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A GENETIC ALGORITHM FOR OPTIMIZING PRODUCTION IN A COLD ROLLED STEEL SLITTING LINE

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Abstract

This paper presents a genetic algorithm for optimizing production in a cold rolled steel slitting line in a steel service center in India. The steel service center needs to generate a sequence of jobs for the slitter that involves the generation of a cutting pattern for each mother coil according to the customer order widths. A cutting pattern is an arrangement of the slitter knives for each mother coil under consideration. The following objectives are considered: 1) minimization of weight deviation for each customer order, 2) minimization of the slitter head setup time, and 3) minimization of the trim loss. The constraints include the following: 1) The sum of all customer order widths of a pattern should not exceed the width of the mother coil considered, 2) A customer order can be in excess or in deficit but not both, 3) A mother coil can have only one pattern associated with it, and 4) The customer order weight deviation should be within acceptable ranges.

For the problem under consideration, a mother coil having the highest width is chosen and all the patterns possible from the given set of customer orders are generated using the Pierce algorithm. Each pattern is assigned a pattern number which is used for encoding in the genetic algorithm. The genetic algorithm selects those cutting patterns that generate trims under a specified limit, penalizes both over-production and under-production and penalizes each additional setup.

The genetic algorithm is validated with a number of test problems. The application of the algorithm resulted in yield improvement to the tune of 5% and reduction of weight deviation for the customers to the tune of 15-20%. The genetic algorithm also generates a number of scheduling options for the steel service center.

Key words: genetic algorithm, optimization, cutting pattern, cold rolled steel slitting

1. INTRODUCTION

This paper presents a problem of optimizing production of cold rolled steel in the steel service center of a large steel producing company in India. The raw material comes in the form of steel coils of various grades and thickness (known as mother coils). The customer orders come in the form of either coils or bundles of sheets (known as baby coils). The slitting line (or slitter) is used to slit the mother coils lengthwise according to a given set of baby coil widths. If the order is a coil order, the baby coil is sent for packing and if it is a sheet order the next step involves cutting the sheets on a cut-to-length line or on a precision blanking line. A customer order for steel usually consists of the width, weight, grade, thickness, technical delivery conditions, and sheet length (for sheet orders only).

A daily problem facing the steel service center is the generation of a sequence of jobs for the slitter. An integral component of the sequence has to be the slitting pattern for each mother coil. A slitting pattern (henceforth known as a pattern) is an arrangement of slitting knives so that baby coils of particular widths can be slit from a mother coil. For example: 500 + 200 + 200 is a pattern, which will produce three baby coils of widths 500 mm, 200 mm and 200 mm from a mother coil of a given width. It is obvi-

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ous that the mother coil width has to be greater than 900 mm (500 + 200 +200).

The production of steel coils need to satisfy the following objectives:

1) minimization of weight deviation for each customer order,
2) minimization of the slitter head setup time, and
3) minimization of the trim loss.

While the problem considered corresponds to the classical trim loss or cutting stock problem, an additional consideration is that of guillotine cuts perpendicular to the coil length. Consider figure 1 (both (a) and (b)) that shows a mother coil opened up lengthwise (in solid lines). The dotted lines show the direction of slitting while A and B are two baby coils to be produced for two customer orders. While (a) is possible because there is a single guillotine cut perpendicular to the coil length, (b) is not possible in practice without damaging the rest of the mother coil. Due to this, there are weight deviations in the customer orders.

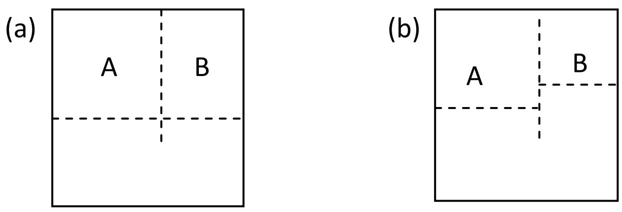


Fig. 1. Perpendicular Guillotine Cut Examples: (a) Single; (b) Double

The rest of the paper is organized as follows. A brief literature review is presented in section 2. Section 3 presents the formulation of the problem. The genetic algorithm based solution scheme is presented in section 4. Section 5 presents the results and discussions of the application of the solution scheme on three test problems. Finally, the conclusions are presented in Section 6.

