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Genetic optimization of JIT operation schedules for fabric-cutting process in apparel manufacture

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Abstract Fashion products require a significant amount of customization due to differences in body measurements, diverse preferences on style and replacement cycle. It is necessary for today's apparel industry to be responsive to the ever-changing fashion market. Just-in-time production is a must-go direction for apparel manufacturing. Apparel industry tends to generate more production orders, which are split into smaller jobs in order to provide customers with timely and customized fashion products. It makes the difficult task of production planning even more challenging if the due times of production orders are fuzzy and resource competing. In this paper, genetic algorithms and fuzzy set theory are used to generate just-in-time fabric-cutting schedules in a dynamic and fuzzy cutting environment. Two sets of real production data were collected to validate the proposed genetic optimization method. Experimental results demonstrate that the genetically optimized schedules improve the internal satisfaction of downstream production departments and reduce the production cost simultaneously.

Keywords Genetic algorithms · Fuzzy set theory · Parallel machine scheduling · Fabric cutting · Apparel

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Introduction

Apparel production is a type of assembly manufacture that involves a number of processes. Fabric-cutting operation is done in a fabric-cutting department, which usually serves several downstream sewing assembly lines. Effective upstream fabric-cutting operation ensures the smoothness of downstream operations, and thus is vitally important to the overall system efficiency. Production scheduling of apparel production is a challenging task due to a number of factors. First of all, fashion trend is always unpredictable, thus just-in-time production is employed to ensure products' short time-to-market. Moreover, in order to cope with the increasing demand on product customization, the quantity of garments per production order tends to be smaller and thus number of production order processed by the manufacturer has been becoming larger. In this paper, just-in-time (JIT) production scheduling of manual cutting department operation is investigated.

JIT scheduling

Production scheduling has been extensively studied, and the previous literature has more focused on some single regular measures, such as mean flow-time and mean lateness. Since the 1980s, the concept of penalizing both earliness and tardiness has spawned a new and rapidly developing line of research in the scheduling field (Baker & Scudder, 1990). In a JIT environment, both earliness and tardiness must be discouraged since early finished jobs increase inventory cost while late jobs lead to customers' dissatisfaction and loss of business goodwill. Thus an ideal schedule is one in which all jobs finish within the assigned due dates. The objectives of early/tardy (E/T) scheduling could be interpreted in different ways, for example minimizing total absolute deviation from due dates, job dependent earliness and tardiness penalties, nonlinear penalties, and so forth (see Baker & Scudder, 1990 for an comprehensive survey).

A main stream of E/T scheduling research is about the scheduling of a group of independent jobs with a common due date (De, Ghosh, & Wells 1991, 1993; Hall, Kubiak, & Sethi 1991; Hall & Posner, 1991; Hoogeveen & van de Velde, 1991). The common due date is either a known property of the problem, or a decision variable to be optimized along with the job sequence. The latter is equivalent to the former for single-machine case when the common due date is large (long) enough (De et al., 1991, 1993; Hoogeveen & van de Velde, 1991). Therefore, the former case of scheduling problem with a known due date can be divided into two classes, namely large due date (unrestrictive case) and small due date (restrictive case). Large due-date problems are analytical solvable (De et al., 1993; Kanet, 1981), while small due date cases are proven NP-hard even with linear E/T penalties (De et al., 1991; Hall et al., 1991; Hoogeveen & van de Velde, 1991). In the more complex case of small due-date, researchers obtained so far limited results for some special cases using various techniques such as explicit enumeration algorithms (Bagchi, Sullivan, & Chang, 1986), branch and bound algorithms (Bagchi, Sullivan, & Chang, 1987; Szwarc, 1989), and pseudo-polynomial dynamic programming algorithms (Hall et al., 1991; Hoogeveen and van de Velde, 1991). In apparel industry, a single-cutting department works on different production orders simultaneously in order to meet the needs of downstream sewing lines. Different from the above common due date cases, each production order, which is composed of a group of smaller jobs, has a distinct due time.

Parallel machine scheduling

The above mentioned studies are mainly for single machine production scheduling. The scheduling of cutting department operation is similar to a traditional parallel machine scheduling (Mok, Kwong, & Wong, 2004). Figure 1 shows an example about the configuration of cutting department.

In parallel machine scheduling, a batch of jobs is scheduled to be processed by any one of a number of available machines so that the best overall system performance is achieved (Cheng & Sin, 1990). In a cutting department, fabric-cutting jobs, which belong to different production orders, are to be processed on one of the parallel spreading tables so that the demand from downstream sewing lines could be timely fulfilled. Research on parallel machines scheduling with JIT context has received much attention in recent years. Cheng & Chen (1994) showed that parallel machine scheduling problem is NP-hard when due-date is a decision variable. Cheng, Gen, & Tozawa, (1995) minimized the maximum weighted absolute lateness on parallel machine using genetic algorithms. Cheng, Chen, & Li (1996) discussed the scheduling of multiple simultaneously available jobs on parallel machines with controllable processing times. Chen & Lee (2002) studied the parallel machine scheduling with a common due window using branch and bound algorithms. However, the above results assume all jobs with a common due date.

Moreover, fabric-cutting scheduling has a distinctive feature that two interdependent processes (spreading and cutting) must be scheduled simultaneously. Spreading operation must be completed before the cutting operation could start. Spreading operation can be accordingly viewed as a setup operation for the cutting process. In addition, fabric-cutting scheduling is a resource constrained scheduling problem (see Section 'Fuzzy duetimes representation'). Ventura & Kim (2003) recently investigated parallel machine scheduling with noncommon due dates and additional resource constraints, however all jobs processing times are assumed constant in their investigation. In fabric-cutting scheduling problem, each job has its individual spreading and cutting processing times.

Fuzzy scheduling

The traditional production scheduling studies assumed the due times are crisp values. In practice, jobs being completed beyond certain due times are sometimes allowed in the apparel industry. It is because apparel manufacturers determine internally the due time windows of various production orders for different production departments including cutting, sewing, pressing and packaging departments, based on the final delivery due dates and production capacity. Such internal due time windows are determined to ensure on time delivery of final products and reduce work-in-progress. Recently, fuzzy set theory has been applied to handle the scheduling problem in fuzzy environment.

Fuzzy set theory (Zadeh, 1965) is an attractive framework for dealing with 'fuzzy' (uncertain) information, and there is indeed an increasing interest in fuzzy scheduling in the academia and industries recently (Słowiński & Hapke, 2000). In the fuzzy scheduling research, fuzzy numbers, an extension of the concept of confidence intervals, are used to model the imprecise time parameters. In this paper, the production-order due-time windows are presented in forms of fuzzy numbers. Genetic algorithms are then used to optimize the cutting department production schedules such that the fabric cut pieces required by the downstream sewing lines for assembly can be maximally satisfied.

