)$$

where $L_{\max}$ denotes the maximum sum of squared differences between two sequences (for n jobs).

4.1.3. *Crossover and mutation*

Based on past analyses (e.g. [4,5,11,6]) and ours performed on the JSPs, particularly, the linear-order crossover (LOX) and position-based mutation (PM) were elected in the final version of the algorithm.

4.1.4. *Population diversity & reproduction policy*

In GAs, elite preserving strategy (EPS) and its variations (e.g. GA references in this paper) almost are the most frequently used strategies in GAs, though other strategies may also be used [9]. Besides, as using EPS, to prevent premature convergence occurring, here as an alternative, the known roulette wheel technique is modified.

$$®_p = r_p \Big/ \sum_p r_p \qquad (8)$$

where $®_p$ denotes the probability of individual chromosome p that may be chosen and r_p the reverse rank of the fitness value of p.

4.2. *Incorporation of TS in GA*

Since tabu search bears the concept of neighborhood search and flexible memory or tabu list. TS [13,1] is suitable for improving the local search in GA. TS may be performed after mutation on each chromosome.

4.3. *Alternative process plans*

Here we assume that the main process plans are used in the first computations of GA. To select a chromosome to consider the alternate process plan in GA, the Boltzmann distribution is used that:

$$B_p = \exp\left(-F_p / KT\right) \Big/ \sum_p \exp\left(-F_p / KT\right) \qquad (9)$$

where F_p denotes the fitness function value of chromosome p, K is Boltzmann's constant (K=1 used in this research), and T temperature. Once a chromosome is selected, a job may be randomly selected to consider its alternate process plan.

5. Numerical example and some computational results

The above algorithms are implemented in MS C++ on a PC.

5.1. *A numerical example*

In this example (Table 1), quantitative criteria were considered as MS, DDS and MU. Qualitative criteria were considered such as

ª Market consideration, MC: for jobs in competitive markets or other requirements (e.g. promotion);

ª And likewise, job profit and/or risk (JR), customer potential orders (PO) and historical business with the firm (HB).

The qualitatively evaluated job-sequence by the AHP procedure is:

(*a*) The qualitatively evaluated job-sequence $[qs_i]_{1\times 10}$ = (2, 8, 3, 1, 9, 7, 6, 5, 4, 10) for the jobs from J_1 through J_{10}.

(*b*) The fitness function

$$F = (0.75)[(0.28)(F_1) + (0.65)(F_2) + (0.07)(F_3)] + 0.25(1 - L)$$

The schedule of this problem therefore obtained by the MC-GA/TS is shown in Table 2, where jobs J_2 and J_7 were scheduled with their alternate process plans while the other jobs were scheduled with the main process plans for the best fitness.

The example demonstrates that scheduling can be evaluated with respect to both qualitative and quantitative objectives. These results can therefore be very useful to manufacturers in their effort to develop efficient production plans.

5.2. *A comparison of GA/TS and GA*

During implementation of the MC-GA/TS algorithm, comparison between the GA/TS algorithm and the GA was also carried out, based on the CPU time required to 100 generations of the GA/TS. In 30 trials, the results of highest fitness function value obtained with each algorithm were obtained. It is indicated that GA/TS not only provided the solution with higher fitness values but also that had a smaller deviation. A further analysis of these results confirmed this observation that: $|t|$ = 49.91 > $t_{\sim = 0.05}$ = 1.69 and reject H_0: $«_{GA/TS} \leq «_{GA}$.

Selected references

[1] B. Adenso-Diaz, "An SA/TS mixture algorithm for the scheduling tardiness problem," *European Journal of Operation Research*, vol.**88**, pp.516-524, 1996.

[2] R. Bharath and J. Drosen, *Neural Network Computing*, NY: McGraw-Hill, 1994.

[3] P.-T. Chang and E. S. Lee, "Ranking of fuzzy sets based on the concept of existence," *Computers and Mathematics with Applications*, vol.**27**, pp.1-21, 1994.

[4] G. A. Cleveland and S. F. Smith, "Using genetic algorithms to schedule flow shop release," *Proc. of 3rd International Conference on GAs*, Morgan Kaufmann, Palo Slto, CA, 1989, pp.160-169.

