

A multi-objective approach based on soft computing techniques for production scheduling in Corrugator manufacturing plants

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Abstract

The corrugator scheduling problem is a difficult problem due to a wide variety of parameters and optimisation objectives that have to be accounted for and the relationships among them. Majority of solution techniques proposed so far only deal with minimizing either, the trim waste or pattern changes, this paper proposes a multi-objective evolutionary algorithm to optimize the WPL objective (weighted planning level) and the cost objectives. Computational experiments were conducted and results were compared against the current shop scheduling method used at a real-life corrugator manufacturing facility. A series of experiments were also conducted to determine the evolutionary algorithm parameters. The improvement on performance metrics encourages us to actually implement the algorithm at the factory.

Key words: SCHEDULING; Genetic Algorithms; multi-objective optimization; corrugator manufacturing.

Resumen

The corrugator scheduling problem is a difficult problem due to a wide variety of parameters and optimisation objectives that have to be accounted for and the relationships among them. Majority of solution techniques proposed so far only deal with minimizing either, the trim waste or pattern changes, this paper proposes a multi-objective evolutionary algorithm to optimize the WPL objective (weighted planning level) and the cost objectives. Computational experiments

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were conducted and results were compared against the current shop scheduling method used at a real-life corrugator manufacturing facility. A series of experiments were also conducted to determine the evolutionary algorithm parameters. The improvement on performance metrics encourages us to actually implement the algorithm at the factory.

Palabras claves: Scheduling ; Genetic Algorithms; multi-objective optimization; corrugator manufacturing.

1. INTRODUCTION

The manufacturing of corrugated cardboard boxes consists of the stages of pattern layout and finishing (i.e. printed, folded and glued) according to specifications that may vary between product styles. Because of its complexity for production management, the most important part of this manufacturing process is the pattern-layout stage. In the literature, the problem of pattern layout optimization is known as the two-dimensional cutting-stock problem. Solution procedures are traditionally based on linear programming models or heuristic algorithms. In real-life practice, however, some plants still schedule corrugator manually. The major reason is that analytical methods and good heuristics do not fully capture the problem complexity. In effect, a pattern layout that is optimal or near-optimal in terms of trim waste may lead to bottlenecks at the finishing stage or to sub-optimal scheduling solutions for the whole plant. In addition, these troubles on production also concern the delivery of final product, affecting in this way due-date related performance indexes.

In this paper, we are interested in proposing a solution approach for the corrugator scheduling problem based on evolutionary algorithms in order to optimise the WPL and cost. The WPL index refers to delivery due-dates performance, finished machines queue management and client-related importance. The 3 aspects mentioned above are used as inputs variables of a fuzzy inference system which will calculate an importance (IMP) factor for order that has to be scheduled (Klir 1995). This factor will be used to calculate the overall WPL index. The cost refers to the running cost, the roll change and pattern change cost, waste trim cost and upgrading cost.

Due to the complexity of parameters to take into account and to the relation between these parameters, the corrugator scheduling problem is a combinatorial optimisation problem. Since an evolutionary algorithm (EA) is an intelligent computer-based optimization technique that has

provided very good results when applied to solve other combinatorial and engineering optimisation problems (Back 1995; Fogel 1995), it seems, thus, interesting to apply EA to solve the corrugator scheduling problem.

The remainder of this paper is arranged as follows. A review of relevant previous research works on the corrugator scheduling problem is presented in section 2. The principal concepts of evolutionary algorithms (EA) are presented in section 3. Section 4 describes the mixed integer multi objective programming corrugator scheduling problem formulation. Sections 5 and 6 are respectively devoted to the detailed description of the proposed EA and to present the results of the computational application against the current scheduling method used in the factory. Finally, section 7 presents some concluding remarks.

