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Intelligent production planning for complex garment manufacturing

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Abstract Apparel production is characterised by labour-intensive manual operations, frequent style changes, seasonal demand and shortening production lead times. With fierce competition worldwide, many manufacturers are switching their production from mass mode to lean mode to shorten their response time to changes. In a complex mixed mode production environment, it is very important to allocate job orders to suitable production lines so as to ensure the effective utilization of production resources and on-time completion of all job orders. In this paper, planning algorithms are proposed for automatic job allocations based on group technology and genetic algorithms. For genetic algorithms based intelligent planning algorithms, single-run and multiple-run genetic algorithms are suggested. Real production data are used to validate the proposed method. The proposed algorithms has been shown being able to substantially improve planning quality. These planning algorithms are currently used by apparel manufacturers in Hong Kong as part of their routine planning operations.

Keywords Apparel production · Production planning · Group technology · Genetic algorithms · Intelligent ERP

Introduction

The apparel industry is characterised as a fast-changing market. Since most apparel products are seasonal in nature, time-to-market is now an essential factor in order for manufacturing firms to compete in an intense market. Giving that consumers' tastes are always changing, the fashion market could probably be considered as one of the most turbulent and fickle markets. It therefore requires a quick response to fashion changes whose rhythms are becoming more and more accelerated in order to satisfy customers' propensity for anything modern and unusual. Therefore, for many years, time-based competition has been a coherent strategic orientation for this industry (De Toni and Meneghetti 2000). In addition, the widespread adoption in the retail sector of 'lean retailing' implies that the supply of fashion garments is continuously being adjusted to consumer tastes. This requires the more frequent re-ordering of garment items in smaller quantities as opposed to the traditional stocking of the store before the season begins and clearance sales at the end (Mayer 2004).

To cope with the short lead-time and small but frequent orders, apparel manufacturers strive to improve their production processes in order to deliver finished products within the expected time frame at the lowest production cost. Production planning is therefore gaining importance in contemporary apparel manufacturing. Traditional production planning research focuses on either long-term, or short-term, or even daily planning. Limited works have been observed that can link these individual tasks together. Early studies attempted to link different levels of planning using a monolithic approach (Graves 1982) in which both long-term and short-term planning problems are combined to yield a very large problem. In practice, the extreme size of these models prevents their computational implementation. In contrast, hierarchical models take a modular approach for linking up long-term and short-term planning together. With the introduction of hierarchical production planning (HPP), theoretical work on the topic has emerged (Axsater and Jönsson 1984; Bitran et al. 1981; Bitran and Hax 1981; Erschler et al. 1986; Hax and Candea 1984; Özdamar 1996). The benefits

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of HPP are well-established. The most significant advantage is the reduction of the computational burden and the ease of addressing decision-making at different levels of management. A variety of HPP applications in different industries have been gradually reported since the 1980s. Most notably, Vicens et al. (2001), Karumanasseri and Abourizk (2002), McKay and Wiers (2003) have studied the use of decision support systems for scheduling and Yan et al. (2002) have applied mixed algorithmic techniques. Additional methods described in the literature that have been used to develop production plans include non-linear integer programming techniques (Rajagopalan 2002), heuristics techniques (Chang et al. 2003; Dejonckherre et al. 2003) and goal programming techniques (Leung et al. 2003). In addition, Rao et al. (2004) utilized a two-stage integer stochastic program in which they determined what products to produce and how much of these products to produce.

However, the extended literature on production planning deal with systems with mainly machine operations, where the production rates of machine operations are, in general, constants (Metaxiotis et al. 2002). If a system involves mainly manual operations, the production rates are sometime unpredictable, which make the results for machine work inapplicable. On the other hand, a real production environment inevitably involves uncertainty issues such as the arrival of rush orders, order cancellations, changes in order due dates, operator efficiency variations, learning curve effects, delays due to a sudden breakdown of critical machines, and absenteeism of operators, etc. The apparel manufacturing environment is typically fuzzy.

To handle complex planning processes, large apparel manufacturers use Enterprise Resource Planning (ERP) computer systems. ERP is modular-based application software that is designed for enterprises to coordinate all the resources, information and activities needed to complete the business process (Hodge 2002). Some apparel companies further integrate their ERP systems with e-business solutions—from consumer-oriented online store fronts to extranets—to strengthen communications and streamline transactions with customers and suppliers in an attempt to derive efficiency gains (Tuunainen and Rossi 2002; Everdingen et al. 2000). For small and medium sized companies, different from large enterprises, they could not afford expensive ERP solutions but remain most operations, including the planning operation, to complete manually. In apparel industry, with the trend of increasingly seasonal demand, the number of jobs orders multiplies but the size of the orders becomes smaller. Apparel manufacturers are switching to lean model production, in which large sewing departments are splitting into smaller, self-balancing, sewing lines. In result, in a single production planning exercise, hundreds and thousands of jobs must be allocated to a mix of sewing lines of different capacities. There are a number of reported studies on intelligent control of garment manufacturing, for example applications in the cutting room operations (Wong et al. 2006).

The main purpose of this paper is to develop intelligent apparel production planning algorithms that allocate job orders to suitable sewing units to ensure the effective utilization of production capacity and on-time completion of all job orders. The intelligent planning algorithms are based on group technology and genetic algorithms and can be used for labour-intensive operation planning. The proposed algorithms are developed as an Excel spreadsheet that can be used by different sizes of company and can even be integrated with advanced ERP solutions. The rest of the paper is organised as follows. Section "Apparel production planning" outlines the production planning practices of the apparel industry. Next, the apparel planning algorithms based on group technology is described in section "Planning algorithms based on group technology". section "Intelligent planning with genetic algorithms" describes the intelligent planning algorithms by genetic algorithms. Section "Case studies and discussion" incorporates case studies and a discussion.

Apparel production planning

Apparel production process

Apparel production is characterised by labour-intensive manual operations, frequent style changes, seasonal demand, and short production lead times. It consists of a series of operations such as designing, sample confirmation, sourcing and merchandising, lay planning, marker planning, spreading and cutting, sewing, washing and finishing and packaging (see Fig. 1). Apparel production is a sequential process where good planning is vitally important. The sewing operation is regarded as the key operation in the whole apparel manufacturing process, the schedule of which is used to define the schedules of other operations. The sewing operation itself consists of many steps depending on the product, but it is viewed as a single operation in this paper because, unlike machine operations, sewing is mainly manual work and different sewing steps are completed within a single sewing unit (sewing line) in a self-balancing manner. In apparel production planning, once the sewing operation schedule is fixed, other operations such as sourcing, spreading and cutting, washing and finishing can be scheduled accordingly by manual planning or by the use of ERP or Material Requirement Planning (MRP) systems.