[5] E. Falkenauer and S. Bouffoix, "A genetic algorithm for job shop," *Proc. of 1991 IEEE International Conference on Robotics and Automation*, 1991, pp.824-829.

[6] D. E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning*, Reading, MA: Addison-Wesley, 1989.

[7] C.-L. Hwang and K. Yoon, *Multiple Attribute Decision Making*, Berlin/ Heidelberg/ NY: Springer-Verlag, 1981.

[8] M. Kuroda and Z. Wang, "Fuzzy job shop scheduling," *Internat. Journal of Production Economics*, vol.**44**, pp.45-51, 1996.

[9] G. E. Liepins and M. R. Hilliard, "Genetic algorithms: foundations and applications," *Annals of Oper. Res.*, vol.**21**, 31-58, 1989.

[10] P. Mellor, "A review of job shop scheduling," *Operational Research Quarterly*, vol.**17**, pp.161-170, 1966.

[11] P. W. Poon and J. N. Carter, "Genetic algorithm crossover operators for ordering applications," *Computers and Operations Research*, vol.**22**, pp.135-147, 1995.

[12] T. L. Saaty, *Fundamentals of Decision Making and Priority Theory with the Analytic Hierarchy Process*, PA: RWS, 1994.

[13] J.-S. Song and T.-E. Lee, "A tabu search procedure for periodic job shop scheduling," *Computers and Industrial Engineering*, vol.**30**, pp.433-447, 1996.

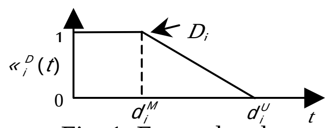

Fig. 1. Fuzzy due date.

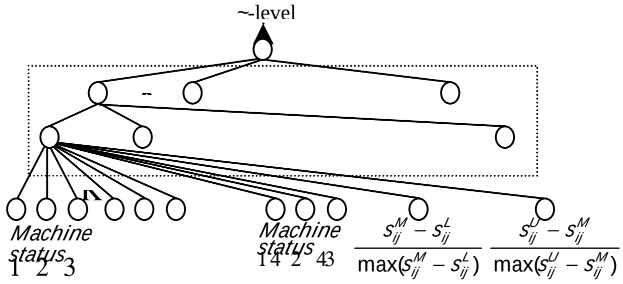

Fig. 2. Structure of the updating BPN.

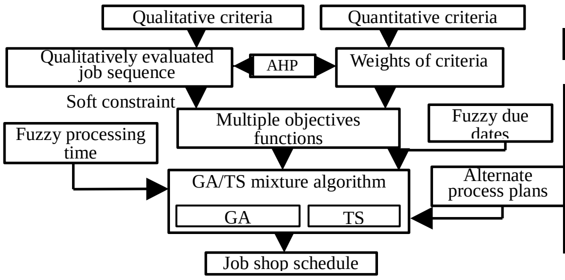

Fig. 3. Framework of the MC-GA/TS.

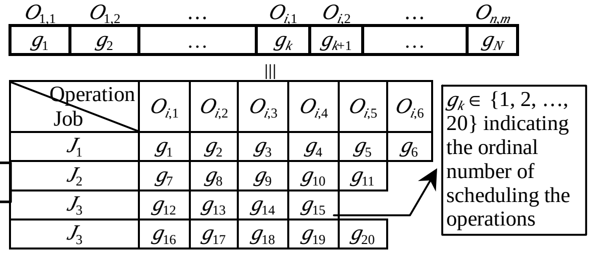

Fig. 4. The modified operation-based representation.

Table 1. 10 jobs with 4 to 6 operations on 8 machines.