The outline of this paper is as follows. Section 'Problem formulation' provides the general description about fabric-cutting system including model formulation, fuzzy due time definition, and job placement mechanism. The next section deals with the general methodology of genetic optimization of fabric-cutting scheduling with fuzzy due times. The proposed method is demonstrated by two real production cases in the following Section, in which the genetically optimized

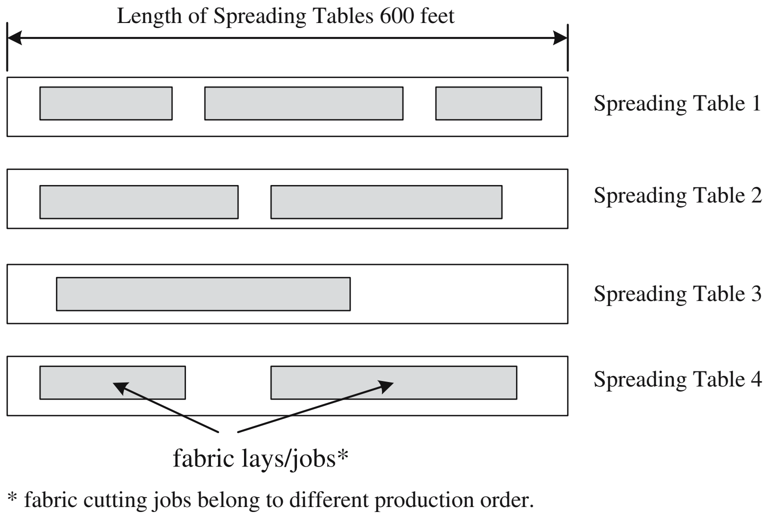

Fig. 1 Layout of a fabric-cutting department consisting of four spreading tables with examples of fabric lays are being spread

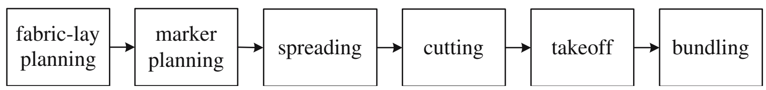

Fig. 2 Workflow of a fabric-cutting department

results are compared with those implemented by the industrial practice. Finally, conclusions and recommendations for future work are outlined.

Problem formulation

In a traditional fabric-cutting department, there are several key operations involved, which are shown in Fig. 2.

The fabric-cutting operation studied in this paper satisfies the following assumptions:

(a) The manual spreading carts for spreading and manual straight-knife cutters for cutting are always available throughout the scheduling period.
(b) Jobs (fabric lays) are always available to be loaded into the system and be processed by any of spreading carts and cutters on any of the parallel spreading tables.
(c) No job can be processed on more than one spreading table simultaneously.
(d) There is no precedence constraint on the jobs.

Nomenclature

A summary of the nomenclature used in this paper is as follows:

n	number of jobs to be processed.
$\boldsymbol{J}$	$\{J_1, J_2, \ldots, J_n\}$, set of jobs (fabric lays).
m	number of spreading tables in the fabric cutting department.
$\boldsymbol{M}$	$\{M_1, M_2, \ldots, M_m\}$, set of spreading tables in the cutting department.
p	number of production orders to be processed.
Θ	$\{\theta_1, \theta_2, \ldots, \theta_p\}$, set of production orders (PO).
$x(\theta, J_k)$	state value indicating whether or not job J_k belongs to production order θ. $x(\theta, J_k) = 1$ if job J_k belongs to production order θ, and $x(\theta, J_k) = 0$ otherwise.
i	job setup (spreading) index and $i = 1, 2, \ldots, n$.
j	job processing (cutting) index and $j = 1, 2, \ldots, n$.
σ_s	setup (spreading) sequence of jobs.
σ_c	processing (cutting) sequence of jobs.
$\chi(J_k)$	quantity of apparel cut-pieces of job J_k.
$\varphi(J_k)$	length of fabric lay of job J_k.
$s(J_i)$	spreading time of job J_i.
$c(J_j)$	cutting time of job J_j.
C_k	completion time of job J_k.
$\tilde{A}$	fuzzy number A.
$\tilde{D}_{\theta_i}(t)$	fuzzy due time of production order θ_i, $i = 1, 2, \ldots, p$.

Efficient manual cutting systems

The system investigated in this paper assumes an *efficient* manual cutting model configuration. In an efficient system, after spreading and cutting operations, fabric pieces are taken away from the spreading tables for bundling operations, which helps to make department for spreading new jobs. In an efficient fabric-cutting department, a group consisting of four operators is normally assigned to each spreading table. The group is divided into two subgroups in which two operators are responsible for fabric spreading and the remaining two operators are responsible for cutting the fabric lay that has been spread. The division of labor allows operators to focus on their competent operations, thus improving the overall efficiency. Spreading operators continue to spread new fabric lays (jobs) once they have finished the present jobs. The purpose is to reduce delay due to the switching between spreading and cutting. Because of the limited length of spreading tables, idle time would occur when there is not sufficient free area on the spreading table available for the new fabric lay. Cutting operators then cut the fabric lays according to the spreading schedule, i.e., $\sigma_s = \sigma_c$, on each spreading table. Obviously, cutting idle time occurs when the cutting operators have finished the current job while the new job is still being spread and is not yet ready to be cut.

Fuzzy due times representation

As discussed in Section JIT Scheduling, both tardiness and earliness are discouraged in a JIT environment. A generic E/T model is represented as

$$f(S) = \sum_k (\alpha_k E_k + \beta_k T_k) \tag{1}$$

where $E_k = \max(0, d_k - C_k)$ is the earliness of job k with completion time C_k and due time d_k, and $T_k = \max(0, C_k - d_k)$ is the corresponding tardiness. In (1), α_k and β_k are penalty weights for earliness and tardiness, respectively. JIT scheduling focuses on the best schedule to minimize the objective function $f(S)$.

In this paper, the due times of different production orders are represented as trapezoidal fuzzy number (TrFN) with the following definition,

$$\mu_{\tilde{D}}(t) = \begin{cases} 0, & t \le d^A \\ \frac{t-d^A}{d^B-d^A}, & d^A < T < d^B \\ 1, & d^B \le T \le d^C \\ \frac{d^D-t}{d^D-d^C}, & d^C < T < d^D \\ 0, & d^D \le t \end{cases} \tag{2}$$

In apparel industry, the factory manager determines departmental due time windows, rather than precise due time, of different production orders so as to ensure smoothness of downstream operations and on time delivery of final products. Such due time windows represent the managerial preference regarding different values of production order completion time.

As shown in Fig. 3, d^A, d^B, d^C, and d^D are crisp real numbers such that $0 \le d^A \le d^B \le d^C \le d^D$. The membership value of these fuzzy numbers expresses the degree of satisfaction associated with corresponding job completion time: complete satisfaction if the job is completed during the time interval of d^B to d^C; the degree of satisfaction increases linearly from time d^A to d^B and decreases linearly from time d^C to d^D; and complete dissatisfaction if the job is completed before $t = d^A$ or beyond $t = d^U$.

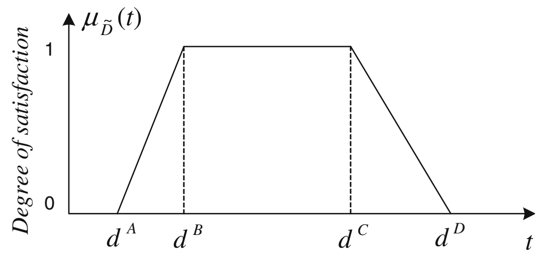

Fig. 3 Trapezoidal fuzzy due date (d^A, d^B, d^C, d^D)

When the due dates are crisp, the weights α and β in (1) denote the decision maker's view on how significant each job's lateness or earliness affects the overall system. In the case of fuzzy due date, the steepness of change between complete satisfaction and complete dissatisfaction (i.e., the side slope) represents the same decision maker's view.

Job placement mechanism

The main objective of fabric-cutting scheduling in JIT environment is to maximize downstream production units' satisfaction. Minimizing production makespan (in other words, minimizing operator idle time) is another key issue. Since each fabric-cutting job involves both spreading and cutting operations, job placement algorithm of manual cutting systems is described here to explain the way for allocating jobs to different spreading tables, and thus to calculate the makespan.

In a cutting department with multiple spreading tables, m, a first-come-first-serve rule is always applied when assigning a sequence of jobs to be processed by different spreading tables. For a given job sequence, σ, jobs are allocated to different spreading tables in accordance with the following placement algorithm.

