A Multi-Heuristic GA for Schedule Repair in Precast Plant Production

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Abstract

A multi-heuristic schedule repair model for schedule conflict resolution is presented and its application in repairing the schedules of a prefabrication plant is described in this paper. The model combines heuristic strategies with Genetic Algorithms to repair schedules with resource constraints. The GA determines the "best" sequence of resolving schedule disturbances using heuristic rules selected from a library of heuristics commonly used in industry. We compare quantitatively the advantages of using this model for schedule repair against existing single-heuristic schedule repair techniques with a multi-criteria evaluation function. Results on the macroscopic and microscopic levels are presented to understand the strengths and weaknesses of the model.

Key words: application of planning and scheduling; dynamic scheduling.

1 Introduction

Our research is based on a real-life application of production planning and (re)scheduling in prefabrication plants. In Singapore, the increased use of prefabricated building components and industrialized building methods has been identified as the means of improving both the overall productivity at the construction site and the quality of the construction facility. The demand for different types of prefabricated building components has been on the increase, especially in public housing and transport infrastructure projects. As a result, the prefabrication plants and the general contractors using these prefabricated components in their projects form a short but economically significant construction supply chain.

The types of prefabricated components used in a construction project and the rate of the project's progress significantly influence the production schedule of the prefabrication plant supplying those components. More specifically, the plant needs to schedule the production of specific components required by the general contractor and deliver them to the construction site by the due dates determined largely by the pace of the construction site schedule. Due to this intimate relationship, a change in component specifications, the quantities required or the due dates by the contractors inevitably leads to a review of the prefabrication plant's production schedule. Conflicts in production schedules arise when the review shows that production resources are over-committed to meet new delivery due dates. At least one of the production operations has to be rescheduled and this is called a (schedule) disturbance. Rescheduling is further complicated as prefabrication plants usually supply different heterogeneous components to a number of construction projects simultaneously at any one time.

In updating the production schedule, plant operators tend to utilize their own preferred heuristic, usually the one that had proven easy to apply and reasonably efficient from past experience. Moreover, the same heuristic is likely to be applied to resolve all schedule disturbances. However, heuristics are known to be problem specific and cannot guarantee good solutions for all cases.

We propose to let an evolutionary search decide the best heuristic to apply to a particular disturbance, as well as the order of resolving disturbances by combining the use of heuristics and genetic algorithms (GA) in a method we call the Multi-heuristics Schedule Repair Model. A custom chromosome representation is proposed to encode the decisions involving the order of resolving disturbances and the heuristic best suited to resolve disturbances. The GA evolves the chromosomes to determine both the "optimal" repair sequence as well as the best combination of heuristics from a pool of selected heuristic strategies. We investigate the efficiency of the proposed schedule repair model in generating high-quality repaired schedules, and compare the schedules generated with the use of this model against those generated by the single-heuristic approaches currently used in the industry. This comparison is based on a multi-criteria evaluation function derived from factors pertinent to industry practices.

2 Literature Review

The wider use of prefabricated building components has led to research on planning and scheduling methods in the precast industry. Warszawski (1982, 1990 and 1999) provided a general framework of the main features to a proposed information for planning, cost and quality control in prefabricated plant operations, based on a mathematical precast scheduling model defined in terms of decision variables. Furthermore, Warszawski (1984) proposed a model for short and long-ranged production planning of components in make-to-order manufacturing systems. Dawood and Neale (1993) developed a computer-based capacity based model using the backward scheduling technique to help managers create long term capacity plan, make better planning decisions and explore options. In the general application of GA for scheduling optimization, Chan et al. (1996) proposed a generic GA model suitable for scheduling and resource allocation problems. The random keys concept (Bean 1994) was used in the model to ensure that there was no illegal schedule. On the application for GA to the optimization of production scheduling of prefabricated components, Chan and Hu (1998, 1999 and 2002) developed a flow shop sequencing model for specialized precast production scheduling, and a hybrid genetic algorithm – constraint programming (GA-CP) approach to solve comprehensive precast scheduling. Leu and Hwang (2001) proposed the usage of GA to obtain optimal resource-constrained production schedules for repetitive prefabricated components.

One development that is pertinent to industrial practice is that of reactive scheduling from artificial intelligence research. Much research on schedule coordination and repair in the manufacturing industry has been done using this scheduling concept (Zwenben et al. 1990; Smith 1994 and Sadeh 1994). However, there has not been much application of such concepts in the construction industry. Similarities between the production processes in the precast factory and the assembly line in the manufacturing process opens the possibility of the transfer of research findings and practical experience of schedule repair between these two areas.