2. RELEVANT LITERATURE

In the literature, researchers have traditionally referred the corrugator production scheduling problem as the two-dimensional cutting-stock problem (also named the trim or trim-waste problem). This problem is a particular case of the cutting and packing problems (Dyckhoff 1990; Sweeney and Paternoster 1992; Hooper and Turton 2000; Hooper and Turton et al. 2001). A state-of-the-art survey on solution approaches for the 2D cutting-stock problem can be found in (Hinxman 1980). The 2D cutting-stock problem is described as follows. A factory produces a material such as linerboard in long rolls of fixed width. Customers order specify a desired number of sheets of a certain length and width. The widths of the cut sheet rarely allow full utilisation of the roll, resulting in trim waste, which often is not salvageable. The possible configurations of pattern layouts are as follows:

The objective is to arrange orders so the sum of sheet widths simultaneously being cut will most closely equal the roll width. This formulation applies to the manufacture of corrugated boxes because the two corrugator knives operate independently. Thus, the choice of two orders to be run at the same time is unaffected by the sheet length of either. A feasible solution involves a set of cutting patterns and the number of times each pattern will be used (a cutting pattern is simply a combination of sheet widths whose sum does not exceed that of the roll). Pattern generation can easily become an overwhelming task since corrugator scheduling also requires the sequence in which the chosen patterns will be run. A complete description of the corrugator scheduling problem is provided in (Cloud 1995; Wiers 1997)

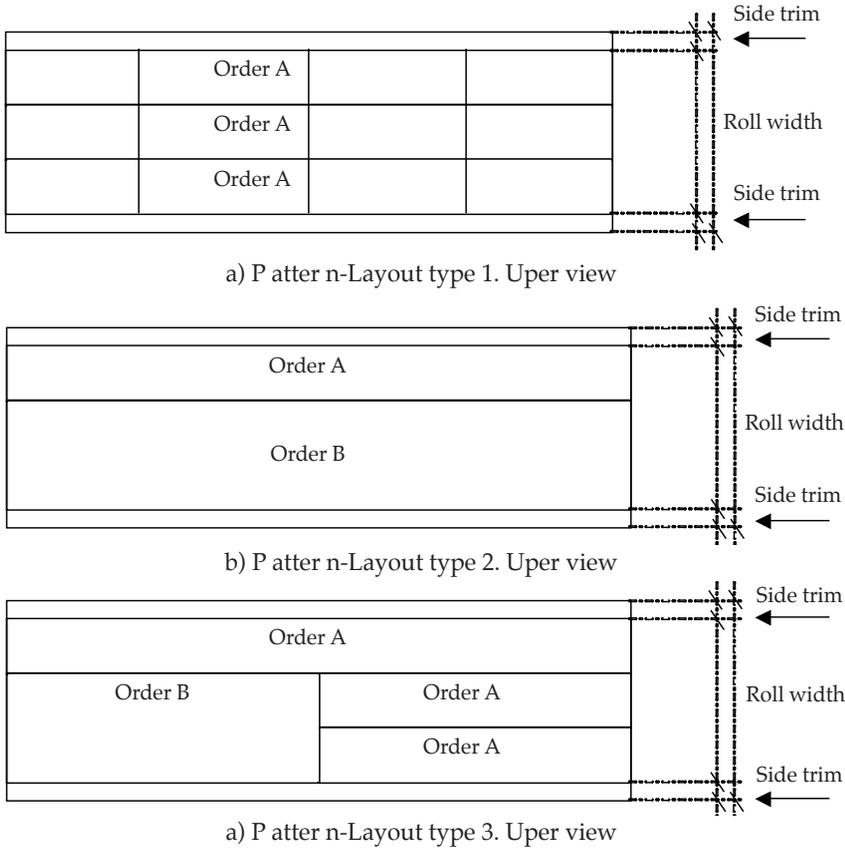


Figure 4. Pattern-Layout type 4. Upper view

Early works on the cutting-stock problem are based on linear programming formulation in order to minimise trim-waste (Paul and Walter 1954; Eisemann 1957; Gilmore and Gomory 1961; Gilmore and Gomory 1963; Wade 1964; Haessler 1975; Dyckhoff 1981; Haessler and Talbot 1983; Acevedo et al. 2003). Although some of these formulations are still very popular and are used in various commercial computational packages, they lead to a big solution space and have difficulties in dealing with non-linear problems, which are most common in the real world. As a result, heuristic solution procedures have become increasingly popular in the literature in order to consider more practical situations in which it is needed a balance between the waste objective and customer service, production costs, and machine and workforce utilisation (Van Wormer 1963; Hinxman 1980; Haessler 1975; Haessler and Talbot 1983; Bookbinder

