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Genetic algorithm applied to the flow shop scheduling problem under effects of fuzzy learning and deterioration with a common fuzzy due date

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Abstract

This research is to develop an approximate solution for a flow shop scheduling problem under the effects of fuzzy learning and deterioration with a common fuzzy due date by applying genetic algorithm technique. Real life is complex and filled with ambiguity and uncertainty. Due dates may not be always determined by a decision maker because of their biased approach and past experiences. Therefore, due dates may be defined in forms of any fuzzy set to encode decision maker's biased approaches and satisfaction levels for completion times of jobs. The objective function of the problem in this research is to maximise decision maker's sum of satisfaction levels with respect to completion times of jobs on a flow shop scheduling environment by applying genetic algorithm technique.

Keywords: Flow shop, fuzzy due date, genetic algorithm, learning effect, deterioration effect.

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1. Introduction

In a general flow shop scheduling problem, there are *m* machines in series and *n* jobs. Each job J_i, where $i \in n$, has separated into operations ($O_{i,1}$, ... $O_{i,m}$) and J_i has *m* different operations on *m* machines in the same order ($O_{i,1} \rightarrow O_{i,2} \rightarrow O_{i,3} \rightarrow \ldots \rightarrow O_{i,m}$) with operation times $P_{i,j}$, where $j \in m$ and $i \in n$. Figure 1 illustrates a Gantt chart for a flow shop schedule with three jobs and three machines. For a general flow shop scheduling problem, decision maker (DM) has to determine the optimal schedule from $n!^m$ possible schedules. DM doesn't always have a chance to search the best schedule by calculating the performance measure for entire solution space. Hence, DM should consider making a tradeoff between calculating all possible schedules and obtaining a faster and approximate solution. The purpose of this study is to apply genetic algorithm (GA) technique to a flow shop scheduling problem under effects of fuzzy learning and deterioration with a common fuzzy due date.

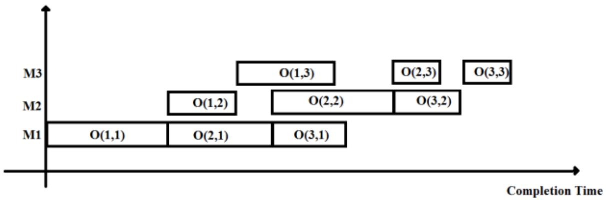


Figure 1. Example of flow shop schedule

The phenomenon of learning effect denotes a decrease in initially determined processing times because of the experience and expertise obtained via constantly repetition of similar tasks on machines or system. Moreover, the phenomenon of deterioration effect denotes an increase in initially determined processing times while jobs are waiting in the queue or are being processed on machines. Both of these effects have been widely studied for more than fifteen years as deterministic in scheduling problems. However, a worker or a machine or a system may not always learn from previous tasks or deteriorate the task as same as previous deterioration amount. These effects may not be always defined in deterministic form due to system characteristics and workplace conditions such as vibration, noise, temperature, air flow rate and pressure. Furthermore, a worker or a system may not always learn steady, i.e., a worker can learn a bit more than previous repetition or he can learn a bit less than previous repetition. Therefore, any form of fuzzy sets can be used to encode inherent uncertainties of these external effects in a scheduling problem. By using a similar approach for due dates, DM may express his satisfaction degrees by comparing completion times of all jobs with a common fuzzy due date.

The remainder of this paper is organised as follows. In Section 2, we present a literature review. Section 3 presents related terminologies about fuzzy set theory and learning/deterioration effect. Section 4 shows the GA technique applied for the problem. In Section 5, solutions of some problems, obtained from proposed GA by using Taillard's (1993) processing times for flow shop problems, are illustrated.