Apparel ERP implementations

As discussed previously, large apparel enterprises adopt ERP systems in an attempt to improve competitiveness and overall system efficiency. Traditional ERP systems complete the

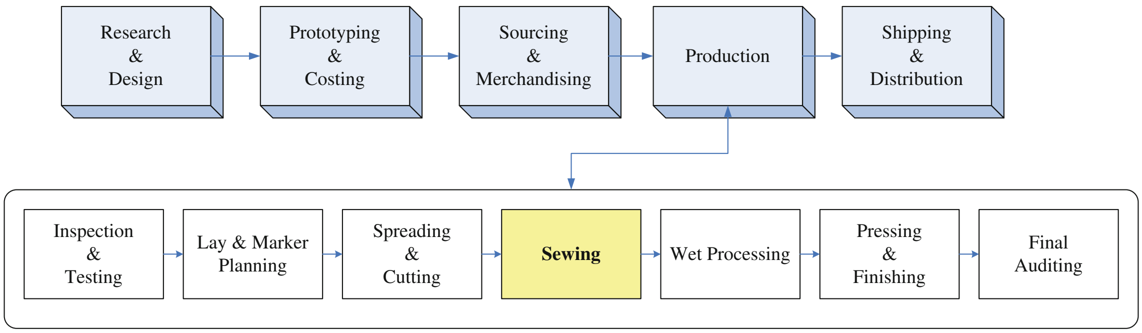

Fig. 1 Outline of apparel production cycle

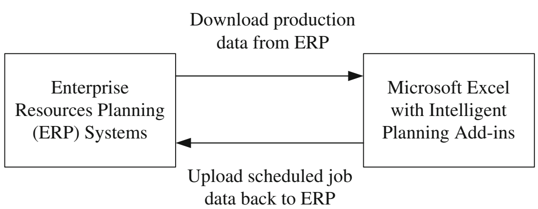

Fig. 2 Data flow between ERP system and the Excel planning spreadsheet

planning exercise by allowing planners to input the production schedules of different job orders. Upon planner deciding the schedule of jobs (the corresponding schedule of sewing operations), the ERP systems can decide the correct resource consumption and the schedule of other operations. The approach of manual planning for sewing schedule in ERP fits the needs of the majority of companies because companies have different strategies and operate under varied constraints.

The trend of switching to lean mode production makes the planning operation even more difficult than before in view of the total number of jobs and the growing complexity of the production facilities. It is extremely difficult, if not impossible, for planners to coordinate and integrate all sorts of information to optimise the planning and to maximise resource utilization. The quality of the planning depends very much on individual planner's experience and knowledge of the shop floor. This paper proposes the use of intelligent planning algorithms using the concept of group technology and genetic algorithms to achieve automatic planning. Such algorithms are programmed in Excel VBA codes and saved as Excel add-ins (.xla or .xll). These Add-Ins can be installed in the Excel spreadsheets, allowing easy implementation for organizations of different sizes. With the spreadsheet platform, individual companies can easily define their own production settings, planning strategies and constraints, and then use the proposed algorithms (add-ins) to accomplish complex planning in a few clicks. For large organizations, the spreadsheet approach allows easy integration with ERP systems. As shown in Fig. 2, job order data are firstly exported from the ERP system to an Excel spreadsheet. Automatic planning is carried out in the spreadsheet using intelligent planning algorithms add-ins. Planners can review the resulting production plan and the capacity balance and can even adjust the plans manually if necessary. The resulting production plan with detailed schedules of all jobs is then imported into the ERP system for the real-time coordination of the production shop floor and other departments.

Planning algorithms based on group technology

Production planning aims at maximising efficiency and minimising inventory. Because apparel production mainly involves manual operations, operators' efficiencies are not constants but variables. Operators gradually improve their efficiency when they get used to the operation procedure. As a result, workers with similar previous experience can usually produce more efficiently and the output quality can be ensured. Consequently, some manufacturers tend to allocate jobs to sewing lines where operators are most familiar with the jobs, which in turn maximises production efficiency. This strategy is using *group technology* for production planning.

Group technology (GT) is a methodology of combining the design of different products to reduce the number of parts or combining products involving similar manufacturing processes to reduce inventories and work in progress (WIP). Since workers are producing similar products all the time, the throughput time and setup time can be largely reduced. With the concept of GT, sewing lines are delegated to produce a specific type of product or to serve one customer. The principle behind this is that the manufacturing processes (sewing operations) of different styles for the same customer are similar, and the manufacturing processes of different customers for similar styles may also be similar. Skilled workers can work in more efficient ways due to the learning curve effect. If job orders of similar products are allocated to the same sewing unit, the efficiency can therefore be increased. Planning algorithms based on the concept of GT are developed in order to maximise the operators' familiarity with the job