and Higginson et al. 1986). The efficiency and effectiveness of heuristic solution procedures, however, depend heavily on the heuristic used. Finding good heuristics is often as difficult as solving the problem itself (Liang 2002). When applied to the corrugator scheduling problem many heuristic approaches to the cutting-stock problem have been unsuccessful either because they attempted to generate patterns sequentially and had trouble with trim loss at the end of a sequential procedure, or because they used linear programming to minimise trim, and performed poorly with regard to number of pattern changes and order congruity (Haessler and Talbot 1983; Bookbinder and Higginson 1986).

The relationship between customer service and trim waste was studied in (Bookbinder and Higginson 1986) using a simulation model. Instead of an optimisation approach, these authors concentrate on to understand the relationship between those different (and contradictory) objective functions. In this paper, we propose an evolutionary algorithm that optimises the WPL index, designed by the authors and cost.

3. EVOLUTIONARY ALGORITHMS

An evolutionary algorithm (EA) is a problem solving technique that uses the concepts of evolution and heritage to produce good solutions to complex problems that typically have enormous search spaces and are therefore difficult to solve. A well-designed EA allows for the efficient and effective exploration and exploitation of the problem's search space of feasible solutions in an effort to identify the global optima, or near optimal, solution to difficult problems. Early applications of EA's are found in the literature to solve complex combinatorial optimisation problems (Back 1995; Fogel 1995).

EA's create and manipulate a group of possible solutions referred to as a population. Each possible solution within the population is called an individual. The population undergoes change throughout the run of the EA thereby evolving the individuals toward a best solution. Within the EA, the population loops through a series of processes a number of times; each executed loop is known as a generation. These processes include an evaluation process, an alteration process, and a selection process (Lang Fang 1994; Deb 1997). These processes may occur in various orders; however, each is required at each generation (Michalewicz 1992). The evaluation process uses an evaluation function that assesses the relative fitness of each individual of the population at each generation. In addition, at each

generation a number of individuals are subjected to some form of change. These alterations are manifested through the use of genetic operators. Genetic operators can be either mutation operators, which introduce small changes within a single individual, or crossover operators, which cut and paste different parts from two or more individuals together in order to create new individuals called offspring. The probability of an individual experiencing some form of transformation within any given generation is subject to the predefined parameters of the probability of mutation, and/or the probability of crossover. Through this process, some, or all, of the individuals are altered and used to create a new population for the next generation. Finally, the EA uses the evaluated fitness of each individual to promote the survival of the best individuals to the next generation. This use of selective pressure encourages the population to converge to a good quality solution. The EA will run for a predetermined maximum number of generations or until some specified terminating condition is met.

When designing EA's, parameters to consider include population size, maximum number of generations, and probability of mutation and/or crossover. Each EA is unique in its design with regard to several important elements. Some of these elements include data structure, genetic operators, method for creating the initial population, constraint handling techniques, evaluation function, selection method, generational policy, parameters, and terminating conditions. However, regardless of the differences, all EA's attempt to evolve the individuals within the population through the use of genetic operators and selective pressures to converge at a suitable solution to complex problems.

4. FORMULATION OF A MIXED INTEGER MULTI-OBJECTIVE PROGRAMMING CORRUGATOR SCHEDULING PROBLEM

The following index set, parameters, decision variable and variables are considered. An element is defined as a possible cutting pattern layout that will produce one of the two orders used completely.

The cutting patterns that create a solution belong to a previously generated set of cutting patterns. The former set must meet the following conditions:

- The side trim of every cutting pattern must oscillate between the maximum and minimum levels allowed. These levels are determined by the corrugator's scheduler.