2. Literature review

Learning and deterioration effects have been widely interested by researchers for a long time. Biskup (1999) was the first one who introduced learning effect in scheduling problems. Some of other pioneers for learning effect in scheduling problems are Mosheiov (2001), Kuo and Yang (2006), Biskup (2008), Mosheiov and Sidney (2003), Wang, Ng, Cheng and Liu (2008), Bachman and Janiak (2004), Mosheiov (2011), Koulamas and Kyparisis (2007), Yin, Xu, Sun and Li (2009), Cheng, Wu and Lee

(2008), Wang and Xia (2005), Lee and Wu (2004), Janiak and Rudek (2009). Deterioration effect denotes that processing time of a job increases as regards to a function dependent on its starting time while that job is being processed on a machine or waiting in the queue. First studies about deterioration effect in scheduling problems were considered by Gupta and Gupta (1988) and Browne and Yechiali (1990). Some of other studies about scheduling problems under deterioration effect were investigated by Mosheiov (1991, 1995, 1998, 2002), Ng, Cheng, Bachman and Janiak (2002), Bachman, Janiak and Kovalyov (2002), Wang and Xia (2006), Wu and Lee (2008), Wang, Daniel, Cheng and Liu (2006), Wang, Ng and Cheng (2008) and Gawiejnowicz (2007).

In flow shop scheduling problems, there are several papers concerning learning and/or deterioration effects. Wang (2006) showed that some single machine and flow shop scheduling problems can be solved in polynomial time for some special cases. Wang, Lin and Shan (2008) investigated the make span minimisation and total completion time minimisation objectives in flow shop scheduling problems under learning and deterioration effects simultaneously and they showed that these problems can be solved in polynomial time for some special cases. Wang and Xia (2006) investigated linear deterioration effect on flow shop scheduling problems these are makespan minimisation and weighted sum of completion time minimisation, respectively. In another study of Wang and Xia (2005), learning effect was considered for flow shop scheduling makespan and flow time problems. Lee and Wu (2004) considered learning effect in a two-machine scheduling problem that's objective is to minimise the total completion time. Wang and Liu (2009) investigated a two-machine flow shop scheduling problem under effect of learning and deterioration in order to minimise total completion time by using a branch and bound algorithm. Wang, Ji, Cheng and Wang (2012) investigated a two-machine flow shop scheduling problem under learning and deterioration effects for minimisation of makespan by using heuristic algorithms and a branch and bound algorithm.

GA is a well-known and preferred probabilistic search technique for optimisation problems by stimulating the process of evolution. In fuzzy flow shop scheduling problems, the most prominent paper related to fuzzy due dates and GA was investigated by Ishibuchi, Yamamoto, Murata and Tanaka (1994). They considered two flow shop problems with fuzzy due date by applying GA and neighbourhood search algorithms. They used the membership function of a fuzzy due date for each job to represent the grade of satisfaction of a DM considering the completion time of that job. The problems were to maximise the minimum grade of satisfaction and to maximise the sum of grades of satisfaction, respectively. Ishibuchi, Murata and Lee (1996a, 1996b) investigated multi-objective fuzzy flow shop scheduling problems – maximisation of the minimum satisfaction grade and maximisation of total satisfaction grades – with fuzzy processing times by using a multi-objective GA. Wu and Gu (2004) proposed a GA for solving a multi-objective flow shop scheduling problem by converting their fuzzy problem into crisp one. Wang, Du and Zhang (2006) proposed a GA algorithm based on the fuzzy logic controller for a fuzzy flow shop scheduling problem with fuzzy processing times. Some of other paper included GA as solution approach for fuzzy flow shop scheduling problems were conducted by Bozejko, Hejducki and Wodecki (2008), Zhou and Gu (2009) and Yimer and Demirli (2009). The papers of Sakawa and Kubota (2000, 2001) and Sakawa and Mori (1999) are good examples for illustrating GA with fuzzy processing times and fuzzy due dates, although these papers are not designed for flow shop problems.

3. Preliminaries

In this section, we present the related fuzzy set terminologies and mathematical notations. Fuzzy set was introduced by Zadeh (1965) to let a set have elements with degrees of membership between 0 and 1. Let X be a non-empty set and $x \in X$, for each element of a fuzzy set $\tilde{A}$ in X, there is a membership function $\mu_A(x) \to [0,1]$ and fuzzy set $\tilde{A}$ can be characterised as follows:

$$\tilde{A} = \{(x, \mu_A(x)) | x \in X\}. \tag{1}$$

A fuzzy number $\tilde{A}$ is a convex and normalised fuzzy set, $\tilde{A} \subseteq \mathrm{R}$. whose membership functions of fuzzy number $\tilde{A}$ is continuous or piecewise continuous and also one of its members has a membership function value such $\mu_A(x) = 1$ at least. The form of triangular fuzzy number (TFN) is the one of most well-known types of fuzzy numbers. The membership function of a TFN is a piecewise continuous function that increases on the interval of [0,1], decreases on the interval of [1,0] and has only one peak equals 1. Fig 2. illustrates the membership function of a TFN $\tilde{A}$ and Eq. (2) shows the piecewise membership function of TFN $\tilde{A}$.