2. LITERATURE SURVEY

This problem contains in itself a trim loss or cutting stock problem. The cutting stock problem considered in this paper involves finding out an optimum cutting pattern that is to be used on a parent stock of material with a known or given width. The steel service centre receives the mother coils and the customer orders are to be fulfilled by cutting the baby coils optimally from the given mother coils.

Gilmore and Gomory (1961, 1963) were the pioneers in the field of cutting stock problem. They had expressed the problem as an integer linear programming problem. Haessler (1971) developed a heuristic procedure for scheduling production of rolls of paper. The procedure, described by him, generates cutting patterns and usage levels sequentially until all the requirements are satisfied. Haessler and Talbot (1983) came up with a 0-1 model for solving the corrugator trim problem. In addition to the trim loss, other factors such as cutting pattern changes and avoidance of split orders were also considered. Their mathematical formulation explicitly took into account the cost of loading a particular stock size on the machine.

The world of evolutionary computing, consisting of techniques such as genetic algorithms and simulated annealing among others has contributed richly to this field. Hinterding and Juliff (1993) had applied a grouping genetic algorithm to the cutting stock problem using a group based mapping of the rods to the available stock sizes.

Search techniques have been applied with a reasonable rate of success to cutting stock problems. Gemmill and Sanders (1990) presented an approximate solution to the 'portfolio' problem. The portfolio problem consists of determining the best combination of sheet or bin sizes to keep in stock in order to minimize wastage. Lutifiyya et al. (1992) applied simulated annealing to the two-dimensional cutting stock problems. Vahrenkemp (1996) used random search to find patterns in Haessler's sequential heuristic.

Wagner (1999) discussed a one-dimensional cutting stock problem in which lumber is cut into bundles. He pointed out to the shortcomings of the Gilmore-Gomory model and also that of Haessler's Sequential Heuristic Procedure in the current context. Although he did not consider setup time as a part of the problem, he took into consideration trim loss, number of bundles cut and the ending inventory levels. His method included the generation of efficient cutting patterns and designing chromosomes that consisted of pattern numbers as the genes.

Liang et al. (2002) proposed an evolutionary algorithm to solve cutting stock problems with and without contiguity. The twin objectives considered were minimizing trim loss and minimizing the number of stocks without wastage. Bak et al. (2011) presented a parallel branch-and-bound method to address the two-dimensional rectangular guillotine strip cutting problem. The authors presented a branching schema in the form of binary trees to represent the horizontal and the vertical cuts. Bortfeldt (2006) presented a GA for the two-dimensional strip packing problem with rectangular pieces. The algorithm does not do any encoding of solutions but generates layer-type structured layouts by manipulating fully defined layouts using specific genetic operators. Ortmann et al. (2010) considered orthogonal, oriented, rectangular, two-dimensional strip-packing and the variable-sized bin-packing problem. They presented a number of improved level-packing algorithms so as to obtain packing that may be disentangled by guillotine cuts. Wei et al. (2009) presented a rectangular packing problem by using a least wasted first strategy which evaluates the positions used by the rectangles. A random local search is used thereafter to improve the results.

3. THE PROBLEM FORMULATION

A slitting pattern is an arrangement of slitting knives for slitting a mother coil. For example if three baby coils each 300mm wide are slit from a mother coil 1000mm wide, then 300 + 300 + 300 is a valid pattern. The aim is to prepare a sequence of slitting patterns on a set of mother coils. While preparing the slitting pattern sequence one has to ensure that the order weight deviations are as low as possible. In other words the excess weight (or the deficit weight as may be the case) delivered to a particular customer has to be minimized.

Minimization of the slitter head setup time is another important consideration. The slitting line studied had a single arbor or slitting head. For each pattern change the line has to be stopped. Hence the minimizing the setup time is a key issue.

Minimization of the trim loss is ensured by generating a number of patterns and then choosing those patterns in the initial stage of the algorithm which generate trim loss less than a fixed limit.