1. allocate the first m jobs, $J_i (i = 1, \ldots, m)$, to the m spreading tables, set $i = m$.
2. if any spreading table has enough area for the job J_{i+1} (free area > fabric length $\phi(J_{i+1})$), allocate J_{i+1} to the first available spreading table and set $i = i + 1$.
3. if there is no spreading table available (free areas of all m tables < fabric length $\phi(J_{i+1})$), wait until enough spreading area is obtained by clearing up the cutting jobs J_j queues.
4. repeat the procedures 2 and 3 until all the jobs in the sequence are allocated.

According to the described job placement algorithm, individual schedules at different spreading tables are defined for a given job sequence. The system makespan time, that is the maximal operation duration of the m spreading tables, can be calculated accordingly. Using this placement algorithm, the parallel-machine (spreading table) scheduling problem becomes a single sequencing optimization problem with multiple objectives to maximize the degree of satisfaction of downstream sewing lines and reduce overall production makespan in JIT context.

Genetic optimization of fabric scheduling

In apparel manufacturing, production planners assign a sequence of jobs (fabric-lays) to different spreading tables for spreading, cutting and bundling. According to the job placement algorithm described in 'Job placement mechanisim', the parallel machine scheduling optimization problem in fabric-cutting department is reduced to a single sequencing optimization problem. Job sequencing problem is a permutation problem with n jobs, and the total number of possible solution is $n!$ (e.g., $n! = 1.24 \times 10^{61}$ for $n = 48$). The search space significantly expands as the number of jobs, n, increases, which make attractive to use genetic algorithms (GAs), a metaheuristic technique, to search for the best job processing sequence in a manual fabric-cutting department.

In fabric-cutting scheduling problem, a group of jobs belonging to a defined set of production orders with different due times are to be processed on one of the parallel spreading tables. Earliness/tardiness scheduling with identical earliness and tardiness penalties for all jobs has showed NP-complete (Baker & Schudder, 1990). In the more complex case when each job has its own earliness and tardiness weightings, it is implausible that optimal schedule for real sized problem can be obtained by conventional time polynomial algorithms. However, GAs solve complex industrial optimization by iterations.

Individual representation

To apply GAs in solving an industrial optimization problem, it is usually assumed that a potential solution to the problem may be represented as a set of variables. These variables ('genes') are joined together to form a string of values ('chromosome'). The string can be of binary digits, integers, or real numbers. Although the binary representation proposed by Holland (1975) is most widely employed, GAs are not restricted to binary representation. The choice of representation depends on the nature of the problem. In this job sequencing problem, integer chromosome representation is proposed to indicate the job processing sequences. An example of integer chromosome representation is shown in Fig. 4.

Chromosome:	3	7	10	1	2	5	8	4	6	9
Job Sequence:	J_3	J_7	J_{10}	J_1	J_2	J_5	J_8	J_4	J_6	J_9

Fig. 4 Chromosome representation

Fitness evaluation

In GAs, a fitness function is defined to measure the fitness of each individual chromosome so as to determine which to reproduce and survive into the next generation. Given a particular chromosome, the fitness depends on how well that individual solves a specific problem. Maximizing degree of satisfaction of the downstream production units is prime scheduling objective in JIT production.

In the genetic optimization of fabric-cutting sequence problem, individual chromosomes represent a job processing sequence. Once a job sequence is defined, jobs are allocated to different spreading tables using the job placement algorithm described in Job placement mechanism. Thus, the completion times of individual jobs are accordingly evaluated. Such jobs are belonged to a set of production orders, and each of these production orders has its distinctive fuzzy due time. For a job J_k belonging to production order θ, θ has a fuzzy due time $\tilde{D}_\theta$. If job J_k completes at time C_k, the degree of satisfaction with C_k with regard to fuzzy due time $\tilde{D}_\theta$ is naturally expressed by means of number $\upsilon(C_k, \tilde{D}_\theta)$ which is defined by

$$\upsilon(C_k, \tilde{D}_\theta) = \tilde{D}_\theta(C_k) \tag{3}$$

Taking Fig. 5 as an example, jobs J_1 and J_2 are completed at time $C_1 = 42$ min and $C_2 = 65$ min, the degrees of satisfaction achieved are 0.5 and 0.85, respectively with regard to a fuzzy due time of $\tilde{D}(t)$ =(38, 46, 60, 94).

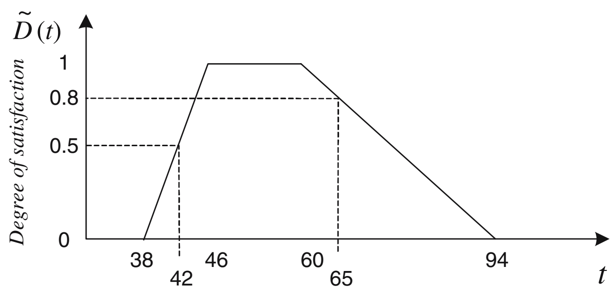

Fig. 5 Degree of satisfaction evaluation

The JIT fabric-cutting schedule can be optimized using GAs such that the overall degree of satisfaction,

$$\Phi_{\mathrm{JIT}}(\sigma) = \left(\sum_{\theta=1}^{p} \sum_{k=1}^{n} \upsilon(C_k(\sigma), \tilde{D}_\theta) \cdot x(J_k, \theta) \right) \cdot w_{\mathrm{DS}} \quad (4)$$

is maximized. In (4), w_{DS} is the weight for degree of satisfaction, and $x(J_k, \theta)$ is the state value, which indicates whether job J_k belongs to production order θ. $x(\theta, J_k) = 1$ if job J_k belongs to production order θ; $x(\theta, J_k) = 0$.

In a fabric-cutting environment, it is very important that the production schedule should be optimized in such a way that the production makespan, the longest completion time among different spreading tables and operator idle times, are minimized. With the use of job placement algorithm, a sequence of fabric-cutting jobs is assigned to different spreading tables and the production makespan is accordingly calculated. The fitness on production makespan of the corresponding individual chromosome is defined as

$$\Phi_{\mathrm{makespan}}(\sigma) = \left(T_{\mathrm{target}} / T_{\mathrm{makespan}}(\sigma) \right) \cdot w_T. \quad (5)$$

where $T_{\mathrm{makespan}}(\sigma)$ is the production makespan for sequence σ, T_{target} is the target completion time, and w_T is the weight of production makespan fitness. With reference to (5), a sequence with smaller makespan time results in larger makespan fitness.

Let Π denote the set of all feasible sequences. For a given sequence $\sigma \in \Pi$, the overall fitness is defined as

$$\Phi(\sigma)_{\sigma \in \Pi} = \Phi_{\mathrm{JIT}}(\sigma) + \Phi_{\mathrm{makespan}}(\sigma), \quad (6)$$

where $\Phi_{\mathrm{JIT}}(\sigma)$, and $\Phi_{\mathrm{makespan}}(\sigma)$ are the fitnesses for degree of satisfaction and production makespan, respectively. It is important to note that genetic optimization methodology can be applied to multi-objective optimization by defining the fitness function accordingly. For example, Wong, Kwong, Mok, Ip, and Chan, (2003) minimized the makespan while maximized the cut-pieces fulfillment rates using GAs.

Genetic procedures

To optimize fuzzy fabric-cutting schedule by GAs, the operation procedure begins by randomly generating an initial population of integer strings in which each string represents a job processing sequence, as shown in Fig. 4. Evolution is caused to occur in this population of strings in accordance with the genetic operations of crossover, mutation, and selection. Applying genetic operations to chromosome may cause lost features in some genes and result in infeasible solutions. In order to prevent such infeasible solution in the job sequencing problem, uniform order-based crossover (see Fig. 6) and inversion mutation (see Fig. 7) are adopted. In the case of selection operation, standard biased roulette wheel selection with elitism (De Jong, 1975; Goldberg, 1989) is employed.