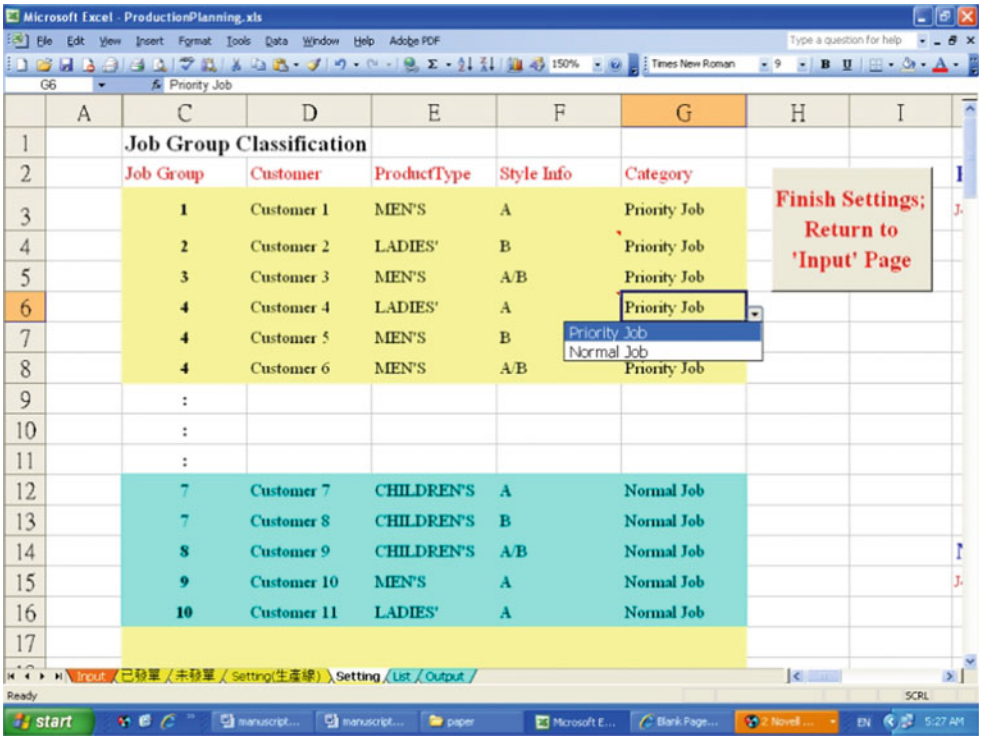

Fig. 3 Excel spreadsheet screen capture for job group classification

and consequently aim to improve the production efficiency and output quality.

Initial settings for production planning

It is necessary to define the production system before the planning exercise, for example the number of sewing lines and the relevant capacity constraints. Apparel companies may assign their workers to work in shifts so as to increase the production capacity of the sewing lines. Shift information should also be defined. In this paper, it is assumed that each production line has two shifts: a day shift and a night shift.

The GT planning algorithm first classifies job orders into different groups based on some defined criteria such as customer information, product type and style characteristics (see Fig. 3). Jobs can be further classified as priority jobs or normal jobs based on the planning strategies of the individual company. Important jobs for which on-time completion is essential are regarded as priority jobs. These are usually jobs from new customers or jobs with an expensive late penalty.

Once the job groups and sewing lines are properly defined, the production planner should define job allocation preference settings by assigning up to ten sewing lines for each job group, in descending order of preferences, as shown in Fig. 4. The job allocation preference setting is defined in terms of job information such as customer information, product type and style characteristics and planners' knowledge of the sewing lines. Preferred sewing lines should be able to produce jobs in a shorter time and to a better quality. Such job allocation preferences can be tailored to the situation of individual companies, and can be modified easily to describe different production situations.

Automatic planning algorithms

Algorithms are developed to allocate jobs automatically to different sewing lines according to the defined job allocation preferences. Priority jobs will be scheduled first, followed by normal jobs. A new job is allocated to the most preferred (first priority) sewing line. In the event that the capacity of the line is not sufficient for the job, work is then allocated to the second preferred (second priority) sewing line, and so on. This process is repeated until all job orders are allocated to the available lines. For each sewing line, the allocated jobs are sequenced according to the job due dates. If multiple shifts (day shift or night shift) are used in that sewing line, a second assignment is needed to allocate job orders to specific production shifts. In other words, job orders are allocated in two assignment exercises: to sewing lines in the first assignment and to production shifts in the second assignment.

In usual practice, workers on the day shift are different from workers on the night shift, even though they work in the same sewing line. For the purpose of better quality control, each job order should be processed by one production shift