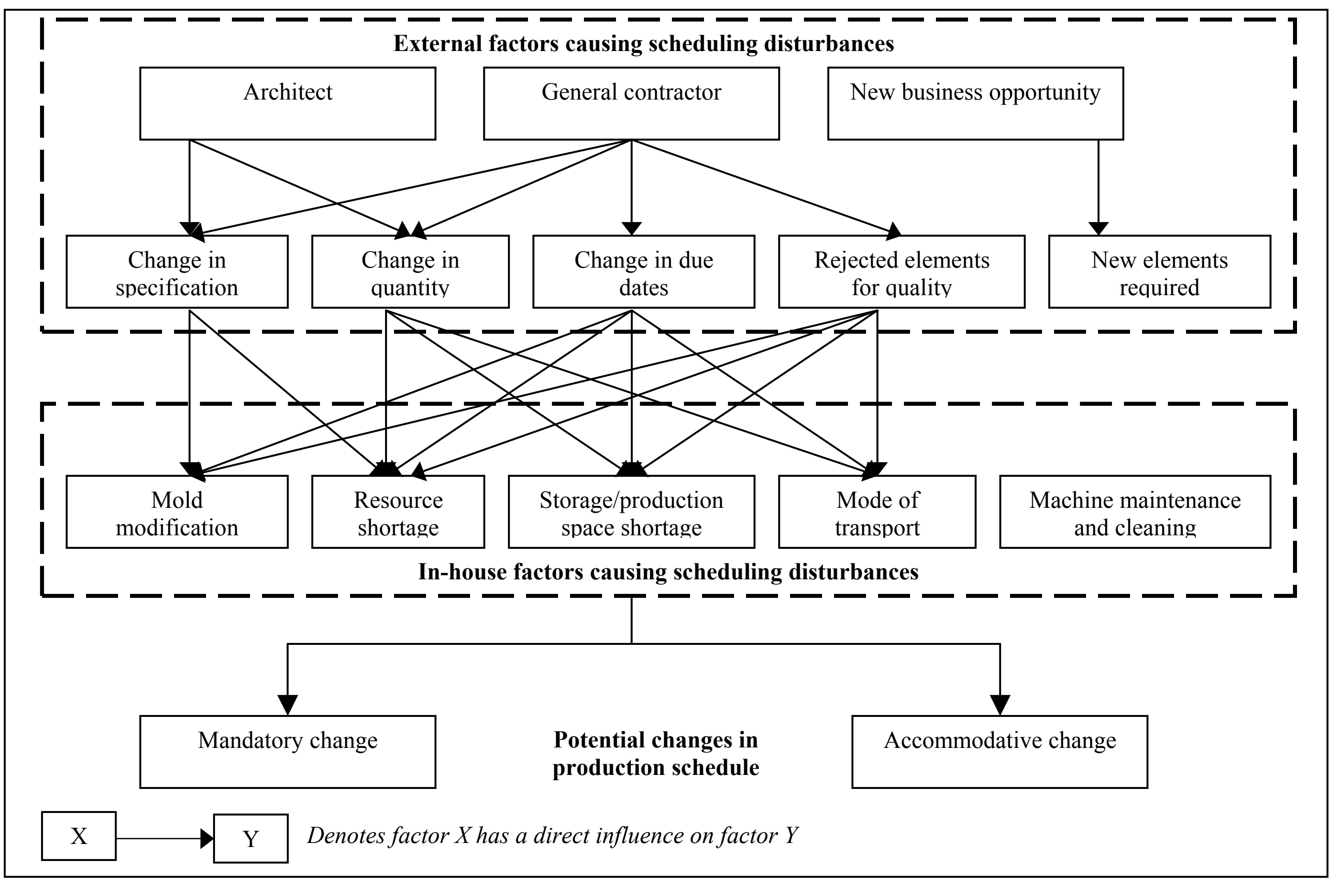


Figure 1: "External" and "In-house" factors causing schedule disturbances

3 Schedule Disturbances and Heuristic Strategies

Important background information on how schedule disturbances occur and the variety of heuristic strategies used was obtained through interviews with industry practitioners during the course of this study.

3.1 Schedule disturbances

There are several common causes of schedule disturbances, ranging from quantity and design specification changes to poor quality and machine breakdowns. These causes have been categorized as either "in-house factors" or "external factors", depending on whether the cause is within the control of the factory or not. Schedule changes may or may not be required in response to these disturbances. For example, the plant operator may choose to forgo new orders and not disrupt existing schedules but is compelled to change his schedules if this involves contractual obligations. Figure 1 illustrates the specific "external" and "in-house" factors causing schedule disturbances, as well as their influences on one another.