- Orders longer than 300 meters must be combined within a cutting pattern no shorter than 300 meters.

The solution of the corrugator scheduling problem will be a subset of elements chosen from the element set that minimizes total cost and maximizes the WPL index.

Index set

- i Index for orders, for all $i=1,2,3\dots I$.
- j Index for elements, for all $j=1,2,3\dots J$.
- k Index for roll size, for all $k=1,2,3\dots K$.

Parameters

- imp_i Relevance value of order i.
- $Q_{ordered_i}$ Quantity of order i
- a_{ij} Quantity of order i produced in element j
- C_{run} Corrugator running cost per hour
- b_j Lineal meters of element j
- C_{paper_c} Paper change cost (includes time cost and waste cost)
- C_{slit_c} Slit change cost (includes time cost and waste cost)
- C_{trim} trim cost per squared meter
- $area_i$ Blank area in squared meter of order i.
- C_{grade_sched} Square meter cost of the grade scheduled.
- C_{grade_i} Square meter cost for grade of order i

Decision variable

- x_j Proportion of element j chosen in the schedule. $0 \leq x_j \leq 1$.

Variables

$$M_i = \begin{cases} 1, & Q_{ordered_i} * 0.95 \leq Q_{sched_i} \leq Q_{ordered_i} * 1.15 \\ 0, & \text{Otherwise} \end{cases}, \forall i$$

$$N_i = \begin{cases} 1, & Q_{sched_i} < Q_{ordered_i} * 0.95 \\ 0, & \text{Otherwise} \end{cases}, \forall i$$

- run_time corrugator running time
- paper_c Number of paper changes
- slit_c Number of independent slit changes
- y_k is 1 if roll size k is used, 0 otherwise
- z_j is 1 if element j is used, 0 otherwise

4.1. Problem formulation

The mixed integer multi-objective programming corrugator scheduling problem can be formulated as follows:

$$\max \sum_{i=1}^I \left[M_i * \left(\frac{\sum_{i=1}^I imp_i}{I} + \frac{1}{I} \right) + N_i * \left(\frac{Q_sched_i}{Q_ordered_i} * \frac{imp_i}{\sum_{i=1}^I imp_i} \right) \right] \quad (1)$$

$$\min C_{run} * run_time + C_{paper_c} * paper_c + C_{slit_c} * slit_c + C_{trim} * trim + C_{up} \quad (2)$$

$$Q_sched_i = \sum_j^J a_{ij} * x_j \quad (3)$$

$$Q_sched_i \leq Q_ordered_i * 1.15 \quad (4)$$

$$run_time = \sum_{j=1}^J \left[\frac{(b_j * x_j)}{0.01 * (b_j * x_j) + 52.6} \right] \quad (5)$$

$$paper_c = \sum_{k=1}^K y_k \quad (6)$$

$$slit_c = \sum_{j=1}^J z_j - paper_c \quad (7)$$

$$trim = \frac{\sum_{j=1}^J (b_j * x_j * roll_w_j)}{\sum_{j=1}^J (b_j * x_j)} \quad (8)$$

$$C_{up} = \sum_{i=1}^I \sum_{j=1}^J [(C_grade_i - C_{grade_sched}) * a_{ij} * x_j * area_i] \quad (9)$$

Objective function (1) maximices the WPL index

Objective function (2) minimices the total cost.

Constraint function (3) calculates the quantity schedule for each order.

Constraint function (4) puts restriction on quantities produced of each order.

Constraint function (5) calculates the running time in hours needed for the corrugator to finish the schedule.

Constraint function (6) calculates the number of paper changes needed.

Constraint function (7) calculates the number of slit changes needed.

Constraint function (8) calculates the trim in squared meters produced by the schedule.

Constraint function (9) calculates the upgrading cost produced by the schedule.