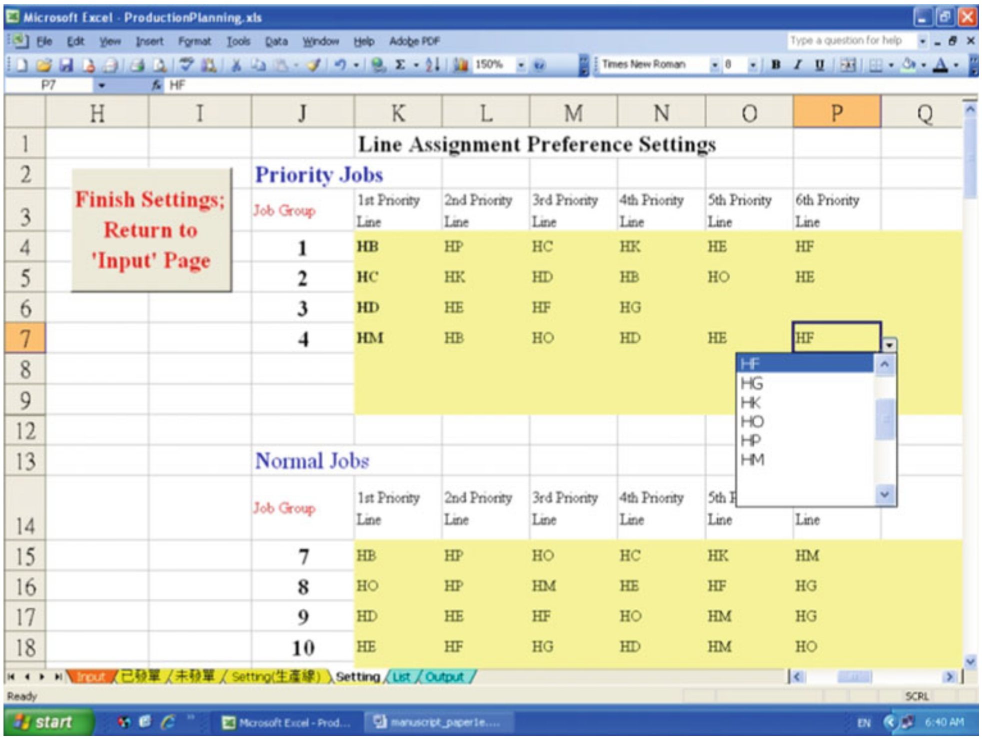

Fig. 4 Excel spreadsheet screen capture for job allocation preference settings

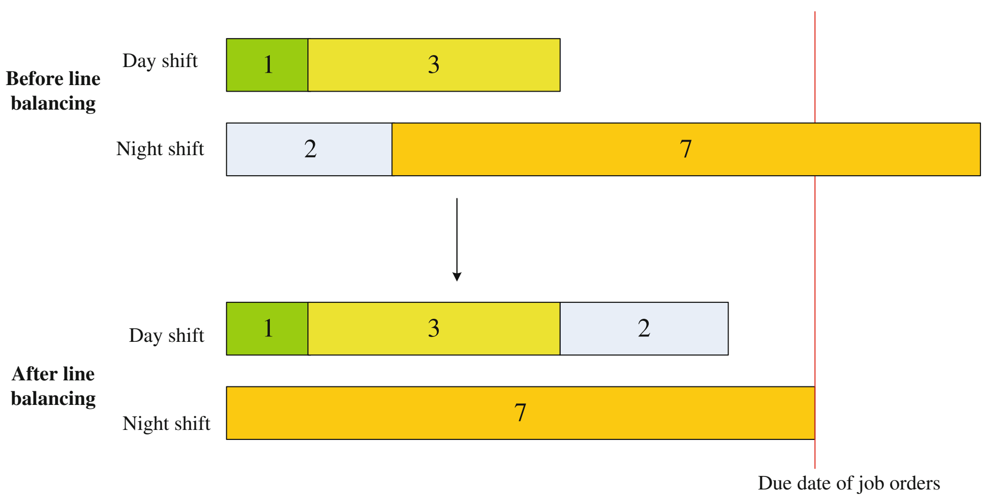

Fig. 5 Load balancing of production shifts

only. Job orders are allocated to the first available production shift based on the earliest start date. A line balancing scheme is then proposed to fine tune the job schedules for each sewing line so as to ensure a proper balance of shift loading and on-time completion of all job orders (or the smallest possible delay in case of over capacity). Take Fig. 5 as an example. Four job orders have been allocated to a sewing line: a one-day job, a two-day job, a three-day job and a seven-day job, with same latest finished dates (the red line in the figure). By allocating jobs to the most available production shifts, the one-day job and the three-day job are allocated to the day shift, while the two-day job and the seven-day job are allocated to the night shift. Before capacity balancing, it can be seen that the seven-day job cannot be completed on time. A line-balancing scheme is used to reallocate jobs to different shifts such that all job orders can be finished on time. In this case, the two-day job is reallocated to the day shift (see Fig. 5).

The traditional latest start date (LSD) method is used to schedule the detailed job orders in the planning algorithms.

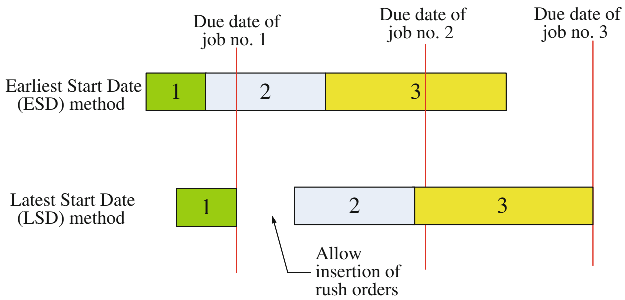

Fig. 6 Production plans by ESD and LSD methods

This is because planning is a rolling exercise in which new jobs are continually inputted. Consequently, the production plan must be reviewed (or re-planned) regularly. In order to allow the insertion of rush orders and to minimise the inventory level, a lean production approach is assumed with job orders scheduled by the latest start date, that is the latest possible time to start a job without causing a delay. As shown in Fig. 6, if jobs are scheduled to the earliest available sewing units (earliest start date method), they will be completed before the proposed due date, which incurs inventory costs for handling the finished goods. By the latest start time method, jobs are processed only when needed, while on-time completion can be guaranteed. In addition, this method indicates where rush orders can be inserted, at the same time reducing unnecessary inventory costs.

Figure 7 shows the process flow of planning job orders based on group technology algorithms. It is important to know that GT planning algorithms are tailor-made algorithms that automate the planning exercise based on predefined job allocation preferences. Job allocation settings are designed for a specific condition. If the condition changes, it is necessary to update the preference setting accordingly. In this case, optimal planning cannot be ensured using customised job allocation preferences. Genetic algorithms are therefore proposed to optimise the apparel planning in this paper.

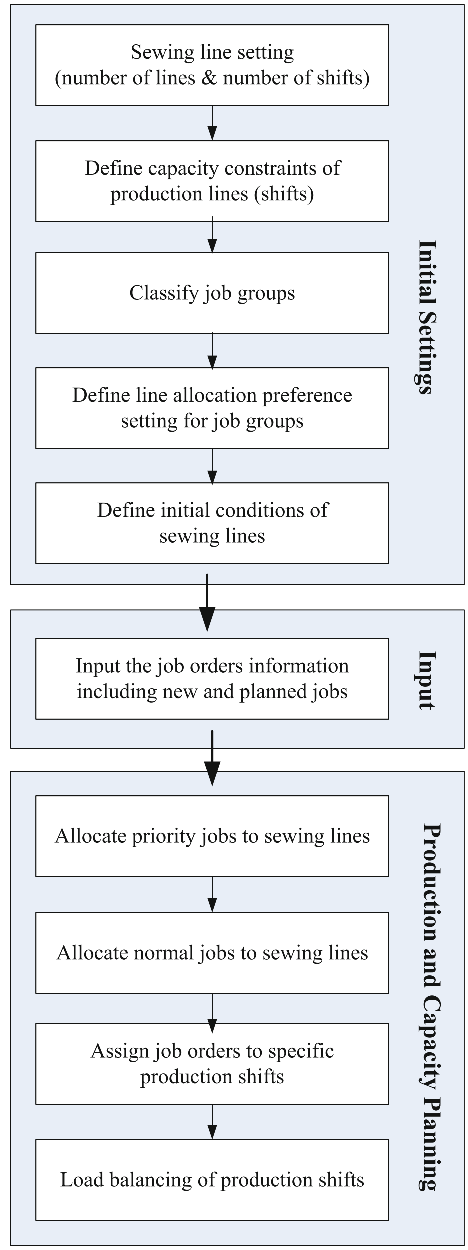

Fig. 7 Production planning of job orders based on group technology

Intelligent planning with genetic algorithms

Genetic algorithms (GAs) are powerful search algorithms that have been successfully applied to different engineering optimisation problems. GAs mimic Darwin's evolutionary process to "evolve" the best solution to a complex problem using the concept of the survival of the fittest in natural selection.

Individual representation

To apply GAs in solving an industrial optimisation 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 choice of representation depends on the nature of the problem. In this paper, integer chromosome representation is used to indicate the job allocation. The length of the chromosome string represents the number of jobs, while the digit values represent the assigned production sewing lines. In the following example, job order 1 is assigned to sewing line 5, job order 2 is assigned to sewing line 8, and so forth.