3.2 Heuristic strategies for repairing schedules

Production scheduling is carried out for a fixed planning horizon (usually 30 days ahead) according to an agreed schedule for delivering components. Among the heuristic rules used by plant operators to reschedule disturbances and repair their production schedules include:

(1) Right shift (RS): resolves conflicts by "pushing" the production forward in time until the disturbance is resolved (Fig. 2.1);
(2) Left shift (LS): a similar strategy that shifts an operation backwards in time. It is particularly useful when a hard constraint that previously prohibited the commencement of the operation is softened or removed (Fig. 2.2);
(3) Opportunistic insertion (OI): makes use of idle days in the schedule to accommodate a disturbance by breaking it into smaller parts and fitting these smaller parts into the schedule in an opportunistic first fit manner. The efficiency of this heuristic rule largely depends on the initial utilization level of the production facilities (Fig. 2.3);
(4) Deterministic Insertion (DI): similar to opportunistic insertion but the disturbances have priority over already scheduled production and displace them from the schedule. The latter are rescheduled using OI (Fig. 2.4);
(5) As-soon-as-possible (ASAP) / Backward Scheduling (BS): the ASAP method schedules the disturbance based on the earliest start time (EST); the BS method

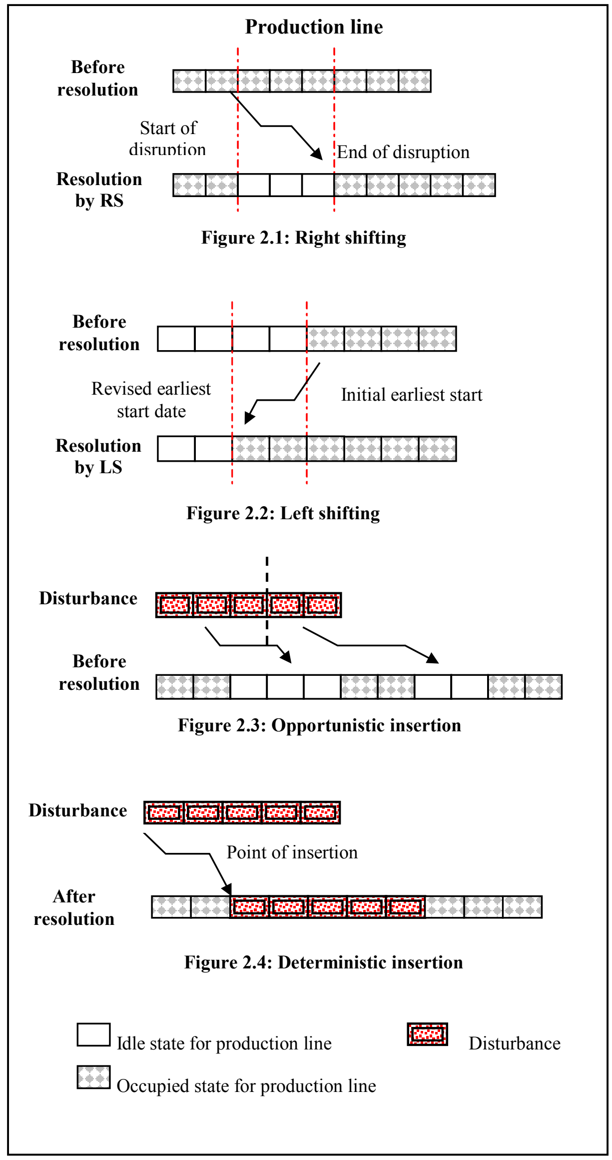


Figure 2.1: Right shifting
Figure 2.2: Left shifting
Figure 2.3: Opportunistic insertion
Figure 2.4: Deterministic insertion

Figure 2: Illustrations of some heuristic rules

schedules the disturbances based on the latest start time (LST);
(6) Multiple mold approach: resolves the disturbance by assigning similar components within the same group of components to any one of several molds capable of producing the components using a OI or DI strategy;
(7) Sub-contracting: this strategy 'outsources' production to other operators and is used when the plant is already producing at its peak capacity or it is economically more beneficial to do so.

The heuristic rules mentioned above were solicited from experienced plant operators through personal interview. The plant operators depended on previous experience when choosing rules to resolve disturbances and did not seem to have a formal quantitative way of deciding on how best to repair schedules. Time pressure often prevented them from trying alternative ways of resolving disturbances or considering the effect of resolving several disturbances together. The multi-heuristics schedule repair model could help address these deficiencies and provide alternative high quality repaired schedules.

4 Multi-heuristic Schedule Repair Model

Our proposed model supports the determination of priority for conflict resolution using heuristic strategies that are best suited to incorporate the conflict-causing disturbances into an existing schedule. The repair actions are also likely to cause further disturbances which then have to be resolved. Therefore, it is necessary to consider not only *how* to resolve the conflict but also the *order* in which the conflicts are to be resolved as both have a bearing on the desirability of the final repaired schedule. The proposed model supports this important consideration by searching for the best combination of conflict-resolving sequence (*order*) and heuristics used (*how*) from many possible combinations using GA.

Genetic algorithms are stochastic search methods based on the mechanism of selection and evolution, and have been successfully applied in scheduling problems including that of precast element production. Details of a GA adaptation for our proposed model are described as follows.