Using all the three objectives, the mathematical formulation of the problem is as given below:

Minimize

$$Y_{1i}*SRTC*[\Sigma_i OWT_i - \Sigma_j X_{jk} * \Sigma_k (WCO_{ik})]$$
$$+Y_{2i}*XSC*[\Sigma_j X_{jk} * \Sigma_k (WCO_{ik}) - \Sigma_i OWT_i]$$
$$+STPC* \Sigma_k [X_{jk} * (A* \Sigma N_{ij}) + (B*MCW_k)] \quad (1)$$

whereŁ

i: index of baby coils (customer orders);
j: index for patterns;
N_{ij}: no. of times order i appears in pattern j;
k: index for mother coils;
MCW, $MCWT$: mother coil width and weight;
OWT: order weight;
A, B: constants for slitter head setup time;
WCO: weight of customer order;
Y_{1i}: 1 if shortage in order i else 0;
Y_{2i}: 1 if excess in order i else 0;
X_{jk}: 1 if pattern j used on mother coil k else 0;
$SRTC$: cost for one unit weight short;
XSC: cost for one unit weight excess;
$STPC$: cost incurred due to a setup;

The constraints:

– The sum of all customer order widths on a particular pattern should not exceed the width of the mother coil which is being cut by the pattern.

$$\Sigma (N_{ij}*BCW_i) < MCW_k \quad (2)$$

– A particular customer order can be in excess or in deficit, but not both. Accordingly the two binary variables Y_{1i} and Y_{2i} cannot both be 0 or 1.

$$Y_{1i} + Y_{2i} = 1 \quad (3)$$

– A mother coil can have only one pattern assigned to it.

$$\Sigma X_{jk} = 1 \quad (4)$$

– As there are acceptable ranges for the customer order weight deviations, the shortage weight has to be less than a fraction of the order weight. Hence

$$Y_{1i} *(\Sigma_i OWT_i - \Sigma_j X_{jk} * \Sigma_k (WCO_{ik}) < D_{1i}* OWT_i \quad (5)$$

– A similar argument exists for the excess weight for a customer order weight.

$$Y_{2i} *(\Sigma_j X_{jk} * \Sigma_k (WCO_{ik}) - \Sigma_i OWT_i) < D_{2i}* OWT_i \quad (6)$$

4. SOLUTION SCHEME

In order to solve the problem, a genetic algorithm-based solution scheme is proposed. After generating the slitting patterns, genetic algorithm (Goldberg, 1989) is used to select the slitting patterns pertaining to the least possible costs in the cold rolled steel slitting line.

4.1. Pattern Generation

Efficient cutting patterns are generated for a particular mother coil and the set of customer orders by using the algorithm by Pierce (1964). Wagner (1999) used the same algorithm to generate efficient cutting patterns in his problem concerned with optimizing lumber bundles. A valid pattern is one whose total width does not exceed the width of the mother coil. An efficient pattern is one whose loss due to trim is less than a specified amount.

The algorithm provides a set of efficient patterns for every mother coil. In the test problems considered in the next section, the mother coil having the highest width is chosen and all the patterns possible from the given set of customer orders are generated exhaustively. Each pattern is assigned a pattern number which will be used to form the chromosome. The set of valid patterns is arranged in ascending order of trim loss (descending order of the total pattern width). The set of valid patterns for other mother coils will be a subset of the set of valid patterns for the widest mother coil. This way repetition of patterns is avoided.

The Pierce algorithm is useful because it generates an exhaustive set of possible patterns for a given mother coil and is quite easy to implement on a computer. Another advantage is that we can generate efficient patterns the way we wish by just changing the allowable trim.

4.2. The Genetic Algorithm

Problem Coding: Concatenated, multi-parameter, fixed point, binary coding is used. Suppose there are 5 mother coils as input to the algorithm. Each of them will be assigned a particular cutting pattern number as determined in the previous step. For example, 40 23 55 76 10 may be five pattern numbers each assigned to one particular mother coil. Then the concatenated binary code for the chromosome considering a block of seven bits for the corresponding pattern number will be: 0101000 0010111 0110111 1001100 0001010.