Chromosome: 5 8 6 4 7 3 9 5

Fitness evaluation

In GA, each chromosome represents a production plan and the effectiveness of this production plan is evaluated. This gives a fitness value to the chromosome. The overall planning objective is to maximize the on-time completion of jobs and operator efficiency. To optimise the production planning by GA, the fitness function is defined as:

$$\Gamma(j) = \frac{A}{\sum_{j=1}^{n} C_T(j) + C_G(j)} \tag{1}$$

where $C_T(j)$ is the time cost of the job order j, $C_G(j)$ is the group-assignment cost of the job order j, and A is a large constant value.

The time cost compares the scheduled completion time and the required shipping date, and is calculated by

$$C_T(j) = \mu \cdot \max(T_p(j) - T_D(j), 0) + \lambda \cdot L \tag{2}$$

where T_p is the expected completion time of job order j, T_D is the shipping due date of the job, and the value of L follows

$$L = \begin{cases} 1 & \text{if } \max(T_p(j) - T_D(j), 0) > 0 \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

μ and λ are weights given to on-time completion and delay penalties, and these weights are decided by management according to their planning strategy. In this paper, the weights are $\mu = 0.1$ and $\lambda = 3$. In Eq. (2), the first part represents the time cost and the second part represents the late penalty. If the job order can be completed on time, the cost is zero. λL in the second part is the penalty given for the delayed completion of the job.

The group assignment cost C_G is defined as:

$$C_G(j) = \sigma \cdot Q_j \cdot (P(j) - 1)^m \tag{4}$$

where σ is a weighting parameter for a group assignment, Q_j is the quantity of job order j, and $P(j)$ is the priority of the assigned sewing line for job order j. If job order j is allocated to the first priority sewing line, $P(j)$ equals 1. If it is allocated to the second priority sewing line, $P(j)$ equals 2, and so on. Since the planner has chosen up to 10 priority lines for each job group, $P(j)$ equals 11 if the job order cannot be allocated to any of the preferred lines. Index m is a multiplier, which can be defined as different values for different job types. For instance, in this paper, $m = 10$ if the job j is a priority job and $m = 6$ if it is a normal job. The weight of the group assignment is set as $\sigma = 10^{-10}$ in this paper.

Apart from the on-time completion of a job, another objective of apparel production planning is efficiency maximization. Owing to the nature of manual operation in apparel manufacturing, it is assumed that the operational efficiency is improved if the workers already have similar experience. If jobs are assigned to preferred lines, the operation efficiency will be higher. Therefore, the efficiency maximisation objective can be achieved by minimising the group assignment costs in Eq. (1).

Genetic operators

There are three main operators in genetic algorithms: selection, crossover and mutation.

Selection

The major objective of selection is to maintain or increase the fitness of the population. Chromosomes are selected from the population to produce the offspring for the next generation, based on their fitness value. The chromosome with a higher fitness value has a higher probability of being retained in the next generation. Selection can be viewed as the way to maintain or increase the fitness of the population. Since selection is based on the fitness values of chromosomes, the characteristics (genes) of the chromosome with a good performance can be retained in the next generation.

There are different kinds of selection methods in genetic algorithms. The best known method is the so-called roulette wheel selection method. In roulette wheel selection, the chromosome which has a higher fitness has a higher probability of being selected to produce the offspring in the next generation. The selection probability of the chromosome is accordingly

$$p_i = \frac{\Gamma(i)}{\sum_{j=1}^{n} \Gamma(j)} \tag{5}$$

where $\Gamma(i)$ is the fitness value of the i-th chromosome.

Crossover

The crossover operator is the most important search operator in genetic algorithms. Crossover is used for the main search mechanism, while mutation is used to ensure that all possible combinations of chromosomes can arise in the population. The purpose of crossover is to combine the useful segments of the parent chromosomes such that the offspring can obtain the good characteristics of both parent chromosomes. Figure 8 shows a single-point crossover that occurs after the third gene of two ten-digit parental chromosomes.

Mutation

Mutation is regarded as a "background operator" in genetic algorithms. Mutation is used to provide new information for the population and also to prevent the population from premature convergence. If both the parent chromosomes have the same value at certain genes, crossover cannot change the value of that gene. Therefore, mutation is used to ensure that all of the points in the search space can be reached. Figure 9

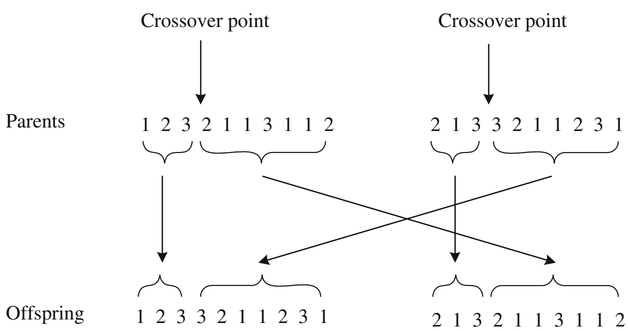

Fig. 8 Single-point crossover

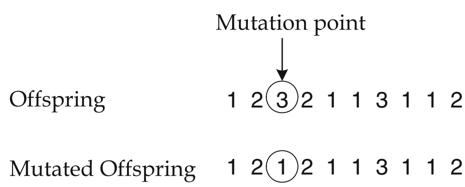

Fig. 9 Random resetting mutation

shows an illustration where the third gene is mutated in such a way that a new gene value of 1 replaces the original gene value of 3.

Two approaches of GA

In this paper, two GA approaches have been used to optimise the job allocation problem. The first approach is that both priority and normal jobs are allocated in one single run. The second approach is that priority jobs are allocated first by one run of GAs, and the normal jobs are then allocated in another run of GAs, with all the scheduled priority jobs as system initial conditions. In the proposed two-run approach of GAs, normal jobs are allocated after priority jobs in order to search out sewing lines with sufficient capacity for these jobs. Figure 10 illustrates the flow of the proposed two-run GAs. The allocation method of job orders from sewing lines to production shifts is the same as that described in section "Automatic planning algorithms". The two-run approach of GAs is proposed because different criteria exist in terms of job allocation, in that some jobs (priority jobs) are more concerned with whether suitable sewing lines are assigned with regard to quality or contract issues, while other jobs (normal jobs) focus more on on-time completion and efficiency issues.