4.1 Constraints

Production scheduling requires allocating resources over time to a set of jobs while satisfying a variety of constraints and objectives. Hard constraints must always be satisfied for a (repaired) schedule to be valid. Soft constraints on the other hand, could be relaxed when necessary. Based on the results of the industry study, we have categorized the hard constraints in our proposed model as functional, capacity and availability constraints, while the soft constraints are delivery and inventory constraints. The representation of these constraints in mathematical terms is necessary for their use in GA. The following section discusses the mathematical formulation of these constraints in terms of binary decision variables defined in Table 1.

Functional constraint: to maintain the production integrity of the prefabrication plant by limiting the types of elements that a specific mold can produce. Although it is possible for a mold to produce several different types of elements, we have restricted this capability to elements within a mold group within which there are only minor variations in mold details. This is necessary as converting a mold to a different mold group is rarely done in practice due to substantial conversion time and costs incurred.

$$\sum_{e=4}^{5}\sum_{m=1}^{4} x_{t,m,e} = 0 \qquad \text{for all } t \qquad \textbf{(1)}$$

$$\sum_{e=1}^{3}\sum_{m=5}^{6} x_{t,m,e} = 0 \qquad \text{for all } t \qquad \textbf{(2)}$$

Capacity constraints: Following industry norms, each

Parameters	Description
$x_{t,\,m,e}$	A binary decision variable, where $x_{t,\,m,e}=1$ means that mould m is assigned to produce element e on day t, whilst $x_{t,\,m,e}=0$ will mean the opposite;
T	t = 0, 1, 2…T, scheduling periods in days;
M	m = 0, 1, 2…M, mould serial numbers;
E	e = 0, 1, 2…E, types of elements to be produced;
$S_{o,e}$	Initial stock of element type e at the beginning of the scheduling period (t = 0);
$S_{t,e}$	Number of element type e in stockyard on day t;
S_e	Maximum allowable storage level of element e in stockyard;
S_e’	Minimum buffer storage level of element e in stockyard;
$R_{t,e}$	Number of element type e required to be delivered on day t;
$D_{t,e}$	Number of element type e delivered on day t;
N_m	Number of changeovers for mould m in the scheduling period;
L_e	Lead time of element type e between production and delivery;
$L_{e,r}$	Minimum lead time required for element type e between production and delivery;
T’	Present time;
T_n	Total number of working days, obtain by subtracting the number of Sundays from T.

Table 1. Parameters for mathematical representations

mold is limited to produce only one element per working day (Equation 3). Therefore the daily maximum capacity of the precast yard is equal to the total number of molds (Equation 4). We have further assumed that there is no production during Sundays and public holidays (Equation 5).

$$\sum_{e=1}^{E} x_{t,m,e} = (0,1) \qquad \text{for all } m,t \qquad \textbf{(3)}$$

$$\sum_{m=1}^{M} \sum_{e=1}^{E} x_{t,m,e} \le M \qquad \text{for all } t \qquad \textbf{(4)}$$

$$x_{t,m,e} = 0 \qquad \text{for } t \in \text{Sundays and public holidays} \qquad \textbf{(5)}$$

Availability constraint: specifies the time required for each produced element to be ready for delivery. A minimum lead time between production and delivery must be observed for the components to attain approximately 70% of their 28-day strength, which refers to the specific strength that concrete gains as it stiffens from an initial plastic state after a setting time of 28 days. Traditional curing takes up to seven days, although the local practice of controlled accelerated curing in a curing chamber reduces this lead time to just two days.

$$L_e \ge L_{e,r} \quad \text{where } L_{e,r} = 48 \text{ hours} \qquad \textbf{(6)}$$

Delivery constraint: specifies the delivery requirements of the components to the construction sites. Due to the large sizes of the prefabricated elements and the shortage of storage space on the construction sites, plant operators are usually not allowed to deliver the elements any earlier than the stipulated date of delivery, nor deliver more than what is required (Equation 7). Furthermore the sum of the initial stock level and the total production of any element before each delivery date should be at least as many as the number of elements required to be delivered (Equation 8).

$$D_{t_1,e} \le R_{t_2,e} \qquad \text{for all } e\text{, where } t_1 \ge t_2 \qquad \textbf{(7)}$$

$$S_{0,e} + \sum_{t=1}^{T'} \sum_{m=1}^{M} x_{t,m,e} \ge \sum_{t=1}^{T'} R_{t,e} \qquad \text{for all } e \qquad \textbf{(8)}$$