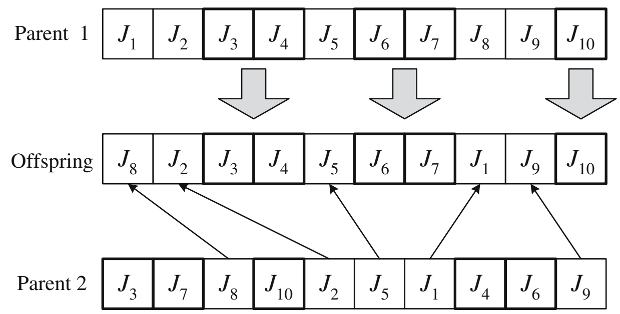

Fig. 6 Uniform order based crossover

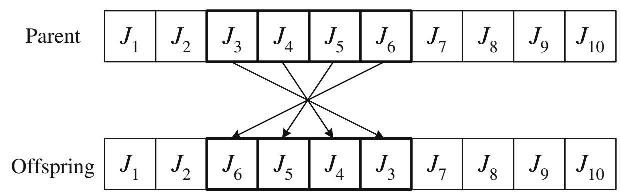

Fig. 7 Inversion mutation

In the evolutionary process, the Darwinian fitness of each chromosome is evaluated by substituting into (7). This evolutionary process is allowed to continue until no significant further improvement is obtained in the fitness of the fittest string. This fittest string thus provides the optimal job processing sequence for the given batch of fabric-cutting jobs. Figure 8 outlines the general methodology proposed in this investigation.

Case studies

Two sets of real production data, denoted as cases A and B, are used to demonstrate the proposed method. All the data listed in Table 1 was obtained from the fabric-cutting department of a Hong Kong-owned apparel manufacturing company located in mainland China. These two-day spreading production schedules were recorded in the fabric-cutting department in each of which 48 jobs were spread and cut by a manual cutting system. The cutting department consists of 4 spreading tables, and the length of each one is 600 feet each, as shown in Fig. 1.

The fuzzy due times of cases A and B are shown in Figs. 9 and 10. The genetic optimization procedure described in 'Genetic Optimization & Fabric Scheduling' is then used to optimize the production schedules. The schedules generated by GAs are maximized for the fitness function (6). In case of complete satisfaction, the degree of satisfaction is 1 when the job is finished exactly within the required time window. For 48-job sequences, the overall degree of satisfaction, Φ_{JIT}, is a real number being not greater than 48 when there is unit

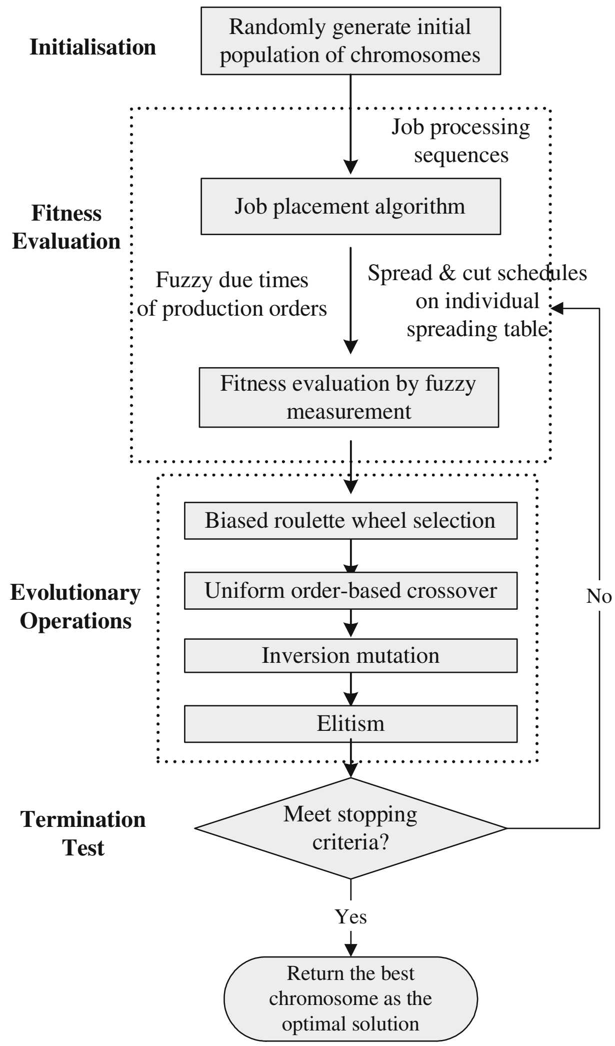

Fig. 8 Methodology outline

degree of satisfaction weighting, that is $w_{DS} = 1$. The target completion time (makespan) is $T_{target} = 1200$ min, however the value of $T_{target}/T_{makespan}$ is a real number less than 1 since overtime is foreseen ($T_{makespan} > T_{target}$). Job sequence is optimized so that $T_{target}/T_{makespan}$ is approaching to 1. The makespan weighting is set as 24 because management regards that the customer satisfaction is twice important as the production cost reduction (through idle time minimization). Therefore, the weights of fitness function (6) are $w_{DS} = 1$ and $w_T = 24$.

Figure 11 depicts the genetic optimization program developed using MATLAB in this research. The production schedules generated by GAs with population size of 200 chromosomes, crossover probability of 0.7, mutation probability of 0.03, and over 200 generations are compared with those based on industrial practice in Figs. 12 and 13. The part (a) of the figures shows the production schedules adopted by industrial practice, and the genetically optimized schedules are shown in part (b). The evolutionary trajectory of cases A and B are shown in Figs. 14 and 15. In each of the production schedule as shown in Figs. 12 and 13, the upper gantt chart shows the spreading operations while the lower gantt chart shows the cutting operations.

The performance of the genetically optimized production schedules is compared with that of industrial practice in Table 2. It is evident that the proposed genetic optimization method is effective in improving the system performance in two aspects. First of all, genetically optimized schedules significantly improve the overall degree of satisfaction, from 38.33 to 42.11 and 41.99 to 45.53 in the cases A and B, respectively. On the other hand, the improvement of satisfaction does not prolong production makespan. Instead, slight improvement of 1 min and 12 min were recorded when compared with industrial practice for the overall system makespan in cases A and B, respectively. Table 3 shows the detail makespan time of different spreading tables with schedules adopted by industrial practice and those optimized genetically. In conclusion, genetic optimization method generates production schedules which improve simultaneously the degree of satisfaction and production makespan.

Conclusions

In apparel industry, production orders tend to split into smaller orders with different product features in response to the growing request on product customization. In order to shorten products' time-to-market, apparel manufacturers work hard towards the direction of just-in-time production. In apparel manufacturing process, the effectiveness of fabric-cutting schedule planning extensively influences the downstream assembly operations, and thus, in turn, is critical to the overall system performance. However, the demand from downstream operation departments may be fuzzy and resource-competing. In this paper, genetic algorithms and fuzzy set theory have been used to generate just-in-time schedules for fabric-cutting process in order to satisfy the fuzzy and resource-competing requests from downstream operating units. Two sets of real production data have been collected to validate the proposed genetic optimization method. Experimental results have demonstrated that the genetically optimized schedules simultaneously improve the internal satisfaction of downstream operation departments and reduce production cost.