5. CPS_{EA}: AN EVOLUTIONARY ALGORITHM FOR CORRUGATOR SCHEDULING

In a broad way, this multi-objective algorithm seeks to improve the following two objectives: Cost and the WPL index. Cost includes the four most relevant types of cost associated with corrugator operation: Running cost, change cost, upgrading cost and side trim cost. The WPL index is calculated based on the IMP value that is exclusive for each order. The IMP value represents the relevance or urgency for planning a determined order. In real corrugator planning, the urgency for planning a determined order is usually determined in an implicit way by the planner's experience and knowledge. For the CPS_{EA}, the IMP value is calculated using a fuzzy inference system. This FIS captures the experience and knowledge of a real life planner, so the need for subjective qualifications is eliminated. The input variables of the FIS are: Due date, queue size of converting machines and order final price. The algorithm will provide an order combinations set for a particular grade (combination of liner and medium paper types required to provide specific product properties to the cardboard) that will correspond to a corrugator schedule.

The main loop of CPS_{EA} is as follows:

STEP 0. Initialization: Generate an initial population pob_arc_0 and create the empty archive $arc = \phi$. Set $t = 0$.

STEP 1. Increment generation counter ($t = t + 1$).

If $t \geq 1$ then create the parents and sons set, pob_arc_t .

$pob_arc_t = arc_t + pob_crom_t$

Where arc_t represents the parents set y pob_crom_t represents the sons set.

- STEP 2. Fitness assignment: Calculate fitness values --fitness_total-- of individuals in pob_arc_t . Perform the sharing function on individuals in pob_arc_t and update fitness_total.
- STEP 3. Sort in descendent way the set pob_arc_t by fitness_total y copy to the set arc_{t+1} the first arc_size individuals.
- STEP 4. Termination. If $t = max_gen$ then stop the algorithm.
- STEP 5. Selection: Perform tournament selection without replacement on arc_{t+1} . $k = arc_size / 10$.
- STEP 6. Recombination. Apply single-point recombination operator. Then, apply uniform recombination operator. Set pob_crom_{t+1} to the resulting population.
- PASO 7. Mutation: Apply pattern-layout mutation operator and proportion mutation operator to pob_crom_{t+1} . Go to STEP 1.

5.1. Solution representation

Each order combination in a corrugator schedule consists of several cutting patterns, which define the way one or more orders are going to be cut. Besides, every scheduling solution must determine the following information:

- Number of cutting patterns to run in the corrugator.
- The length of every cutting pattern.

A scheduling solution will be thus represented as a vector of integer number denoting the identification of the selected cutting patterns, and as a vector of numbers ranged between 0 and 1 representing the proportion of the total length to be produced for each selected cutting pattern.

It is to notice that the total length of a particular cutting pattern will be determined by the first of the two orders that completes its particular number of units requested. Hence, we can deduce the following statements:

- A solution will be represented by two chromosomes.
- The chromosomes will not necessarily have the same size because two solutions may be formed by a different number of cutting patterns.

The characteristics of the possible cutting patterns are explained in section 4.

5.2. Initialisation

The following heuristic procedure was developed in order to create the initial population of the EA:

- 1 Define the maximum and minimum side trim allowed.
- 2 Based on the parameters defined in the previous step, generate the set of acceptable cutting patterns. That is, all possible combinations in pairs of orders to cut whose side trim are between the maximum and the minimum allowed.
- 3 Calculate the length of the acceptable cutting patterns.
- 4 Do until the proportion planned of a random number of orders to be planned is at least 100%:
 - 4.1 Choose randomly an acceptable cutting pattern, which has not been chosen before, and its length.
 - 4.2 Calculate the proportion planned of each order to be planned.

5.3. Fitness function evaluation

Fitness_{total} in STEP 2 is calculated as follows:

$$fitness_total(i) = [S(i)] + [W_{WPL} \times S_{WPL}(i)] + [W_{COSTO} \times S_{COSTO}(i)]$$

Where,

$$S(i) = |\{j | j \in pob_arc_i \wedge i \succ j\}|$$

$$S_{WPL}(i) = |\{j | j \in pob_arc_i \wedge WPL_i \geq WPL_j\}|$$

$$S_{COSTO}(i) = |\{j | j \in pob_arc_i \wedge COSTO_i \leq COSTO_j\}|$$

$|\cdot|$ denotes cardinality of a set, and the symbol \succ stands for Pareto dominance relation. The values W_k represents the weight or relevance of objective k . In this case, W_{WPL} y W_{COSTO} were determined in 0.85 y 0.15, respectively.