Inventory constraint: limits the number of prefabricated components to be stored in the inventory. It also specifies the level of buffer inventory. In short, the inventory constraint serves to define the operating range for stock levels of each prefabricated component. Due to space constraints, the total number of produced components that can be kept in a plant's stockyard is limited. However, plant operators are highly resourceful in 'seeking' new avenues for storing inventory and have been known to store elements temporarily on transportation trailers. They also keep a minimum number of various components to serve as buffers to unexpected or urgent demand. Therefore the cumulative number of any produced components less delivered in any period should be less than the maximum allowable storage limit but more than the minimum buffer level.

$$S_e' \le S_{0,e} + \sum_{t=1}^{T} \sum_{m=1}^{M} x_{t,m,e} - \sum_{t=1}^{T} D_{t,e} \le S_e \qquad \text{for all } e \qquad \textbf{(9)}$$

4.2 Objective functions

Local precast plants produce prefabricated components mainly on a contractual basis, apart from producing some standard elements for anticipated demand. Plant operators have to meet contractual due dates for deliveries while keeping an acceptable level of inventory in the stockyard to buffer any unanticipated demand. Counting the number of elements that was not delivered on time and the number of over or under-stocked elements in the inventory will then reflect on the efficiency of the (repaired) schedules.

Plant operators also try to make full use of their molds and minimize the number of changeovers required. Efficient element to mold assignment is therefore important to efficient scheduling, as that will minimize the cost of changeovers. Hence, the number of changeovers incurred becomes our third parameters for evaluating (repaired) schedule efficiency.

Plant operators tend to minimize the number of idle days during the planning horizon, as it is seen as a waste of resources. However, they have to balance between the costs and effects of excessive production. Production of any particular element on a permanent basis will keep the number of mold changes down and improve the mold utilization rate. However it will also increase the over-stocking of the element thereby affecting the production of other components, which can result in late deliveries for the latter.

It is clear then that the operators have to seek a balance between the different objectives of meeting due dates, minimizing mold changes, maintaining optimum inventory levels and keeping non-productive working days to the minimum. The mathematical representations of these parameters are as follows:

Number of elements in excess/inadequate inventory level: the inventory level of any element is best maintained at an optimum range for spatial and buffer considerations. Therefore the total number of elements in excess of or below desired inventory levels should be minimized

$$\text{Min } Z_S = \sum_{t=1}^{T} \sum_{e=1}^{E} \{(S_{t,e} - S_e)^+ + (S_e' - S_{t,e})^+\}$$

where $(S_{t,e} - S_e)^+ = \max\{0, (S_{t,e} - S_e)\}$

$$(S_e' - S_{t,e})^+ = \max\{0, (S_e' - S_{t,e})\} \qquad \textbf{(10)}$$

Number of mold changes: in order to produce different elements of the same mold group, a mold must undergo minor modification, thereby incurring both cost and time. Therefore, efficient element to mold assignment is needed to minimize the total number of mold changeovers.

$$\text{Min } Z_M = \sum_{m=1}^{M} N_m \qquad \textbf{(11)}$$

Number of elements not delivered on due dates: failure to deliver the stipulated number of elements on time would incur financial penalties and bring detriments to the reputation of plant operators. Therefore the total number of elements not delivered on time should also be minimized.

$$\text{Min } Z_D = \sum_{t=1}^{T}\sum_{e=1}^{E}(R_{t,e} - D_{t,e}) \qquad \textbf{(12)}$$

Number of effective idle days: the maximum number of elements that can be produced per day is M, and the total production capacity within a planning horizon cannot be more than MT_n. A more accurate reflection of the number of idle days would therefore be represented by:

$$\text{Min } Z_I = \frac{1}{M}\left(MT_n - \sum_{t=1}^{T}\sum_{m=1}^{M}\sum_{e=1}^{E} x_{t,m,e}\right) \qquad \textbf{(13)}$$

Due to the different units of measurement of the 4 evaluation parameters, it would not be meaningful to add them directly; hence, there is a need to normalize them into a dimensionless quantity. One approach is to divide each parameter by a constant (e.g. the mean value of a distribution) and then sum up the numbers into an efficiency index. However this would result in a biased analysis favoring parameters which exhibit high variability thus resulting in high normalized values, as these tend to dominate the efficiency index.

We have used 4 planning rules and the integer programming approach to generate 25 pseudo-schedules at various resource utilization levels. The hard constraints were observed in the creation of these schedules to be used for our repair algorithms. These schedules were then evaluated separately using each of the four parameters, resulting in a range of performance evaluations for each of the four parameters. The raw evaluation values were mapped onto a range between 0 and 0.25 by means of linear regression. Doing so meant that we assumed that each of the 4 parameters was equally important. The summation of the four parameters created a dimensionless objective function which minimized the dominance of any parameter. This normalized objective function gave an indication of the relative performance on each parameter.