Case studies and discussion

Three different sets of real production data were used to test the performance of various planning algorithms. The first

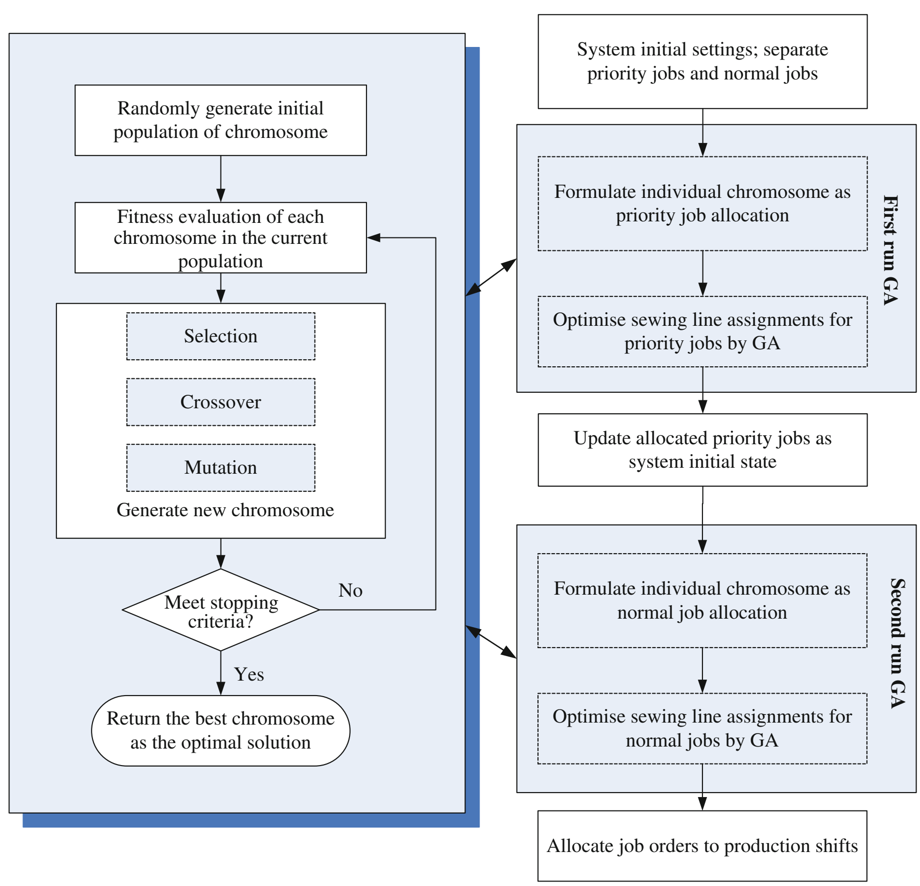

Fig. 10 Two-run GAs

Table 1 Job allocation results comparison for three datasets (priority jobs)

	Planning algorithms by single-run GA	Planning algorithms by two-run GA	Planning algorithms by GT
First data set where priority jobs are allocated to			
1st Priority line	192747(45.54%)	246076(58.14%)	272227 (64.32%)
2nd Priority line	142818 (33.74%)	130123 (30.74%)	100000 (23.63%)
3rd Priority line	62820 (14.84%)	47066 (11.12%)	51038 (12.06%)
4th Priority line	24880 (5.88%)	0	0
Other priority lines	0	0	0
Second data set where priority jobs are allocated to			
1st Priority line	209278 (70.20%)	284023 (95.27%)	286317 (96.04%)
2nd Priority line	88388 (29.65%)	14095 (4.73%)	11801 (3.96%)
3rd Priority line	452 (0.15%)	0	0
4th Priority line	0	0	0
Other priority lines	0	0	0
Third data set where priority jobs are allocated to			
1st Priority line	277453 (26.70%)	337346 (32.46%)	541433 (52.09%)
2nd Priority line	307441 (29.58%)	357040 (34.35%)	224418 (21.59%)
3rd Priority line	239941 (23.09%)	215406 (20.73%)	160044 (15.40%)
4th Priority line	98752 (9.50%)	65597 (6.31%)	0
Other priority lines	115742 (11.14%)	63940 (6.15%)	113434 (10.91%)

data set has 988,638 jobs to plan, of which 423,265 are priority jobs and the remaining 565,373 are normal jobs. The second data set consists of 803,891 jobs with 298,118 priority jobs and 505,773 normal ones. The third data set has 1,385,121 jobs, of which 1,039,329 are priority jobs and 354,792 are normal ones.

The GT planning algorithms emphasize particularly whether or not job orders can be allocated to priority sewing lines, while GA planning algorithms place more emphasis on whether or not job orders can be finished on time. Therefore, it can be seen from Table 1 and Fig. 11 that the higher percentage of priority jobs has been allocated to the first priority (most preferred) lines by GT algorithms in all three data sets. The results of GAs show that jobs have been allocated to sewing lines according to the defined preferences. Moreover, it can be seen in Table 1 that a higher percentage of priority jobs can be allocated to the first priority sewing lines by two-run GAs than single-run GAs.

On the other hand, GAs out perform GT algorithms in terms of job on-time completion. It can be seen from Table 2 that the on-time cost of results from the GT algorithms is higher than that from GAs. Since GT algorithms place more emphasis on allocating jobs to preferred sewing lines, fewer jobs can be finished on time and the resulting on-time cost is therefore higher. GAs, both single run and two-run, can achieve a better total fitness in all three datasets. This implies that GAs can better balance the two objectives of allocating job orders to preferred lines and on-time completion of all jobs. This is because GAs optimise job allocation, but GT

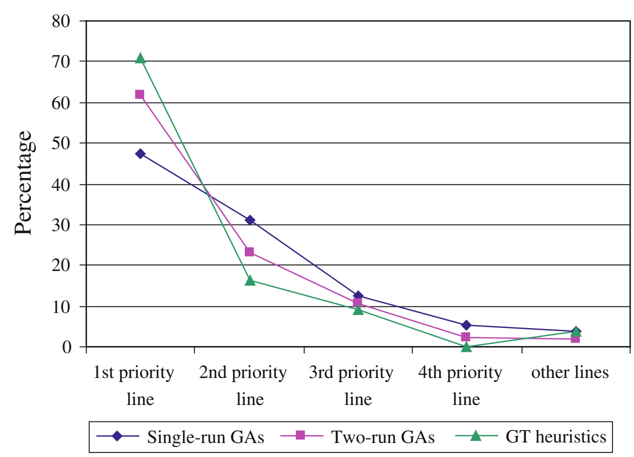

Fig. 11 Percentage of prioriy jobs being allocated to preferred sewing lines (average of three datasets)

algorithms are only planning heuristics that cannot guarantee optimal planning.