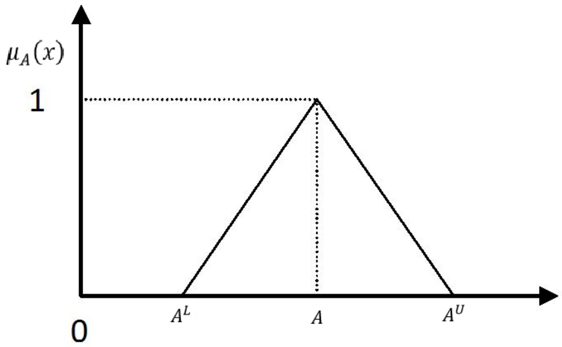


Figure 2. The membership function of TFN $\tilde{A} = \{A^L, A, A^U\}$

$$\mu_A(x) = \begin{cases} \dfrac{x - A^L}{A - A^L}, & if\ A^L \le x < A \\ 1, & if\ x = A \\ \dfrac{A^U - x}{A^U - A}, & if A < x \le A^U \\ 0, & otherwise \end{cases} \tag{2}$$

The arithmetic operations on an interval for two TFN $\tilde{A}$ and $\tilde{B}$ as follows:

$$\tilde{A}(+)\tilde{B} = \left(A^L + B^L, A + B,\ A^U + B^U\right) \tag{3}$$

$$\tilde{A}(-)\tilde{B} = \left(A^L + B^U, A - B,\ A^U - B^L\right) \tag{4}$$

$$\tilde{A}(\mathrm{g})\tilde{B} = \left(\min\left\{A^L * B^L, A^L * B^U, A^U * B^L, A^U * B^U\right\}, A * B, \max\left\{A^L * B^L, A^L * B^U, A^U * B^L, A^U * B^U\right\}\right) \tag{5}$$

$$\tilde{A}(/)\tilde{B} = \left(\min\left\{A^L / B^L, A^L / B^U, A^U / B^L, A^U / B^U\right\}, A / B, \max\left\{A^L / B^L, A^L / B^U, A^U / B^L, A^U / B^U\right\}\right) \tag{6}$$

The expected value $E(\tilde{A})$ of a TFN $\tilde{A}$ can be found by using the method Liu and Liu (2002) as follows:

$$E(\tilde{A}) = \frac{A^L + 2A + A^C}{4} \tag{7}$$

Biskup (1999) introduced how position based learning effect can be considered in scheduling problems. Let P_r be basic processing time of the job assigned at position r in the sequence and its actual processing time $P_{[r]}$ can be calculated as follows:

$$P_{[r]} = P_r r^{a}, \tag{8}$$

where a is learning effect coefficient for scheduling environment $(-1 < a < 0)$. Mosheiov (1991) showed the actual processing time $P_{[r]}$ of a job depends on its starting time and $P_{[r]}$ increases when starting time of that job increases under linear job deterioration effect. Let $S_{[r]}$ be starting time of the job at position r, $P_{[r]}$ can be calculated as follows:

$$P_{[r]} = P_r + BS_{[r]}, \tag{9}$$

where B is linear deterioration effect coefficient for scheduling problems $(0 < B < 1)$ Both of these effects can be used in scheduling problems simultaneously as follows:

$$P_{[r]} = \left(P_r + BS_{[r]}\right) r^{a}. \tag{10}$$

In this study learning and deterioration effects are in form of TFN. Therefore Eq. (10) can be regulated as follows:

$$P_{[r]} = \left(P_r + \tilde{B}S_{[r]}\right) r^{\tilde{a}}, \tag{11}$$

where $\tilde{B} = \left\{B^L, B, B^U\right\}$ and $\tilde{a} = \left\{a^L, a, a^U\right\}$.