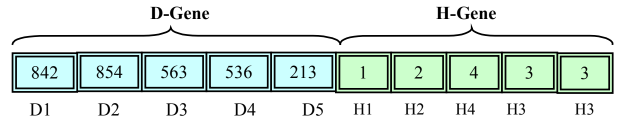


Figure 3: Chromosome representation

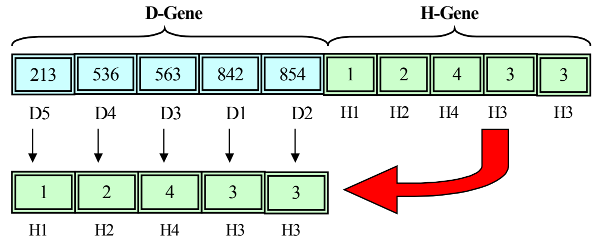


Figure 4: Decoding of chromosome

The higher the index value, the poorer was the performance ranking.

The objective function is therefore defined as:
Min Z = 0.2275 + 0.0008Z_S + 0.0076Z_M + 0.0042Z_D + 0.0264Z_I **(14)**

4.3 GA representation

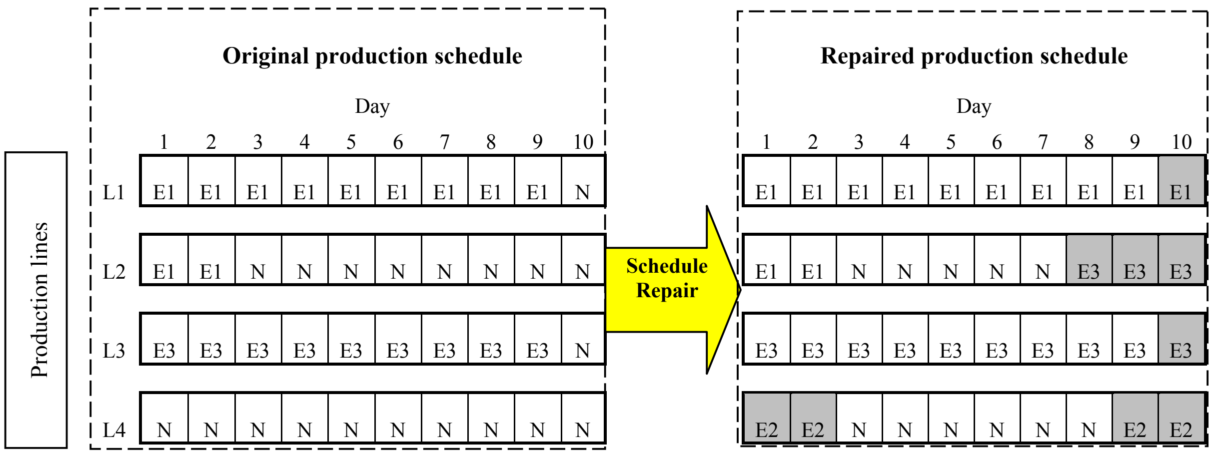
As shown in Fig. 3, the chromosome string is made up of equal number of D-genes (disturbance gene) and H-gene (heuristic genes). Each conflict to be resolved is represented by a pair of D and H-genes. The D-genes encode real numbers that serves as sort keys to determine priority of resolution, whilst the H-genes encode the ordinal value of the heuristics used to resolve the conflict. The properties of each disturbance and the resolving algorithm for each heuristic are defined on their respective tabu.

To decode the chromosome, the sequence of resolving conflicts is determined by sorting the disturbances in increasing order of the D-gene values. The corresponding heuristics defined in the H-genes are then used to incorporate the disturbances into an existing schedule, as illustrated in Fig. 4. In this case, the sequence of conflict resolution with corresponding heuristics is: D5 (H1) → D4 (H2) → D3 (H4) → D1 (H3) → D2 (H3).

There are several parameters that can determine the performance of GA but their optimal values cannot be ascertained by applying fixed rules. In fact, optimal GA parameters are known to be notoriously difficult to determine (Myers and Hancock 2001). These parameters include the population size, the number of iterations performed, the crossover rate, the mutation rate and the termination criterion.

Disturbance	Element Type	Quantity	Due Date for Delivery	Nature of Disturbance
D1	E1	1	Day 5	To replace a rejected element
D2	E2	2	Day 7	Design change to E2 element
D3	E3	2	Day 9	Design change to E3 element
D4	E3	2	Day 5	To replace a rejected element
D5	E2	2	Day 7	To replace a rejected element

Table 2. Characteristics of disturbances



- The Multi-heuristic Schedule Repair Model determines the "optimal" sequence (D1→D2→D4→D3→D5) and the "best-suited" heuristic to incorporate each disturbance defined in Table 2 into the original schedule.
- Each cell represents an element type scheduled to be produced in a specific production line on a particular day. For example, production line L1 is scheduled to produce element type E1 on the first day of the original production schedule. "N" denotes no production; therefore production line L4 is not schedule for any production in the original schedule.
- Grey cells in the repaired production schedule represent the incorporated disturbances.