The apparel manufacturing environment is typically dynamic. Apart from the uncertainties caused by the fuzzy and resource-competing internal demands, job processing times

Table 1 Detailed job characteristic

(A)-Job (X_n)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Production order (ϕ)	4	1	3	7	6	8	8	8	8	7	5	9	2	8	6	2	9	6	2	6	6	2	4	8
Qty of garment (χ)	30	116	114	66	15	224	224	224	300	118	300	10	200	300	98	14	4	200	42	52	42	140	13	21
Marker length (φ)	103	136	139	132	89	130	130	130	130	172	158	106	175	130	169	87	85	175	91	171	91	170	93	73
Spreading time (s)	50	90	90	57	30	161	161	161	209	104	233	20	170	209	87	29	19	170	60	53	60	121	28	34
Cutting time (c)	24	47	47	47	24	47	47	47	47	47	47	47	47	47	47	24	24	47	24	47	24	47	24	24
(A)-Job (X_n)	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48
Production order (ϕ)	9	6	5	7	2	7	6	3	9	3	9	1	8	4	3	6	6	6	4	2	2	3	4	9
Qty of garment (χ)	2	33	300	94	33	14	140	146	8	2	3	78	224	53	228	316	14	58	104	98	316	94	6	5
Marker length (φ)	68	91	158	132	91	137	170	140	81	73	72	105	130	171	148	170	87	170	171	169	170	132	101	81
Spreading time (s)	17	48	233	77	48	23	121	113	23	16	18	59	161	96	172	254	29	57	174	87	254	77	21	20
Cutting time (c)	24	24	47	47	24	47	47	47	24	47	24	47	47	24	47	47	24	47	24	47	47	47	24	24
(B)-Job (X_n)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Production order (ϕ)	2	1	1	3	2	2	2	2	2	2	3	4	5	4	3	1	4	1	1	3	1	2	3	3
Qty of garment (χ)	33	140	316	224	3	8	316	4	14	5	21	94	118	94	116	13	146	33	30	300	200	140	224	224
Marker length (φ)	91	170	170	130	72	81	170	85	87	81	73	132	172	132	136	93	140	91	103	158	175	170	130	130
Spreading time (s)	48	121	254	161	18	23	254	19	29	20	34	77	104	77	90	28	113	48	50	233	170	121	161	161
Cutting time (c)	24	47	47	47	24	24	47	24	24	24	24	47	47	47	47	24	47	24	24	47	47	47	47	47
(B)-Job (X_n)	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48
Production order (ϕ)	5	3	1	2	6	6	1	2	4	3	1	1	3	1	2	1	2	4	1	1	5	2	4	2
Qty of garment (χ)	14	78	58	42	300	300	42	2	228	224	6	14	300	104	10	15	98	114	98	53	66	200	2	52
Marker length (φ)	137	105	170	91	130	130	91	68	148	130	101	87	158	171	106	89	169	139	169	171	132	175	73	171
Spreading time (s)	23	59	57	60	209	209	60	17	172	161	21	29	233	174	20	30	87	90	87	96	57	170	16	53
Cutting time (c)	47	47	47	24	47	47	24	24	47	47	24	24	47	24	47	24	47	47	47	24	47	47	47	47

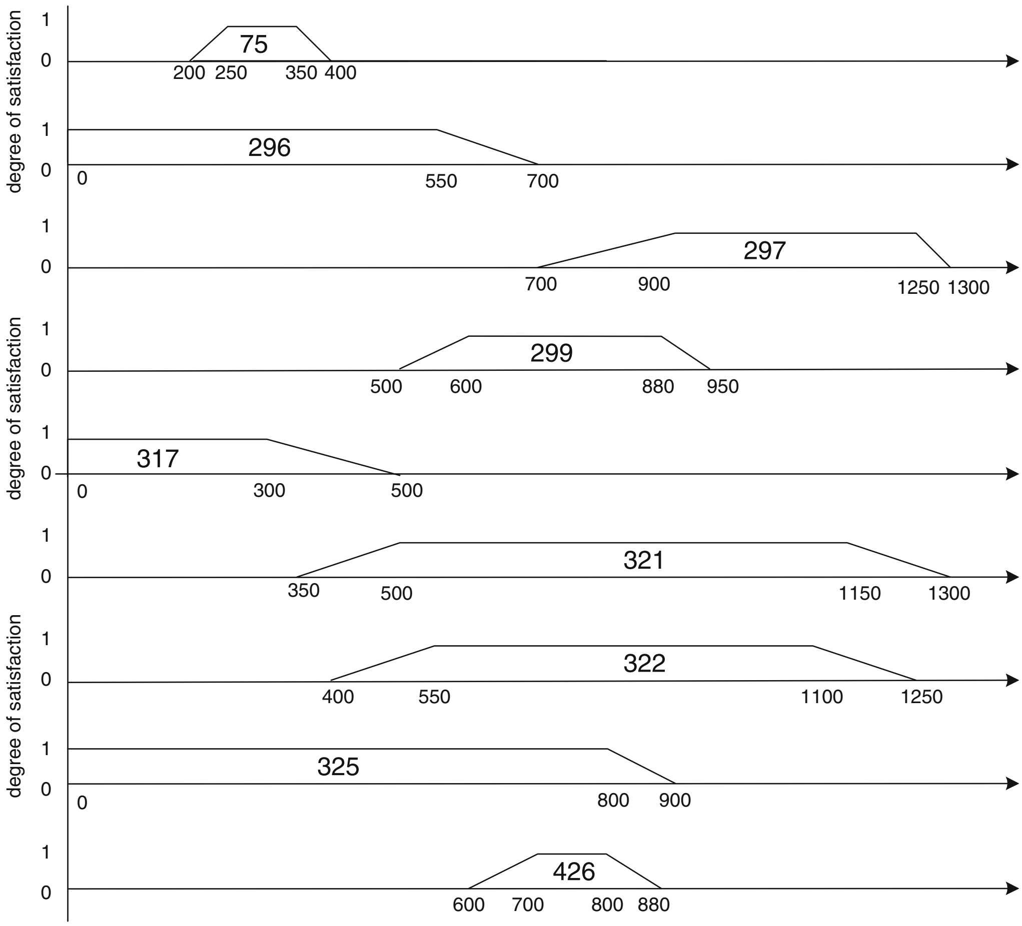

Fig. 9 Fuzzy due times of production order (Case A)

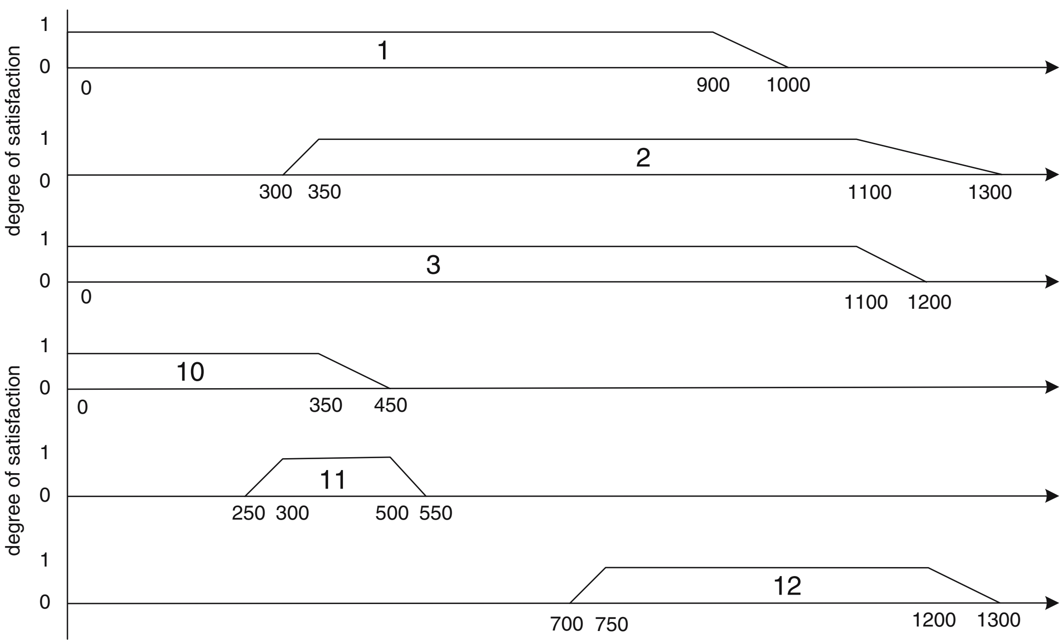

Fig. 10 Fuzzy due times of production order (Case B)