In a classic scheduling problem, due dates are non-fuzzy numbers and if a job is completed until its due date, then this job is not a tardy job. However, this approach doesn't allow DM to express his satisfaction degree for each job's completion. Fuzzy number can be used in order to flex a job's due date and denote the satisfaction degree of DM in numbers. Figure 3 illustrates a classic due date and a fuzzy due date for a completion time of any job.

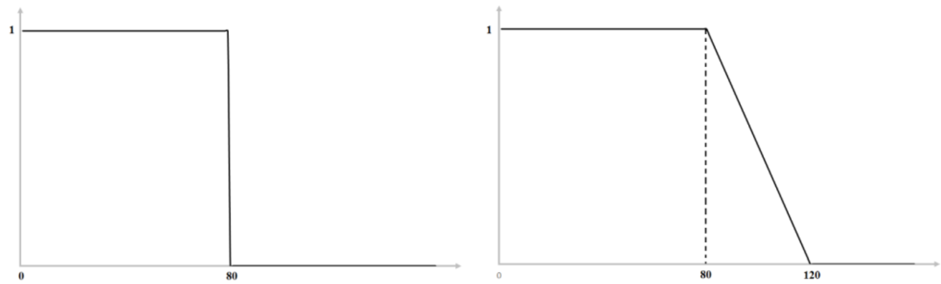


Figure 3. Classical due date and fuzzy due date examples

As seen in Figure 3, deterministic due dates do not express the satisfaction degree of DM for a completion time of any job. By using classical due dates, if a job is completed at 81, then this job does not satisfy DM because it is greater than 80. On the other hand, if DM chooses fuzzy numbers to define due dates, the job that's completion time is 81 provides a satisfaction degree which is close to 1. The membership function of fuzzy due date $\tilde{d}$ for completion time C_i of a job can be written as follows:

$$\mu_d\left(C_i\right)=\begin{cases} 1, & if\ C_i \le \underline{d} \\ \dfrac{C_i-\underline{d}}{\bar{d}-\underline{d}}, & if\ \underline{d}<C_i<\bar{d} \\ 0, & if\ C_i \ge \bar{d} \end{cases}, \tag{12}$$

where $\underline{d}$ is the lower bound of fuzzy due date and $\underline{d}$ is the upper bound of fuzzy due date. In this study, the objective is to maximise the sum of satisfaction degrees for all jobs under fuzzy learning and deterioration effects with a common fuzzy due date. The objective function of the problem is as follows:

$$max\sum_{i=1}^{n}\mu_{d^{\pi}}\left(C_i^{\pi}\right), \tag{13}$$

where π is index for all possible schedules and the mathematical model try to find a schedule having maximum total grade of satisfaction of DM.

4. Genetic algorithm

GA is a well-known metaheuristic method that applies some processes such as crossover and mutation processes in the evolution to selected solutions (chromosomes) from initially generated solution population in order to generate better solutions and find an optimum solution. Pairs of solutions that will be transmitted next generation are randomly selected to operate crossover and mutation processes, respectively. Figure 4 illustrates a flow diagram for a general GA.

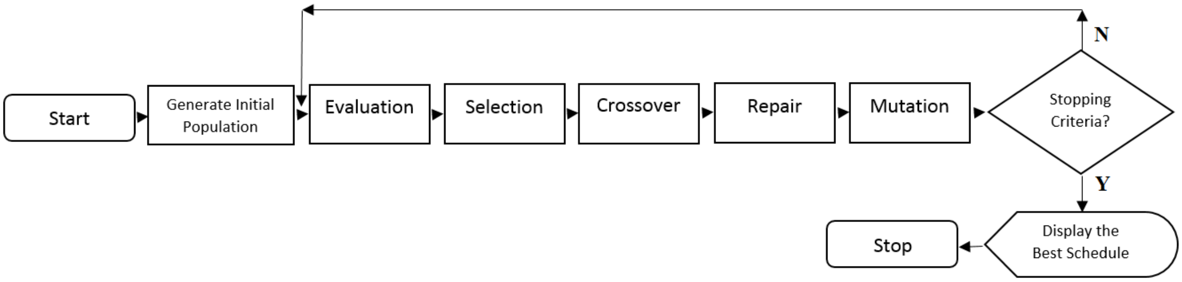


Figure 4. Flow diagram of GA

The evaluation process of GA in this study depends on the fitness values of each solution in the population and the fitness values (F_k) of each solution is calculated as follows:

$$F_k=\sum_{i=1}^{n}\mu_{d^k}\left(C_i^k\right), \tag{14}$$

where k is the index for solutions in the population and $k \in P$. Each member of population is a permutation of n numbers where n is number of jobs. C_i^k is the completion time of job i under effects of fuzzy learning and deterioration. In order to reduce complexity and time requirement for calculation, we use the expected values (see Eq. (7)) of learning and deterioration effect coefficients while calculating C_i^k as follows:

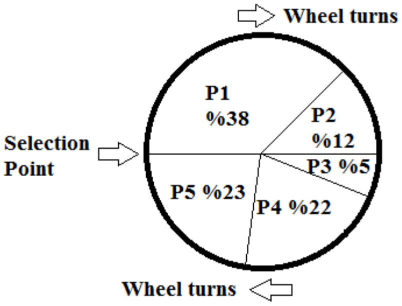
$$C_i^k=\begin{cases} C_{r,M}^k, & if\ the\ job\ at\ position\ r\ on\ the\ last\ machine\ M\ is\ job\ i\ \forall r \\ 0, & otherwise \end{cases}, \tag{15}$$

$$C_{r,m}^{k} \geq C_{r-1,m}^{k} + P_{[r],m}^{k} \quad \forall r, m, \tag{16}$$

$$P_{[r],m}^{k} \geq \left(P_{r,m}^{k} + E\left(\tilde{B}\right) S_{r,m}^{k}\right) r^{E(\tilde{\alpha})} \forall r, m, \tag{17}$$

where m is index for machines $m \in M$ and also $C_{r,m}^{k}$, $P_{[r],m}^{k}, P_{r,m}^{k}$ and $S_{r,m}^{k}$ is the completion time, actual processing time, basic processing time and starting time of the job at position r on machine P_m respectively.

The selection process of solution that will be transmitted to next generation in this study depends on roulette wheel selection as shown in Figure 5.



Population	Fitness f(x)	% of Total	Expected f(x) / $\bar{f}(x)$	# of copy for next generation
P1	95	38	1.90	3 ≃ 1.90 / 0.628
P2	30	12	0.24	0 ≃ 0.24 / 0.628
P3	12.5	5	0.10	0 ≃ 0.10 / 0.628
P4	55	22	0.44	1 ≃ 0.44 / 0.628
P5	57.5	23	0.46	1 ≃ 0.46 / 0.628
	Sum: 250 Avg: 50 Max: 95	Sum: 100 Avg: 20 Max: 38	Sum: 3.140 Avg: 0.628 Max: 1.9	

Figure 5. Roulette wheel selection

Once a pair of solutions is selected, crossover can take place to produce offspring solution. A crossover probability of 1.0 indicates that all the selected solutions are used in reproduction i.e., there are no survivors and these doesn't mean that population stays the same. In this study, crossover probability P_c is equal to 1 contrary to the recommendation that P_c should be between 0.65 and 0.85. We apply single-point crossover technique for this study. Firstly, for selected pair of solution, a random integer x between 1 and number of jobs n is selected. Then the sub-elements of each population from first element to element x (or from element x to first element) are swapped. After this swap operation a repair operation may be needed to obtain a feasible solution as shown in Figure 6. This swap operation is applied for selected solution pair on each machine with different random integers. Genotype representation or encoding for this study is permutation presentation of jobs for each machine.