The sharing function used in CPS_{EA} , introduced by Goldberg and Richardson (1987), derates and individuals's fitness by an amount related to the number of similar individuals in the population (Mahfoud, 1995). Specifically, an individual's new *shared function*, f' , is equal to its old fitness

f divided by its *niche count*. An individual's niche count is a sum of *sharing function* (*sh*) values between itself and every individual in the population (including itself). The shared fitness of a population element *i* is

$$fitness_total'(i) = \frac{fitness_total(i)}{\sum_{j=1}^n sh(d(i,j))}$$

The sharing function *sh* is a function of the distance *d* between two population elements. It returns a '1' if the elements are identical, a '0' if they exceed some threshold of dissimilarity, and intermediate levels of dissimilarity. The threshold of dissimilarity is specified by a constant, σ_{share} ; if the distance between two population elements is greater than or equal to σ_{share} , they do not affect each others's shared fitness. Most commonly-used sharing functions, which is the one used in this paper, are of the form,

$$sh(d) = \begin{cases} 1 - \left(\frac{d}{\sigma_{share}}\right)^\alpha, & \text{si } d < \sigma_{share} \\ 0, & \text{otherwise.} \end{cases}$$

In the above equation, α is a constant (typically set to 1) used to regulate the shape of the sharing function.

5.3.1. *The weighted planning level WPL.* The WPL measures the non-monetary convenience of a particular corrugator schedule. It is designed to determine how close is a particular corrugator schedule to the one that optimizes the business as a whole, not only seen with a productive point of view, but a customer-service point of view as well.

The calculation of the WPL index is as follows:

For each order *i*

if $Q_ordered_i \times 0.95 \leq Q_scheduled_i \leq Q_ordered_i \times 1.15$

$$WPL = WPL + \frac{IMP_i}{\sum_i IMP_i} + \frac{1}{number_of_orders}$$

If $Q_scheduled_i < Q_ordered_i \times 0.95$

$$WPL = WPL + \frac{Q_scheduled_i}{Q_ordered_i} \times \frac{IMP_i}{\sum_i IMP_i}$$

Else if $Q_scheduled_i > Q_ordered_i \times 1.15$

$$WPL = WPL - \frac{current_generation}{max_generation} \times \left(\frac{Q_scheduled_i}{Q_ordered_i} - 1 \right)$$

End if
End if
Next i

Where $Q_ordered_i$ represents the quantity ordered in order i ; $Q_scheduled_i$, the quantity scheduled of order i ; $Number_of_orders$, the numbers of orders to be scheduled and IMP_i , the importance of order i .

A fuzzy inference system was designed to determine the IMP values. The input values of this inference system are the due date of the order, the queue size of the converting machines that will use that particular order in its productive process and the price of the order. Membership functions for these fuzzy variables are provided in appendix A. Triangular shapes were chosen to represent the fuzzy variables presented above. The defuzzification method chosen was the centroid method. The output variable of the FIS is the IMP value. The range of the IMP value is 0 to 1, where 1 represent the highest importance and 0 the lowest.

5.3.2. The cost function. A corrugator scheduling cost evaluation method is implemented, based on (cloud, 1995). The cost function represents the total cost per 100 lineal meters. Four cost elements are calculated:

1 Running cost: This cost represents the corrugator running cost. The running cost are the cost incurred in the time required to reach maximum speed after a paper, size or independent slitter turn and the time required to complete the run. A corrugator cost per hour is calculated including direct labour cost, indirect labour cost, maintenance cost, power cost and fuel cost.