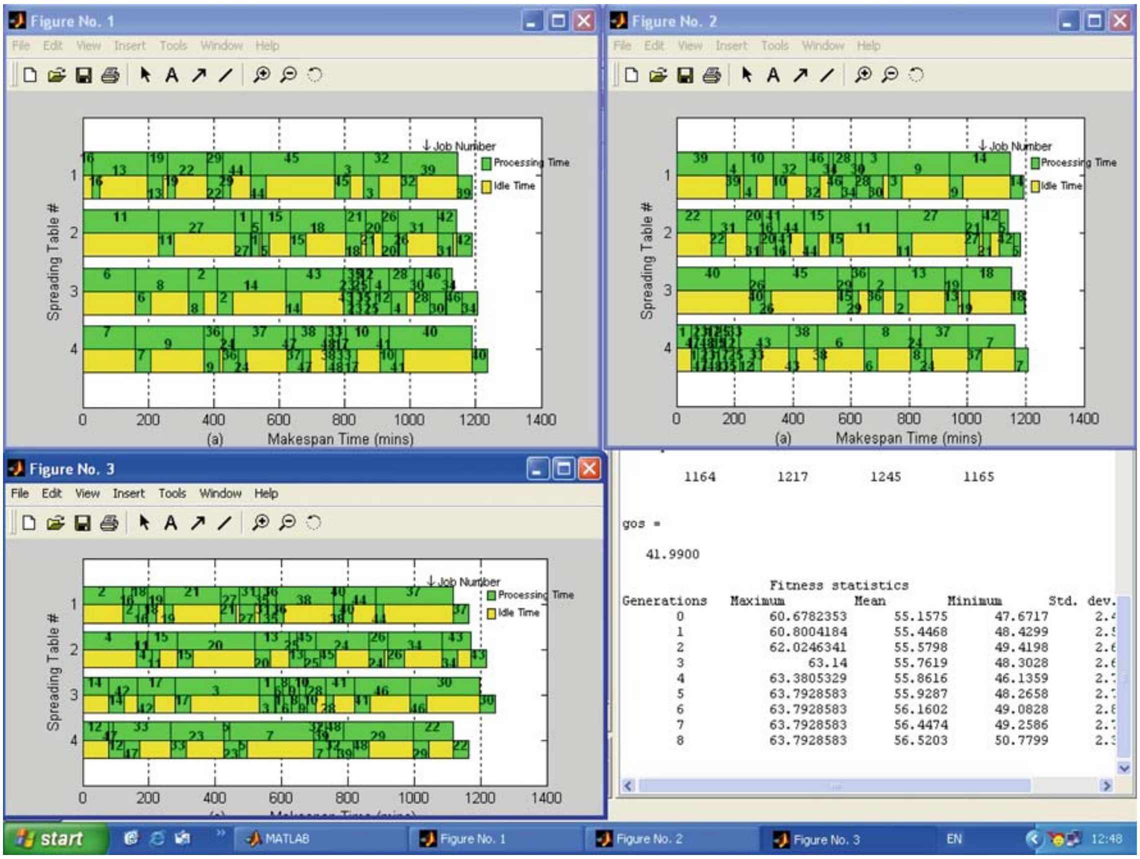

Fig. 11 Matlab genetic optimization program

Table 2 Performance comparison of industrial practice and genetically optimized results

	Φ_{JIT}	$T_{makespan}$	$\Phi_{makespan}$	Φ_{total}
Ind (case A)	38.33	1237	23.28	61.61
GA (case A)	42.11	1236	23.30	65.41
Ind (case B)	41.99	1245	23.13	65.12
GA (case B)	45.53	1233	23.36	68.89

Table 3 Makespan time comparison

	Table 1	Table 2	Table 3	Table 4	Makespan
Ind (A)	1190	1188	1206	1237	1237
GA (A)	1236	1214	1171	1171	1236
Ind (B)	1164	1217	1245	1165	1245
GA (B)	1160	1227	1233	1170	1233

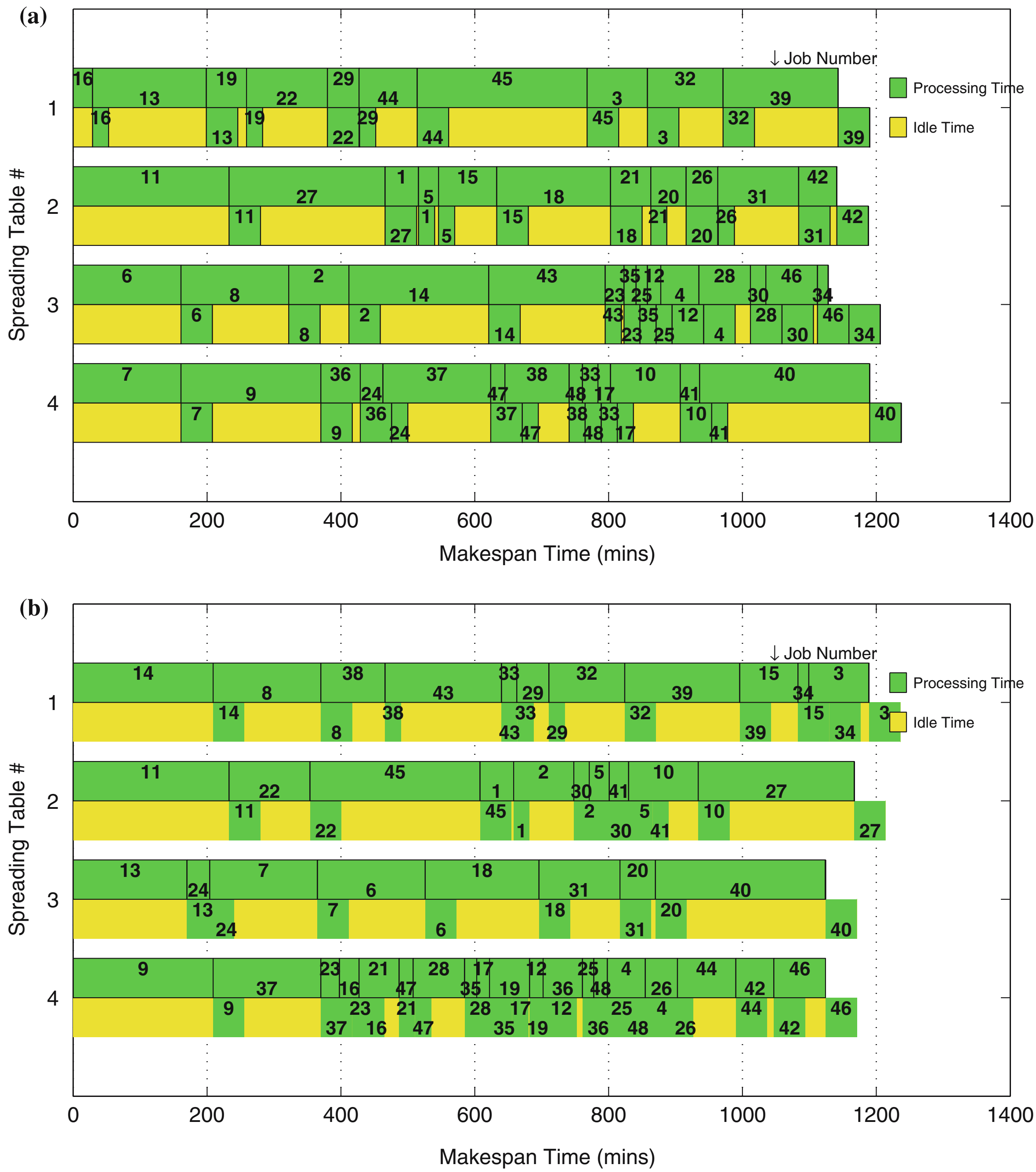

Fig. 12 Case A: (**a**) production schedule adopted by industrial practice, and (**b**) genetically optimsed production schedule