Moreover, in terms of allocating priority and normal jobs in separated runs, GAs require fewer generations to reach a solution than doing this in one single run. The result of the group-assignment fitness (the reciprocal of the group-assignment cost $1/C_G$) and the total fitness for one data set are used to show the difference of the two approaches of GAs. It can be shown from the total fitness in Fig. 12b, d that fewer generations are needed for two-run GAs to search a solution. For example, the GAs results of the third data set were

Table 2 Production planning cost comparison of three data sets

	Planning algorithms by single-run GA	Planning algorithms by two-run GA	Planning algorithms by GT
First data set on-time cost $\sum C_T$	0	0	93.3707
Group-assignment cost $\sum C_G$	0.221263	2.10597	1.45300
Total fitness Γ	4.519516	0.47484	0.01054
Second data set on-time cost $\sum C_T$	0	0	39.9122
Group-assignment cost $\sum C_G$	0.005073	0.003701	0.024273
Total fitness Γ	197.1207	270.1910	0.025040
Third data set on-time cost $\sum C_T$	33.8454	0	58.8582
Group-assignment cost $\sum C_G$	38.3195	7.181704	35.1989
Total fitness Γ	0.01386	0.139243	0.01063

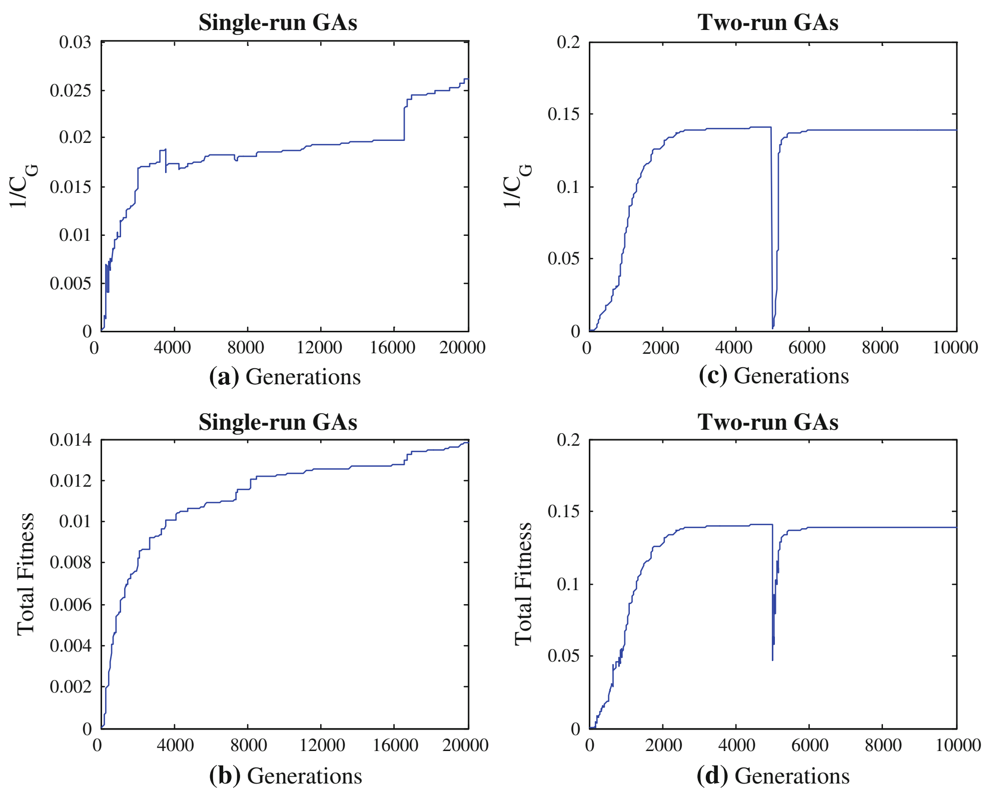

Fig. 12 Fitness comparison of single-run GAs and two-run GAs

obtained by a 20,000-generation of single-run GAs; but with the same population size of 300, two-run GAs took fewer generations to obtain job allocation results (total 10,000 generations, i.e., two 5,000-generations). The difference is because GAs can search the optimal solution more easily within a smaller searching space.

As shown in Fig. 12c, the final group-assignment cost after the two runs of GAs (the value at 10,000 generations) is higher than that after the first run (the value at 5,000 generations in the figure). This is because the scheduled results of the first run are kept as the system initial conditions in the second run of GAs, where more jobs are allocated to the sewing lines. Therefore, the final group-assignment cost has incorporated group-assignment costs of that in the first run for priority jobs.

It can also be seen from the results that if more jobs are to be allocated in one single planning exercise, GAs require more generations to reach a solution. Data set 3 has the largest number of job orders (about 50% more than data sets 1 and 2), and a single-run GA took 20,000 generations to search