Job	PP[a]	Operation sequence: Machine no.\\P_{ij}, $j = 1, …, n_i$	Due date
J_1	M[b] A[c]	3\(13, 16, 20), 4\(10, 12, 16), 7\(17, 20, 24), 1\(13, 16, 20), 6\(12, 15, 19), 8\(12, 14, 18). 5\(14, 17, 21), 4\(10, 12, 16), 7\(17, 20, 24), 3\(14, 16, 20), 2\(13, 16, 19), 6\(12, 14, 18).	(105, 115)
J_2	M A	8\(10, 12, 14), 3\(6, 8, 11), 1\(14, 16, 20), 2\(5, 7, 9), 5\(8, 10, 13), 7\(14, 17, 20). 2\(10, 12, 15), 3\(6, 8, 11), 1\(14, 16, 20), 6\(5, 7, 9), 5\(8, 10, 13), 4\(15, 18, 22).	(125, 135)
J_3	M A	3\(13, 16, 21), 2\(8, 10, 13), 4\(10, 12, 16), 5\(10, 12, 15), 8\(17, 20, 24). 1\(13, 17, 21), 6\(8, 10, 13), 7\(10, 13, 16), 5\(10, 12, 15), 2\(17, 20, 24).	(140, 150)
J_4	M A	6\(13, 16, 20), 5\(7, 8, 11), 4\(7, 9, 12), 2\(21, 24, 28), 7\(8, 10, 13), 1\(8, 10, 12). 8\(13, 17, 21), 3\(7, 8, 11), 7\(7, 10, 12), 2\(21, 24, 28), 4\(8, 11, 13), 1\(8, 10, 12).	(110, 120)
J_5	M A	1\(9, 12, 15), 3\(17, 20, 24), 7\(12, 16, 21), 5\(11, 14, 18). 2\(10, 12, 15), 8\(17, 20, 24), 4\(13, 17, 21), 5\(11, 14, 18).	(130, 140)
J_6	M A	1\(15, 18, 23), 4\(9, 12, 15), 2\(6, 8, 10), 8\(14, 16, 21), 5\(7, 9, 11), 6\(15, 18, 23). 3\(16, 18, 23), 7\(11, 13, 15), 2\(6, 8, 10), 4\(14, 18, 21), 5\(7, 9, 11), 1\(16, 18, 23).	(115, 130)
J_7	M A	2\(7, 9, 12), 7\(14, 16, 20), 1\(13, 16, 21), 8\(17, 20, 25), 5\(9, 12, 14). 6\(8, 10, 13), 4\(14, 16, 20), 3\(13, 16, 21), 8\(17, 20, 25), 5\(10, 12, 15).	(110, 120)
J_8	M A	4\(12, 15, 19), 6\(21, 24, 28), 7\(14, 16, 20), 2\(6, 8, 11), 4\(10, 12, 16), 8\(12, 14, 18). 3\(12, 15, 20), 6\(21, 24, 28), 7\(14, 16, 20), 2\(6, 8, 11), 1\(10, 12, 17), 8\(12, 14, 18).	(120, 135)
J_9	M A	2\(8, 10, 13), 1\(10, 13, 17), 7\(12, 16, 21), 5\(10, 12, 15), 4\(16, 18, 22), 3\(17, 20, 23). 6\(8, 11, 13), 8\(11, 14, 17), 7\(12, 16, 21), 3\(10, 12, 15), 4\(16, 18, 22), 5\(17, 20, 23).	(120, 130)
J_{10}	M A	8\(8, 10, 13), 5\(12, 16, 18), 3\(19, 24, 30), 2\(13, 16, 21), 6\(7.5, 9, 13). 1\(9, 10, 13), 4\(12, 16, 18), 3\(19, 24, 30), 7\(14, 16, 21), 6\(7.5, 9, 13).	(130, 138)

[a]PP: Process plan; [b]M: Main; [c]A: Alternate.

Table 2. Schedule of the 10 jobs on 8 machines.