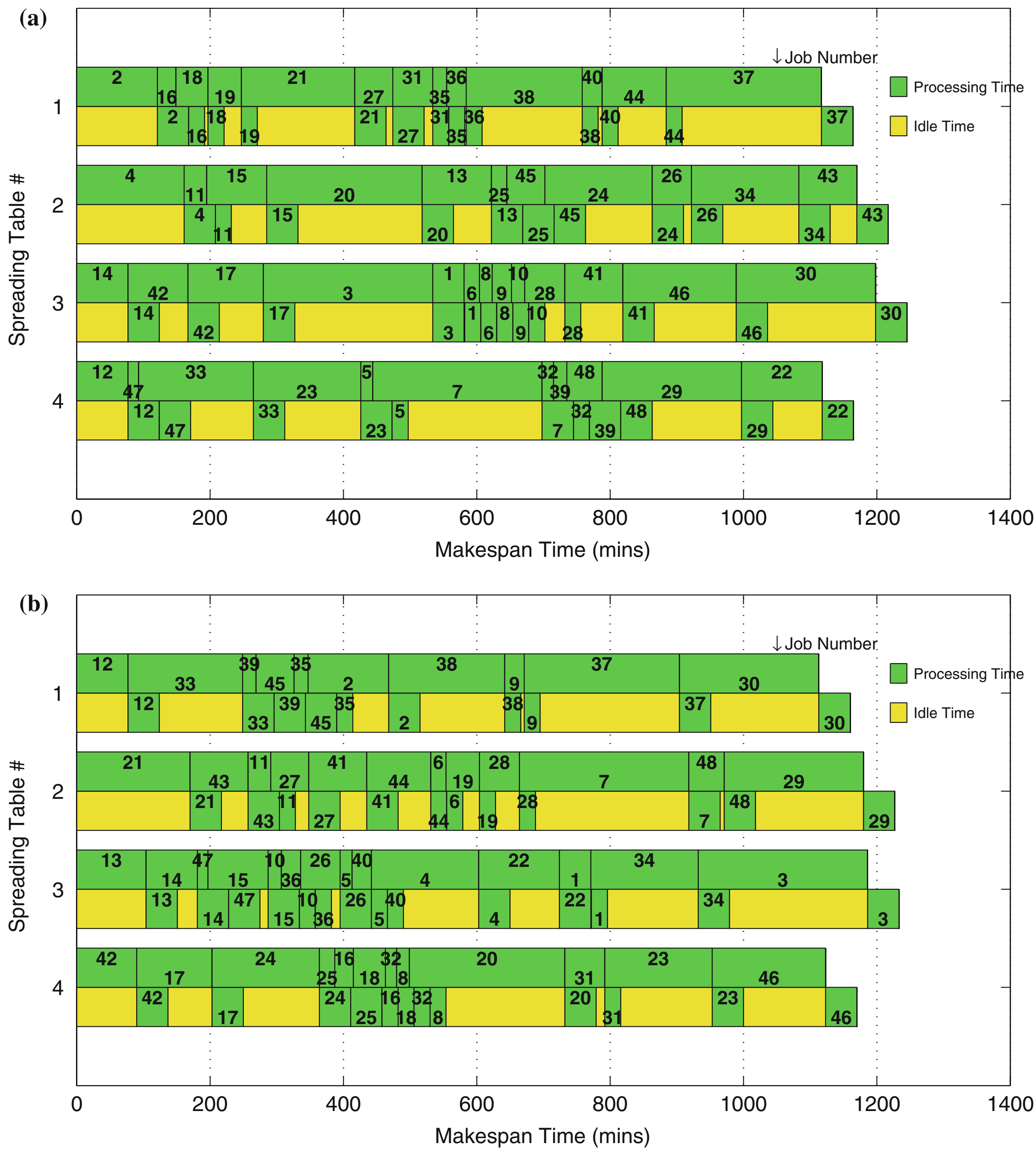

Fig. 13 Case B: (**a**) production schedule adopted by industrial practice, and (**b**) genetically optimized production schedule