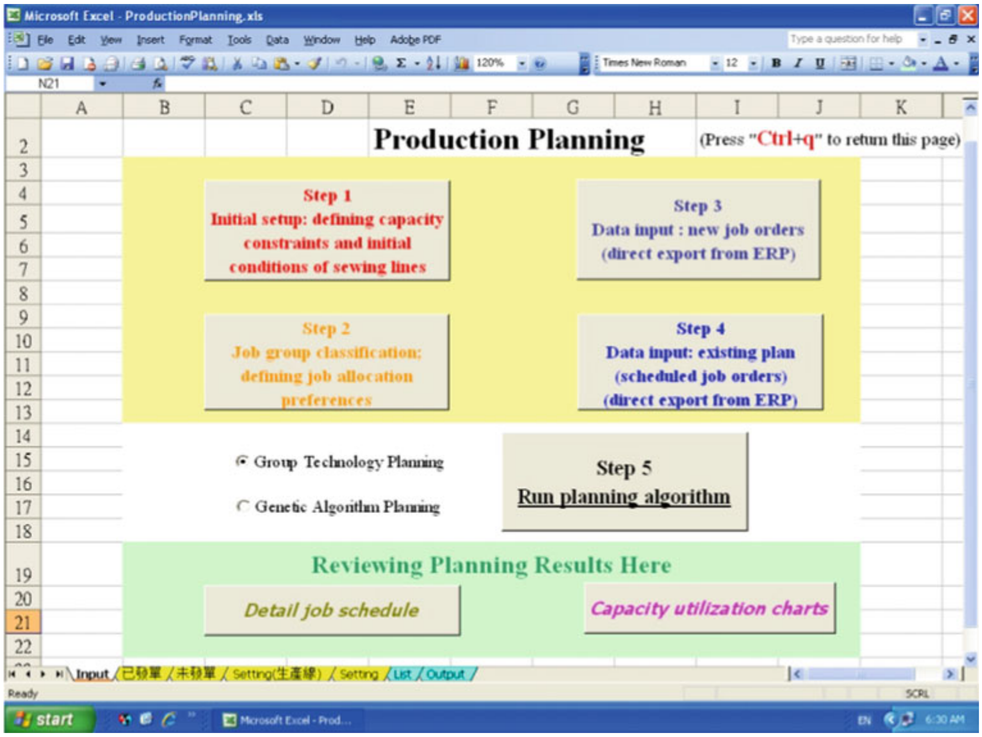

Fig. 13 User interface of Excel planning spreadsheet

the optimal plan, which is double the number of generations required for data sets 1 and 2. It is again a problem of searching space, in that if more jobs are allocated in a planning exercise, then this is represented by a longer integer chromosome and the potential combinations increase exponentially. In such a case, the optimisation problem becomes more challenging. This is shown by splitting the searching into two runs that can drastically reduce the searching time, as data set 3 took the same number of generations (5,000 + 5,000 generations) to search the optimal plan as that in data sets 1 and 2 in two-run GAs. Besides, from the total fitness, it can be seen that two-run GAs obtained the best results among the three algorithms for the huge data set 3.

There is a choice between single-run GAs and two-run GAs. If allocating job orders in two separate runs, higher priority jobs can be allocated to preferred lines. However, there is a chance that the capacities of these sewing lines will be used up quickly, with the result that some jobs must be completed by non-preferred lines.

In planning GT algorithms, jobs are allocated based on predefined allocation preference settings. Preference settings must be updated whenever the situation is changed. It is not guaranteed that the production plan obtained is an optimal one. However, GAs search for the optimal plan based on a defined fitness function, and GAs can easily be adapted to different planning objectives by changing the definition of the fitness function. For the GT planning algorithms, it is less easy to adapt to objective or condition changes. For example, as shown in Fig. 4, the preferred sewing lines for the Job Group 1 are lines HB, HP, HC, etc. The job orders of job group 1 are allocated to sewing line HB until it does not have enough capacity left for new jobs, then the job orders are allocated to the second preferred sewing line (i.e. line HP) until it is again fully occupied. If the conditions have changed, in that there are no differences in terms of assigning job orders to either HB or HP for job group 1 orders, planning algorithms cannot manage such preference changes. The only solution is to change the algorithm itself. However, in the case of GAs, it is only necessary to change the weights in the fitness function. GAs are therefore more robust than GT if the strategies or preferences are changing frequently. In GAs, the optimal production plan can be found once a fitness function is defined.

Although the overall performance of GAs is better than that of GT, GT is quicker at finding a solution. It is a choice between performance and time. GT planning algorithms take less than one minute to complete automatic planning and to obtain a result, while GAs take much longer time (3 h or more) to obtain a result. Single-run GAs take longer than two-run GAs. Without considering the better planning quality of GAs, the time required for GAs to generate an optimal production plan is still much less than doing this manually. The proposed production planning algorithms have demonstrated substantial improvements in terms of planning quality and efficiency, and such algorithms are currently being used by apparel manufacturers in Hong Kong for routine planning operations. Figures 13 and 14 are screenshots of user

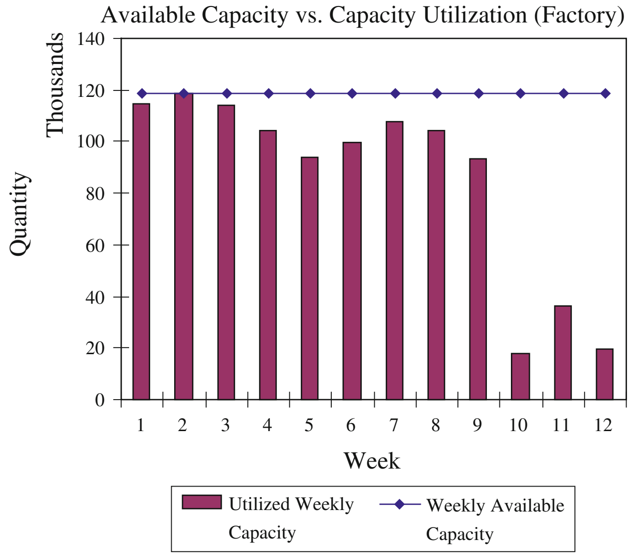

Fig. 14 Planning results shown in comparing available and utilized resources

interfaces and the resulting capacity utilization charts of the Excel planning spreadsheet. The algorithms are also flexible when it comes to handling issues such as inserting rush orders, changing order due dates and size, etc. The proposed planning solutions have proved to be user friendly and cost effective for the industry.

Conclusions

Apparel production planning is a challenging task in that job orders must be allocated to suitable production lines to ensure the effective utilization of resources and the on-time completion of all job orders. In this paper, intelligent planning algorithms have been proposed for automatic job allocations in apparel manufacturing based on group technology and genetic algorithms. In order to speed up the planning efficiency, two GA approaches including single-run and two-run GAs have been developed to optimise the job allocation problem. The proposed algorithms have been built as Excel add-in functions, allowing apparel organizations of different sizes to easily define their manufacturing systems and complete the complex planning on Excel spreadsheet in a few clicks. The proposed functions have also been integrated with large ERP systems in some apparel companies to improve the production planning effectiveness and efficiency. In this paper, real production data has been used to validate the methods. The proposed planning algorithms have demonstrated a substantial improvement in terms of planning quality and efficiency. These intelligent algorithms are currently adopted by apparel manufacturers in Hong Kong for their routine planning operations.

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