Figure 5: Repaired schedule determined by GA

In our proposed model, a two-point crossover is used to combine the gene values of two chromosomes to create a new pair of chromosomes. Mutation operates on a single chromosome and produces a new genotype by making a random change to the value of one or more of the genes in the chromosome string. The settings for these key parameters are: population size (100), number of iterations (500), probability of crossover (0.85) and mutation (0.001). These values were determined by fine-tuning default values over several runs of the GA on a similar problem.

The PGAPack operated on a Silicon Graphics workstation in the UNIX environment was adopted as the GA software used. It is a parallel genetic algorithm library that is intended to provide most of the capabilities needed for encoding GA applications in an integrated, seamless and portable manner.

5 Experiments

The application of our proposed model presented involves the schedule repair of four molds over a period of two weeks (10 work days). The plant produces three types of elements, namely E_1, E_2 and E_3, which can be produced by any of the four molds with minimal modification. Five disturbances occur during the planning period and the characteristics of these disturbances are shown in Table 2.

Seven heuristic rules were selected to be included in the heuristics pool. Six of the heuristics were based on the multiple mold approach where more than one mold could be used to resolve a conflict. The search for the point of insertion into the original schedule can be performed in a parallel manner across all mold schedules simultaneously or for each mold schedule in sequence. The first 6

Method of Resolution	Multi-heuristic	S/BS/OI	P/ASAP/OI	S/ASAP/OI	P/BS/OI
Low utilization level (0.5-0.64)					
Total number of idle days (days)	1.25	1.25	1.25	1.25	1.25
Total number of late deliveries (elements)	0	0	0	0	2
Total number of over/under stocking (element-days)	27	25	21	19	19
Total number of mould changes (times)	3	7	5	7	7
Best Index	0.3049	0.3337	0.3153	0.3289	0.3373
Multiple-heuristic yield	0%	9.45%	3.41%	7.87%	10.63%
Middle utilization level (0.65-0.80)					
Total number of idle days	0.25	0.25	0.25	0.25	0.25
Total number of late deliveries	2	4	4	3	5
Total number of over/under stocking	17	5	6	9	8
Total number of mould changes	5	6	6	7	6
Best Index	0.2941	0.3005	0.3013	0.3071	0.3071
Multiple-heuristic yield	0%	2.18%	2.45%	4.42%	4.42%
High utilization level (>0.8)					
Total number of idle days	0	0	0	0	0
Total number of late deliveries	8	9	9	9	9
Total number of over/under stocking	32	32	28	36	31
Total number of mould changes	6	7	7	8	8
Best Index	0.3323	0.3441	0.3409	0.3549	0.3509
Multiple-heuristic yield	0%	3.55%	2.59%	6.80%	5.60%

Table 3. Best performance of multi-heuristic approach compared to the single heuristics

heuristics are denoted as S/ASAP/OI, S/BS/OI, S/ASAP/DI, P/ASAP/OI, P/BS/OI, P/ASAP/DI. The last heuristic considered is sub-contracting. In the naming scheme employed, the first part of the name sequence denotes the search sequence (parallel or sequential), the second part denotes the direction of search (from the beginning or from the end), and the last part denotes the manner of insertion (opportunistic or deterministic fit).

To test our proposed model, 15 schedules were artificially constructed using a random process to give mold utilization rates varying from 0.6 to 0.8; this range was chosen to reflect the utilization rates commonly seen in local practice. The initial inventories for E1, E2 and E3 are assumed to be 6, 2 and 6 elements respectively. For each of these schedules, a test was conducted using the baseline / original schedule as a basis within which to schedule the disturbances shown in Table 2. The GA procedure was then used to construct modified schedules wherein the disturbances had been inserted. The result of one such test is shown in Fig. 5 as space does not allow showing the results of all the tests.

Another 4 sets of experiments were conducted, again using the same baseline schedules but this time allowing GA to apply only one of four heuristics (S/ASAP/OI, S/BS/OI, P/ASAP/OI and P/BS/OI). These 4 heuristics were chosen because they are industry's favorites.

The performance of our proposed multi-heuristic schedule repair model is compared to the single-heuristic approach at both the macro and microscopic level. At the macroscopic perspective, we compare the evaluation index values obtained by both approaches. The improvement obtained by the multi-heuristic approach is also discussed. At the microscopic level, we analyze the performances in terms of each of the physical parameters that constitute the evaluation index.

5.1 Macroscopic analysis

Having verified that the index values satisfy the normality and correlation tests, 4 separate sets of paired-sample t-tests were performed to evaluate the significance of the difference between the mean index values of our multi-heuristic model with each of the 4 single-heuristic approaches.