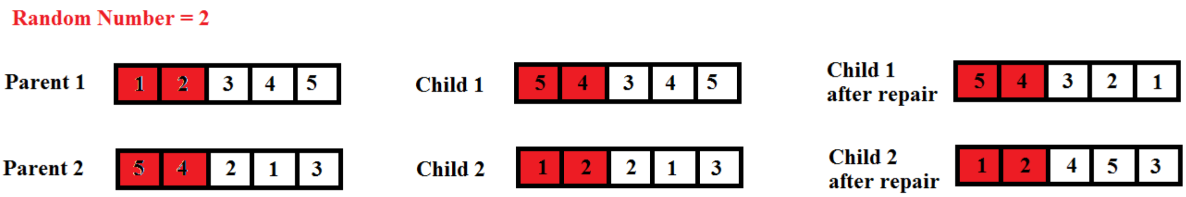


Figure 6. Crossover and repair operations for a pair of solutions with five jobs

For mutation process in this study, we use swap operation for two randomly selected jobs in a selected population and thus mutation probability is $P_m = 1/n$. The mutation process for a selected solution for 10 jobs is shown in Figure 7.

Figure 7. Mutation operation for a solution with 10 jobs

After mutation process, new fitness value of each solution in new population is recalculated and if the stopping criteria is formed then GA will stop and display the best schedule that GA have found until stopping. The stopping criteria of this study is number of generation determined previously by DM.

5. Numerical examples

To illustrate numerical examples and their results, Taillard's (1993) processing times for 20–5, and 20–10 (n - m) flow shop problems are used in proposed GA. In this study, fuzzy learning effect is set as $\tilde{a}$ = {–0.9, -0.8, -0.7} and fuzzy deterioration effect is set as $\tilde{B}$ = {0.01, 0.1, 0.2}. The lower and upper bounds of the fuzzy common due date $\tilde{d}$ for these problems are calculated by using the recommendation of Rios-Solis and Sourd (2008) for a crisp common due date problem as follows:

$$\underline{d} = h * \frac{\sum_i^n \sum_j^m P_{i,j}}{m}, \tag{18}$$

$$\overline{d} = \underline{d} * \frac{3}{2}, \tag{19}$$

where h is a restrictive factor that allows DM to define how much schedule must be restricted and $\tilde{d}$ = $\left[\underline{d}, \overline{d}\right]$. Restrictive factors h are set as 2 and 6 for 20–5 and 20–10 flow shop scheduling problems. P_c and P_m values are 1.0 and 1/ n, respectivelty. The stopping criteria of GA for these problems is 1000 generations. Each initial population for problems consists of 30 solutions. The proposed GA has been written by using VB.NET in Visual Studio 2015 and MS Access database via a standard desktop computer that has CPU of Intel Core i5, 2.8 GHz and 4 GB RAM. The results for the problems can be seen in Table 1 and 2.

Table 1. Results for 20–5 flow shop scheduling problems

n	m	h	Problem	Total grade of satisfaction	CPU time (hr:min:sec)
20	5	2	TL001	20.000	00:48:19
			TL002	19.559	00:43:02
			TL003	19.769	00:52:31
			TL004	19.454	00:41:07
			TL005	19.619	00:51:04
			TL006	19.981	00:42:20
			TL007	20.000	00:39:58
			TL008	20.000	00:44:53
			TL009	19.958	00:40:57
			TL010	19.672	00:54:56

Table 2. Results for 20–10 flow shop scheduling problems

n	m	h	Problem	Total grade of satisfaction	CPU time (hr:min:sec)
20	10	6	TL011	19.614	01:10:17
			TL012	18.527	01:07:32
			TL013	19.081	01:13:43
			TL014	18.369	01:10:35
			TL015	19.074	01:10:32
			TL016	18.359	01:07:58
			TL017	19.627	01:10:03
			TL018	19.208	01:11:31
			TL019	19.930	01:10:31
			TL020	19.158	01:08:48

6. Conclusion

In this study, flow shop scheduling problems under fuzzy learning and deterioration effect with a common fuzzy due date were investigated and we proposed a GA to maximise total grade of satisfaction for completion times of jobs compared to a common fuzzy due date. The performance of proposed GA, as can be seen in Tables 1 and 2, shows that large scale problems can be solved with this proposed GA. Each result of problems is close to number of jobs and this situation denotes that almost all jobs are completed until the lower bound of common fuzzy due date. However, if DM selects a bit less restrictive factor h than current ones for the problem, these results may change.

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