- 2 Change cost: This cost represents the waste and hours incurred in change preparation and execution, i.e. roll preparation and mounting, slitter head setting and turning.
- 3 Side Trim waste cost: Side trim waste cost is included in the total cost. Side trim waste can be minimised, but it is necessary because of different reasons related to the operation of the corrugator and the quality of the corrugated material produced.
- 4 Upgrading cost: This cost represents the cost incurred in upgraded orders. Upgrading cost is incurred when an order is scheduled in a higher grade than the one that the client ordered. Upgrading can be necessary when there are no others orders in the same grade that can help schedule an order with a high IMP index.

5.4. Selection

The original tournament selection procedure is used to pick k parents randomly and after a few calculations it returns the best of them (Lang Fang, 1994).

The value of k is set as the 1/10th of the original population size.

5.5. Recombination

Two recombination operators are defined: One point crossover and uniform crossover, i.e. in each crossover the offspring is 4 sons. The crossover operators are described below:

- One point crossover consists on picking a number that is less than the chromosome size. The offspring will be formed with the genes inherited from the parents located before the position determined by the number selected, and the genes located after that position will switch each other.
- In uniform crossover, every gene coming from the first parent has a probability of 0.5 of switching position with the corresponding gene in the second parent (Lang Fang, 1994).

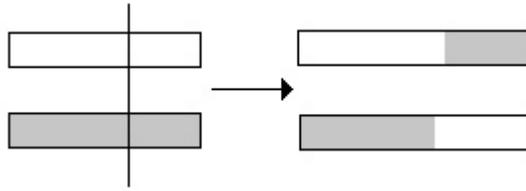


Figure 5. One point crossover

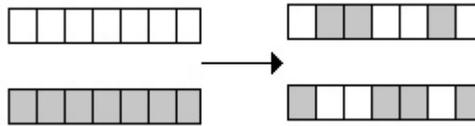


Figure 6. Uniform crossover

5.6. Mutation

Two mutation operators are determined:

- Cutting pattern addition mutation, which adds a cutting pattern randomly along the chromosome.
- Proportion mutation, which generates a new proportion for an existing cutting pattern.

5.7. Termination

The number of generations is the stop criteria for the algorithm.

6. EXPERIMENTAL STUDY

The implementation of CPS_{EA} involves the selection of several parameters. This selection is determined by a design of a series of experiments as follows:

- A 3^3 experiment which was used to determine the values for maximum generations, archive size and initial population size.

- Using the parameters values found in previous experiments, a 2³ experiment which was used to determine the values for mutation probability and mutation value.
- Using the parameters values found in previous experiments, several runs were conducted to determine the σ_{share} value.

These experiments suggest which factors are key in achieving good performance and also suggest good values. The values for the parameters in CPSEA used are: Maximum generations, 75; archive size, 75; initial population size, 1250; mutation probability, 0.5; mutation value, 0.1 and σ_{share} 2.

The results obtained using CPS_{EA} after setting the good parameter values were compared with the results provided by the company using the current manual production schedule. 8 different order sets were selected to represent the different schedules for the corrugator. The order sets used consist on a variety of grades, dimensions and units requested, paper widths available and queue status in converting machines.

The results are showed in tables 1 and 2.

Table 1. Cost evaluation

	MANUAL	CPS _{EA}
P1	1,58	1,71
P2	1,35	1,40
P3	1,34	1,64
P4	1,23	1,29
P5	1.06	1,45
P6	1,01	0,90
P7	1,01	0,85
P8	0,83	1,72

Table 2. WPL evaluation

	MANUAL	CPS _{EA}
P1	\$ 14.300	\$ 13.080
P2	\$ 13.895	13.840
P3	\$ 13.340	12.085
P4	\$ 10.780	10.910
P5	\$ 10.530	10.470
P6	\$15.510	12.620
P7	\$15.937	13.150
P8	13.220	10.930

Three different statistical tests were conducted in order to investigate the performance of the CPS_{EA} compared to the manual scheduling method. The three statistical tests conducted were the paired-comparison t-test, the Wilcoxon sign test and the Wilcoxon ranked sign test.