Generation of Initial Population: The chromosome size (*chromsize)* is equal to the product of number of mother coils and the number of bits to be used for coding each pattern number. It is easy to visualize the population as a two-dimensional array of bits with number of rows equal to the number of chromosomes in a generation (*popsize)* and number of columns equal to *chromsize*. In this problem a *popsize* of 200 is chosen. The *chromsize* is dependent on the particular problem. By simulating the toss of an unbiased coin each bit position is filled with a 0 or 1 and thus the entire population is generated in this problem.

Calculation of Fitness and Scaling: In GA the minimization problem is handled by subtracting the objective function from a constant, thus transforming it into a maximization problem. The fitness function here is:

$$Fitness = (MAXWT - cost), \tag{7}$$

where *MAXWT* is a very high constant.

Linear scaling is used to map the set of raw fitness values to a set of scaled values so that there is an increased amount of discrimination between the good, average and poor chromosomes.

Selection of Parent Chromosomes: The roulette wheel technique and the remainder stochastic sampling with replacement are used for the selection of the parent chromosomes.

Crossover and Mutation: An integer position k along the string is selected uniformly at random between 1 and l-1, where l is the chromosome length. Swapping all the characters between k+1 and l inclusively creates two new strings. The mutation is carried out by randomly changing 0s to 1s and vice versa.

Handling of Constraints: The penalty function approach is used to handle the constraints. Static penalties are used in three ranges. Penalty coefficient is 0 for less than 10% order weight deviation. It is 10 for 10-30% deviation and 100 for more than 30% deviation.

The GA Parameters: Population size = 200, number of runs = 25, probability of crossover = 0.7, probability of mutation = 0.033.

5. RESULTS AND DISCUSSIONS

The results are expressed in terms of a set of slitting patterns (one for each mother coil). From that we can calculate the weights of each baby coil (customer order). For the sake of simplicity a ±10% range has been considered acceptable.

Three test problems of increasing complexity are considered for solving. The first problem considers 4 mother coil widths and 4 customer order specifications. The second problem considers 4 mother coils and 7 customer orders. The third problem considers 5 mother coils and 7 customer orders. Table 1 shows the input data for the third problem.

As seen in the above table, all the customer orders are satisfied within the specified range. Some orders are just near the threshold of the allowable range. It can be seen that bigger orders are satisfied in a better way. It is also seen that heavier a coil is, the better is its utilization.

Table 1. The Input Data for Problem 3

Mother Coils		Baby Coils		Baby Coils	
Width (mm)	Weight (t)	Width (mm)	Weight (t)	Width (mm)	Weight (t)
1200	18	1100	15	400	10
1000	20	950	17	250	7
850	15	800	15	100	2
750	15	700	14		
700	13				

The solution in terms of the slitting patterns and customer order weights is given in table 2.

Table 2. Solution in terms of Slitting Patterns and Customer Order Weights

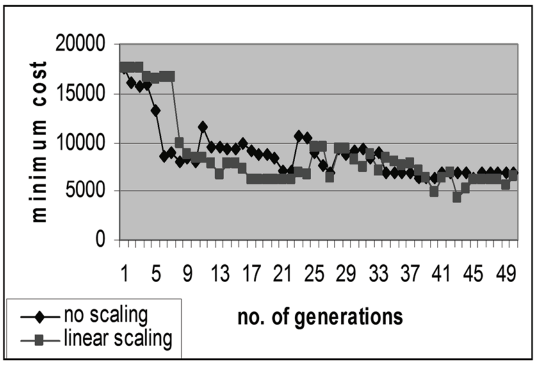
Slitting Patterns		Customer Order Weights			
MC Width	Slitting patterns	Customer ord. width	Cust. Ord wt.	Allowable range (10%)	Actual wt. obtained
1200	1100 + 100	1100	15	13.5 – 16.5	16.5
1000	950	950	17	15.3 – 18.7	19
850	800	800	15	13.5 – 16.5	14.12
750	700	700	14	12.6 – 15.4	14
700	400 + 250	400	10	9 – 11	11.43
		250	7	6.3 – 7.7	7.14
		100	2	1.8 – 2.2	1.5