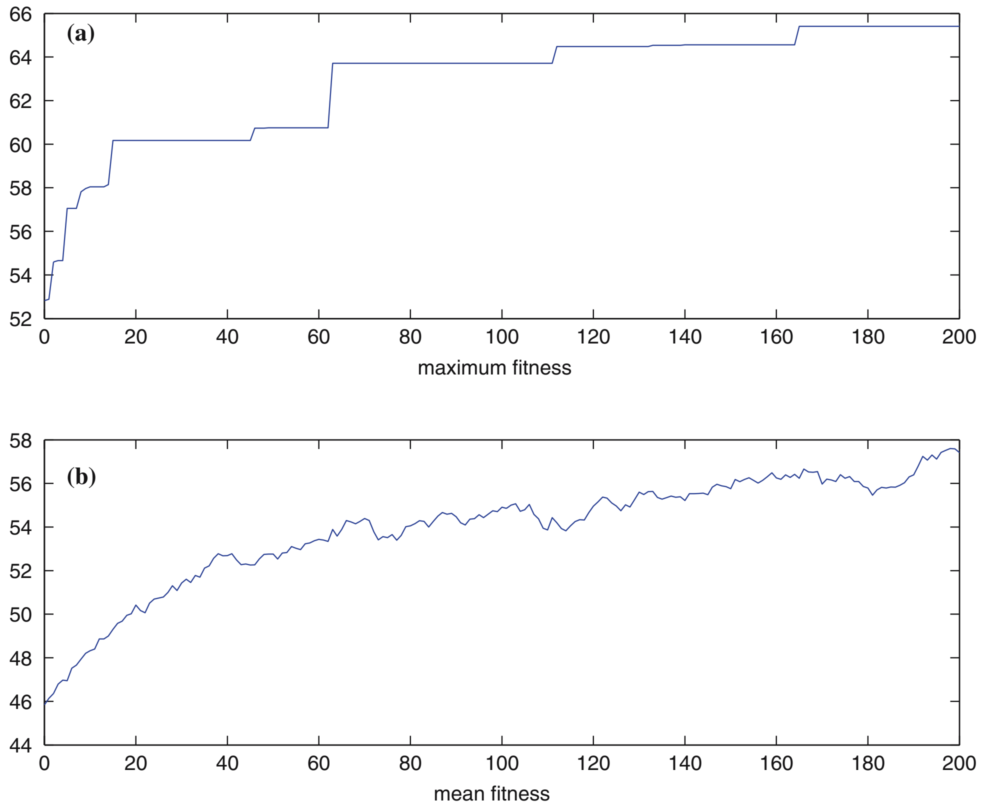

Fig. 14 Genetic optimization performance of case A

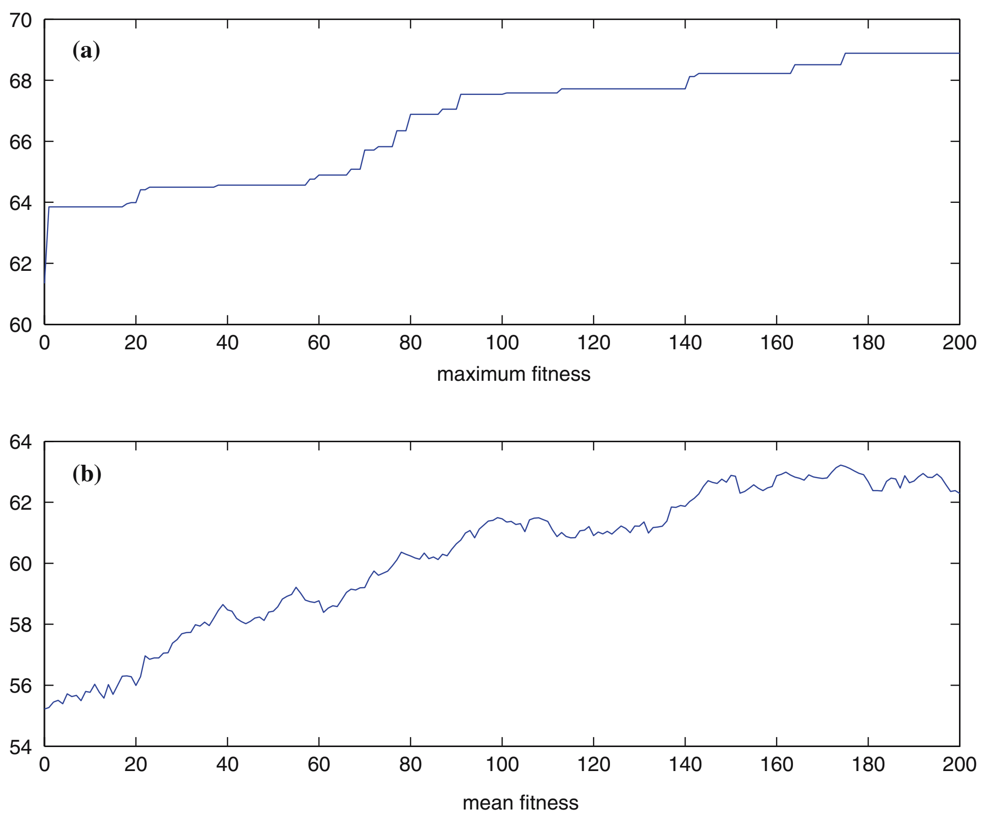

Fig. 15 Genetic optimization performance of case B

are fuzzy due to human factors, machine breakdowns, and insertion of rush orders, etc. (Mok et al., 2004). The research on the optimization of JIT schedules with fuzzy job processing time and production order due times is currently under investigation by the research team.

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References

Bagchi, U., Sullivan, R.S., & Chang, Y.L. (1986). Minimizing mean absolute deviation of completion times about a common due date. *Naval Research Logistics Quarterly, 33*, 227–240.

Bagchi, U., Sullivan, R.S., Chang, Y.L. (1987). Minimizing mean square deviation of completion times about a common due date. *Management Sciences, 33*, 894–906.

Baker, K.R., & Scudder, G.D. (1990). Sequencing with earliness and tardiness penalties: A review. *Operations Research, 38*(1), 22–36.

Chen, Z.L., & Lee, C.Y. (2002). Parallel machine scheduling with a common due window. *European Journal of Operational Research, 136*(3), 512–517.

Cheng, R., Gen, M., & Tozawa, T. (1995). Minmax earliness/tardiness scheduling in identical parallel machine system using genetic algorithms. *Computers & Industrial Engineering, 29*, 513–517.

Cheng, T.C.E., & Chen, Z.L. (1994). Parallel-machine scheduling problems with earliness and tardiness penalties. *Journal of Operational Research Society, 45*(6), 685–695.

Cheng, T.C.E., Chen, Z.L., & Li, C.L. (1996). Parallel-machine scheduling with controllable processing times. *IIE Transactions, 28*(2), 177–180.

Cheng, T.C.E., & Sin, C.C.S. (1990). A state-of-the-art review of parallel-machine scheduling research. *European Journal of Operational Research, 47*, 271–292.

De Jong, K.A. (1975). *An analysis of the behavior of a class of genetic adaptive systems*, Doctoral dissertation. University of Michigan, Ann Arbor.

De, P., Ghosh, J.B., & Wells, C.E. (1991). Scheduling to minimize weighted earliness and tardiness about a common due-date. *Computers & Operations Research, 18*(5), 465–475.

De, P., Ghosh, J.B., & Wells, C.E. (1993). On the general solution for a class of early/tardy problems. *Computers & Operations Research, 20*(2), 141–149.

Dubois, D., Fargier, H., & Fortemps, P. (2003). Fuzzy scheduling: modeling flexible constraints vs. coping with incomplete knowledge. *European Journal of Operational Research, 147*, 231–252.

Goldberg, D.E. (1989). *Genetic algorithms in search, optimisation, and machine learning*, Addison-Wesley.

Hall, N.G., & Posner, M.E. (1991). Earliness-tardiness scheduling problems, I: weighted deviation of completion times about a common due date. *Operations Research, 39*(5), 836–846.

Hall, N.G., Kubiak, W., & Sethi, S.P. (1991). Earliness-tardiness scheduling problems, II: deviation of completion times about a restrictive common due date. *Operations Research, 39*(5), 847–856.

Han, S., Ishii, H., & Fujii, S. (1994). One machine scheduling problem with fuzzy duedates. *European Journal of Operational Research, 79*, 1–12.

Holland, J.H. (1975). *Adaptation in natural and artificial systems*. Ann Arbor, MI: University of Michigan Press.

Hoogeveen, J.A., van de Velde, S.L. (1991). Scheduling around a small common due date. *European Journal of Operational Research, 55*, 237–242.

Ishibuchi, H., & Murata, T. (2000). Flowshop scheduling with fuzzy duedate and fuzzy processing time. In R. Słowiński, & M. Hapke (Eds.): *Scheduling under Fuzziness* pp. 113–143. Heidelberg, New York: Physica-Verlag.

Ishibuchi, H., Yamamoto, N., Misaki, S., & Tanaka, H. (1994). Local search algorithms for low shop scheduling with fuzzy due-dates. *International Journal of Production Economics, 33*, 53–66.

Kanet, J.J. (1981). Minimizing the average deviation of job completion times about a common due date. *Naval Research Logistics Quarterly, 28*, 643–651.

Mok, P.Y., Kwong, C.K., & Wong, W.K. (2004). Optimisation of fault-tolerant fabric-cutting schedules using genetic algorithms and fuzzy set theory. *European Journal of Operational Research*, forthcoming.

Szwarc, W. (1989). Single machine scheduling to minimize absolute deviation of completion times from a common due date. *Naval Research Logistics Quarterly, 36*, 663–674.

Słowiński R., & Hapke, M. (2000). *Scheduling under fuzziness*. Heidelberg, New York: Physica-Verlag.

Ventura, J.A., Kim, D. (2003). Parallel machine scheduling with earliness-tardiness penalties and additional resource constraints. *Computers & Operations Research, 30*(13), 1945–1958.

Wong, W.K., Kwong, C.K., Mok, P.K., Ip, W.H., & Chan, C.K. (2005). Optimization of manual fabric-cutting process in apparel manufacturing using genetic algorithms. *International Journal of Advanced Manufacturing* Technology, DOI 10.1007/s00170-004-2161-0.

Zadeh, L.A. (1965). Fuzzy sets. *Information and Control, 8*, 338–353.