The result of these test confirm the statistical significance of the better performance of the CPS_{EA} compared to the manual method evaluated

with the cost function. In fact, CPS_{EA} will generate schedules whose total cost will be 10% better than the cost yielded with the manual method. This translates in savings of about US\$170.000 per year in a medium-sized box plant.

Even though 6 of the 8 problems compared show better performance of the CPS_{EA} evaluated with the WPL function, this improvement is not statistically significant on the 0.05 level. P-values were in the range of 0.07 to 0.11. It is to notice that tests show an average improvement of 16% of the CPS_{EA} compared to the manual method measured with the WPL function, which encourage the researchers for conducting further experimentation.

7. CONCLUSIONS

This paper proposed a multi-objective evolutionary algorithm (EA) for production scheduling in a corrugator manufacturing plant, with the objective of optimizing the weighted planning level (WPL). The proposed algorithm also provides some insights about the trim lost and costs incurred when upgrading the corrugator. In addition to the improvement in the WPL, the algorithm is enough flexible to incorporate the empirical knowledge of the production manager when selecting the most appropriate schedule for the factory. Reduction in upgrading costs is also obtained after the application of the algorithm. These features make our algorithm very attractive for actual implementation in the Company.

For future work, we intend to address the multiple-objective optimization problem using a more global approach. For instance, optimal solutions for the cutting-stock problem at the first stage of processing cardboard boxes may induce some problems when sequencing production tasks at the finishing stage of the corrugator. A balance between on-time customer delivery and optimization of production resources has to be achieved in order to maintain the competitiveness in today's global market.

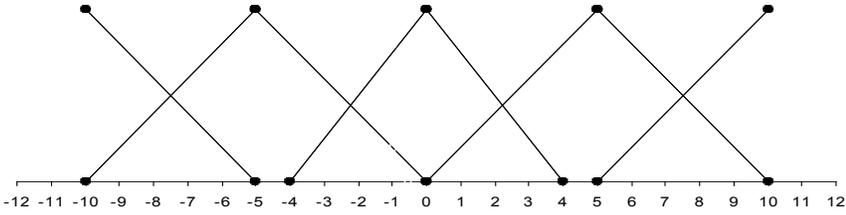
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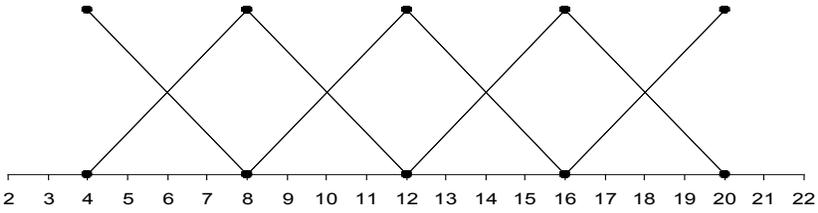
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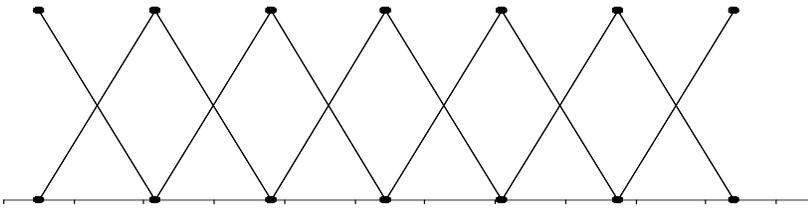
Appendix A



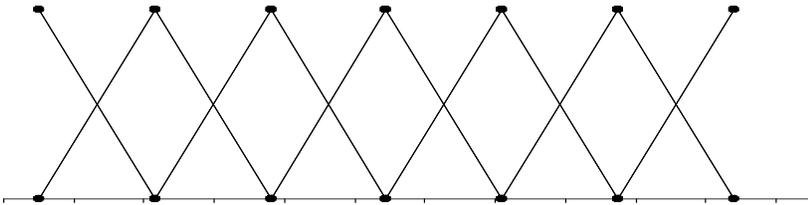
Membership functions for "due date".



Membership functions for "queue size".



Membership functions for "order price".



Membership functions for the output variable "IMP".