The tests revealed results that were very encouraging. Our multi-heuristics model has, in all the 4 separate t-tests, produced lower mean index values than each of the 4 single-heuristic approaches with p-values very close to

Mean value	Single heuristic tested against	Alternative hypothesis	P-value
Index	S/BS/OI	< 0	0.001
	P/ASAP/OI	< 0	0
	S/ASAP/OI	< 0	0
	P/BS/OI	< 0	0
Late delivery	S/BS/OI	< 0	0.055
	P/ASAP/OI	< 0	0.357
	S/ASAP/OI	< 0	0.036
	P/BS/OI	< 0	0.002
Mould change	S/BS/OI	< 0	0.001
	P/ASAP/OI	< 0	0
	S/ASAP/OI	< 0	0
	P/BS/OI	< 0	0
Non-optimal inventory	S/BS/OI	>0	0.013
	P/ASAP/OI	not = 0	0.48
	S/ASAP/OI	not = 0	0.362
	P/BS/OI	>0	0.023

Table 4. P-values for paired sample t-tests testing the difference of the multi-heuristics approach against the various singe heuristics

zero. Such p-values allow us to conclude strongly that there is significant statistical evidence supporting our claim that the multi-heuristics model performed better than any of the single-heuristic approaches in schedule repair. Recalling that the index value is made up of 4 different parameters, this suggests that our model generated solutions that dominated those obtained with the single-heuristic approaches.

In terms of the yield, our proposed model outperformed any single heuristic by up to 13.09%. The case where the multi-heuristic approach could only perform as well as a single heuristic occurred when the molds experienced high utilization rates. The lack of idle days for schedule repair in these schedules limited what any repair strategy could do. Table 3 illustrates the cases where the multi-heuristic approach performed best against the 4 single heuristic at 3 different levels of utilization.

The performance of the multi-heuristic approach versus that of the single heuristic appears marginal when measured on our evaluation index formulation. However, the gains become more tangible when translated to real physical measures like the number of late deliveries or mould changes, which are significant to the plant operators. The operators would typically prefer not to incur any late deliveries due to either contractual obligation or fear of marring the plant's reputation. Therefore, a yield of 5% on an index value of 0.3 would translate to an equivalent (0.3*0.05/0.0042) 3.57 elements reduction in late deliveries or a (0.3*0.05/0.0008) 18.75 elements-days reduction in excess/inadequate inventory during the 10-day repair period.

5.2 Microscopic analysis

The same sets of statistic tests were performed on 3 of the 4 parameters that constituted the evaluation index. The relative performance of the multi-heuristic approach is then compared with each of the 4 single-heuristic approaches. The results of these tests are summarized in Table 4.

Plant operators prefer to keep both the number of late deliveries and the number of mold changes during production to the minimum. While overstocking is also undesirable, it can be resolved with relative ease in comparison. From the test results, it is observed that the multi-heuristic model excelled in producing repaired schedules with a minimal number of mold changes. This efficient element to mold assignment is significant as changes in the molds disrupt the workflow of the production lines and incurred additional changeover costs.

Having kept the number of mold changes to a minimum, the multi-heuristic approach continued to perform remarkably well in minimizing the number of late deliveries incurred in the repaired schedules it generated. Statistics revealed that the multi-heuristic model produced repaired schedules that have a lower mean number of late deliveries than 2 of the single-heuristic approach at 5% level of significance and 1 of them at 10% level of significance. However, there was not enough to show that the number of late deliveries is lower when compared to the P/ASAP/OI heuristic.

The multi-heuristic approach did not fare as well in minimizing the number of elements in excess/inadequate inventory. In fact, the multi-heuristic approach produced repaired schedules that have significantly higher mean values of excess/inadequate inventory compared to two of the single heuristics (S/BS/OI and P/ASAP/OI). However, this mean value is not significantly different from the mean values of the two other single heuristics.

This analysis indicated that the multi-heuristic schedule repair model was able to do better than any single-heuristic approach; the repaired schedules achieved more efficient mold utilization and fewer late deliveries. More significantly, these improvements were attained at only a slight, or no increase in the value of excessive/inadequate inventory.

6 Conclusions

We have applied the multi-heuristic schedule repair model on a realistic planning and (re)scheduling problem for a prefabrication plant. The initial experimental results indicate that this multi-heuristic approach is effective in resolving schedule disturbances, demonstrably more so than the single-heuristic approaches currently used in industry. The evaluation index used as the objective function incorporates most of the parameters of concern to industry practitioners including efficient element to mold assignment and minimal late deliveries with little or no compromise to the inventory level. It can be used to generate non-dominated schedules in conjunction with the search procedure of the GA.

However, the scope of the model is quite limited and is restricted to schedule repair. For example, it does not address the need for better schedule coordination between elements of the supply chain, particularly between the construction site and the production plant. Further work is in progress to look into this aspect of precast production scheduling. Ideally, this will then allow both the plant operator and the construction manager to negotiate the preferred outcome in a co-operative rather than adversarial manner.

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