Job	Operation sequence: Machine no.**gene**\\$S_{ij}$\\$E_{ij}$, $j = 1, …, n_i$
J_1	3**1**\(0, 0, 0)\(13, 16, 20), 4**11**\(14, 16, 18.7)\(24, 28, 34.7), 7**15**\(25.3, 28, 32.5)\(42.3, 48, 56.5), 1**19**\(44.1, 48, 53.9)\(57, 64, 73.9), 6**36**\(59.3, 64, 70.6)\(71.3, 79, 89.6), 8**42**\(90.6, 96, 104.5)\(102.6, 110, 122.5)|.
J_2	2**21**\(8, 10, 13)\(20, 22, 28), 3**22**\(28.9, 32, 36.8)\(34.9, 40, 47.8), 1**29**\(59.2, 64, 70.8)\(73.2, 80, 90.8), 6**38**\(75.3, 80, 87.4)\(80.3, 87, 96.4), 5**39**\(82.4, 87, 93.5)\(90.4, 97, 106.5), 4**51**\(104.5, 109, 116.3)\(119.5, 127, 138.3)|.
J_3	3**4**\(14.1, 16, 18.5)\(27.1, 32, 39.5), 2**10**\(28.8, 32, 36.9)\(36.8, 42, 49.9), 4**27**\(61, 65, 71.2)\(71, 77, 87.2), 5**44**\(104.5, 109, 116.4)\(114.5, 121, 131.4), 8**46**\(119.2, 124, 132.6)\(136.1, 144, 156.6)|.
J_4	6**8**\(8.7, 10, 12)(21.7, 26, 32), 5**9**\(23.2, 26, 30)\(30.2, 34, 40.9), 4**17**\(52.1, 56, 62)\(59.1, 65, 74), 2**18**\(61, 65, 71.1)\(82, 89, 99.1), 7**23**\(84.5, 89, 95.6)\(92.5, 99, 108.6), 1**25**\(94.8, 99, 105.2)\(102.8, 109, 117.2)|.
J_5	1**5**\(16.1, 18, 21.2)\(25.1, 30, 36.2), 3**33**\(36.7, 40, 45)\(53.7, 60, 69), 7**53**\(94.4, 99, 105.8)\(106.4, 115, 126.8), 5**55**\(116.4, 121, 128.4)\(127.4, 135, 146.4)|.
J_6	1**2**\(0, 0, 0)\(15, 18, 23), 4**13**\(25.3, 28, 32.5)\(34.3, 40, 47.5), 2**20**\(38.4, 42, 47.5)\(44.4, 50, 57.5), 8**30**\(46.1, 50, 55.2)\(60.1, 66, 76.2), 5**49**\(71.1, 76, 82.8)\(78.1, 85, 93.8), 6**52**\(82.4, 87, 93.5)\(97.4, 105, 116.5)|.
J_7	6**3**\(0, 0, 0)\(8, 10, 13), 4**14**\(36.2, 40, 44.9)\(50.2, 56, 64.9), 3**34**\(55.9, 60, 65.8)\(68.9, 76, 86.8), 8**41**\(71.1, 76, 83.4)\(88.1, 96, 108.4), 5**43**\(92.5, 97, 104.8)\(102.5, 109, 119.8)|.
J_8	4**6**\(0, 0, 0)\(12, 15, 19), 6**16**\(23.1, 26, 30)\(44.1, 50, 58), 7**28**\(58.7, 64, 71.2)\(72.7, 80, 91.2), 2**31**\(84.2, 89, 96)\(90.2, 97, 107), 4**35**\(92.5, 97, 103.6)\(102.5, 109, 119.6), 8**45**\(105, 110, 118.5)\(117, 124, 136.5)|.
J_9	2**7**\(0, 0, 0)\(8, 10, 13), 1**12**\(26.7, 30, 34.1)\(36.7, 43, 51.1), 7**24**\(44.3, 48, 53.5)\(56.3, 64, 74.5), 5**26**\(58.9, 64, 70.9)\(68.9, 76, 85.9), 4**37**\(72.8, 77, 84)\(88.8, 95, 106), 3**54**\(93.1, 100, 109.4)\(110.1, 120, 132.4)|.
J_{10}	8**32**\(0, 0, 0)\(8, 10, 13), 5**40**\(31.3, 34, 38.8)\(43.3, 50, 56.8), 3**47**\(71.1, 76, 83.4)\(90.1, 100, 113.4), 2**48**\(93.3, 100, 109.1)\(106.3, 116, 130.1), 6**50**\(109.4, 116, 125.6)\(116.9, 125, 138.6)|.