Variation with Scaling and Selection Scheme: The linear scaling outperforms the scheme having no scaling. This is due to the fact that in absence of scaling the good chromosomes cannot be segregated from the other close but mediocre ones. Two selection schemes, namely the roulette wheel and the remainder stochastic sampling with replacement were considered. The remainder stochastic sampling with replacement (SRSWR) outperforms the roulette wheel (RWHEEL) selection scheme. Figure 2 shows the convergence of the GA for problem 3 with (a) scaling and (b) with selection scheme.

6. CONCLUSIONS

This paper presents a typical problem of order sequencing which occurs in a steel service center. The purpose of this work was to determine a sequence of slitting patterns on a given number of mother coils so that the baby coils produced (corresponding to each customer order) have a weight within the allowable range apart form the considerations of minimization of slitter setup times and the trim loss. The problem also has a number of constraints to be satisfied.

(a)



(b)

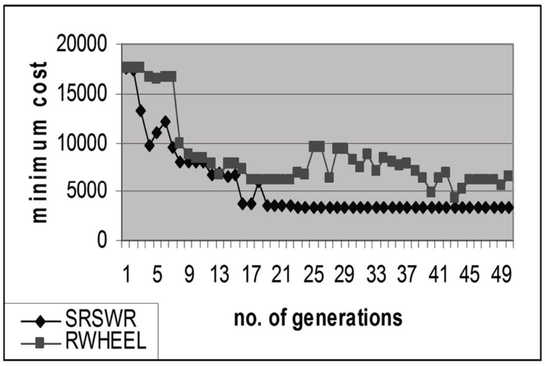


Fig. 2. Convergence of GA for Problem 3: (a) with Scaling; (b) with Selection Scheme

It was found that the genetic algorithm based methodology performs reasonably well for the three test problems considered. The static penalty function has performed well for the given problems. There has been a small effect on the objective function due to change in the constraint intervals. Scaling has been found to improve the performance of the algorithm. Barring the first problem, remainder stochastic sampling with replacement is a better option than roulette wheel selection scheme.

Since the genetic algorithm searches for the best sequence of patterns from what is available, it is imperative to generate the patterns in a proper way. The algorithm performs best as seen on a small number of mother coils and customer orders. This can be practically used to generate schedules for a plant on a shift by shift basis. In the highly constrained search space the GA performs reasonably well. The novelty of the paper lies in combining a known sequence generation algorithm with a genetic algorithm that attempts to minimize customer order weight deviations, slitter head setup time and the trim loss.

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GENETYCZNY ALGORYTM OPTYMALIZACJI PRODUKCJI W LINII CIĘCIA STALI WALCOWANEJ NA ZIMNO

Streszczenie

Autorzy artykułu przedstawiają zagadnienie dotyczące algorytmu optymalizacji produkcji na linii cięcia stali walcowanej na zimno w wytwórni stali w Indiach. Wytwórnia ma za zadanie stworzenie ciągu stanowisk do obsługi nożycy, co wiąże się z wykonaniem wzorca cięcia dla każdego kręgu pilotującego, zgodnie z zamówieniem klienta co do szerokości cięcia. Wzór cięcia stanowi układ noży dla każdego kręgu pilotującego. Rozważane są następujące zadania: 1) zminimalizowanie odchyłek wagi przy każdym zamówieniu, 2) zminimalizowanie czasu ustawienia głowicy nożycy, 3) zminimalizowanie strat materiału w wyniku cięcia. Ograniczenia dla optymalizacji są następujące: 1) suma wszystkich szerokości zamówień danego wzoru nie powinna przekraczać szerokości rozważanego kręgu pilotującego, 2) zamówienie danego klienta może być albo w nadmiarze albo w niedomiarze, lecz nie równocześnie w obu przypadkach, 3) krąg pilotujący może mieć tylko jeden wzorzec przypisany do niego, 4) odchyłki wagi w zamówieniach klientów powinny zawierać się w dopuszczalnym zakresie.

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