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A production planning and scheduling problem focused on both productivity and quality issues in tannery industries

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Abstract

We investigate the production planning and detailed scheduling of multiple-stage flexible flow shops, making products that require different production cycles. The production process can be configured in several ways, involving both different processing phases and times, depending on specific treatments required by the processed job. Jobs require operations on a unique raw material item and its quality features can require specific processing phases as well as lead to different processing times. We investigate, through the succession of a MILP and a CP model, the impact of quality-related aspects on processing times and hence on the overall planning and scheduling problem. An actual case from a leather tannery industry derived from the M2H – Machine To Human" (project code CBYX592), INNONETWORK 2017, Regione Puglia is investigated.

Keywords: scheduling, production planning, flexible flow shop, constraint programming, quality, tannery

1. Introduction

The focus of this work is the production planning and detailed scheduling of a multiple-stage flexible flow shop, making products that require different production cycles. The actual case that inspired our research is the production planning of a tannery. Each order is characterized by a required finished material (a well-defined type of leather), with different requirements both in terms of quantity and quality and must be preferably completed within a given due date. The required finished material is obtained through several tanning processes that transform the raw material (in the so called "wet blue" state) into the required finished product. The quality map associated with each available hide of raw material influences both the production cycle to be chosen, i.e. which steps need to be done on the shopfloor, and the duration of each step.

The decision on the hides to be used for each order has, hence, two impacts: the former on production costs, related with the quality of the hides chosen to serve each order, and the latter on production times, since better quality hides typically require less processing, leading to faster times to fulfill an order. At least two main objectives must be hence considered: cost minimization and delay minimization. The former is a typical production objective, while the latter is a typical customer satisfaction related objective. Most of the times the two objectives collide: using less expensive materials choices might lead to larger delays and, vice versa, promptly satisfying customers' orders could require the usage of more expensive materials instead of using more adequate material, that could require longer processing times.

In order to be able to manage the complexity of the decision process, the problem can be separated into two distinct decision moments: (i) which raw material will be used for each order and (ii) when to start each processing operation and on which machine when more than one is possible. This is a common assumption made in most production planning systems, where material requirements are processed considering standard lead times, without dealing with the detailed aspects of actual production scheduling. Clearly, this approach cannot provide the theoretical optimal solution, but it allows to successfully

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solve the problem in real cases.

Section 2 presents the main references for the case, while sections 3 and 4, respectively, introduce the proposed approach used to address the two sub-problems the original problem is divided into. Section 5 presents an application of the approach to a test case, while section 6 concludes the work pointing out some future work that will soon be made to improve the achieved results.

2. Literature review

Scheduling problems cover a wide range of applications from computer engineering to the manufacturing field. The critical aspect in most scheduling applications is given by the associated combinatorial optimization problem, that can be very complex. In particular, the job-shop scheduling problem (JSP) is among the hardest combinatorial optimization problems in the scheduling environment. The classical JSP requires to assign a set of jobs to a set of machines, with the objective to minimize a certain criterion. Each job has an associated processing path throughout the available machines [1]. It has been shown that the JSP is NP-hard [2], and hence only small instances can be solved to optimality.

In last years, there is a trend in the research domain to solve a much more complex version of the job shop problem that is referred to as the flexible job-shop scheduling problem (FJSP)[1]. FJSP is considered an extension of the classical JSP and parallel machine environments where each operation can be processed by any capable machine from a given subset. In brief, the FJSP can be viewed such the composition of two sub-problem: 1) the routing sub-problem that assigns each operation to a machine among the set of capable machines and 2) the scheduling sub-problem that define the operation starting times on all machines in order to obtain a feasible schedule that optimize a given objective ([1], [3]). The literature credits Bruker and Schile [4] for being among the first ones to have addressed the FJSP: they developed a polynomial graphical algorithm for solving the flexible job shop problem with two jobs. Reviews FJSPs works distinguishing between two classes of optimization approaches used to address the flexible job shop problem: mathematical modeling and meta-heuristic approaches. Reference [5] presents an overview of mathematical models formulated for FJSP: it classifies the contributions based on the different type of binary variables: sequence-position variable, precedence variable and time-indexed variable. The comparison of five different formulations is conducted and such analysis suggests to use precedence variable based models for FJSP. This paper also points out that there are different formulations of FJSP such as with set up time, buffer size constraint, multi-objective etc, but not enough work has been done on FJSP with lot streaming consideration. Most literature contributions propose heuristic approaches such as dispatching rules, local search and meta-heuristic procedures, in order to being able to solve larger instances [6]. In particular, reviews meta-heuristic approaches, especially focusing on three main types: genetic algorithms, tabu search and particle swarm optimization (Chen et al. [20], Zhang [21], Pezzella et al. [6], Saidi-Mehrabad and Fattahi[22], Brandimarte [15], Dauzére-Pérés and Paulli [10], Hurink et al. [11], Saidi and Fattahi [19], Xia and Wu [1], Girish, Jawahar [23], Peng et al. [27], Kato et al. [29]). The meta-heuristics cited can also be combined and applied to FJSPs as a hybrid algorithm [7].

Chaudhry and Khan [25] have proposed a vaste survey on FJSP problems. They classified the literature based on:

- Objective types;
- Solutions;
- Tecniques (14 major categories: Ant Colony Optimization, Evolutionary algorithms, Tabu Search, Integer/Linear Programming, Mathematical Programming, Hybrid techniques, etc.)

They observed that many contributions (94%) were pure research and only 12 papers (6%) addressed real-world industrial applications. A more recent review [27] collects the various contributions based on the type of solution method for the problem:

- Exact algorithms;
- Heuristics;
- Meta-Heuristics.

The authors point to artificial intelligence as one of the major future research new development trends of the manufacturing industry.

Further classification for the FJSP, identifies two main categories of solution methods: hierarchical approach and integrated approaches [6]. Integrated approaches are more complex than hierarchical ones, but they usually provide better results (Dauzére-Pérés and Paulli [10], Hurink et al. [11], Mastrolilli and Gambardella [12], Jia et al. [13], Pezzella et al. [6], Shokouhi [26]). Hierarchical models reduce the difficulty by solving a sequence of associated sub-problems (Brandimarte [15], Paulli [16], Tung et al. [17], Kacem et al. [18], Saidi and Fattahi [19], Xia and Wu [1], Kato et al. [29]).

A new assumption for the FJSP is presented in [8]: each job represents a set of identical jobs of the same type, hence leading to the definition of a required quantity per job, meaning that each job needs to be processed more times. The approach used to consider this aspect in the FJSP is defined operations overlap, i.e. the consecutive operations required by the same job can be overlapped on different machines. An explanatory example is provided in [8] and the limitation of overlap is given by structural constraints, such as the dimensions of the box to be packed or the capacity of the container used to move the pieces from one machine to the next. FJSP with overlapping in operations result strongly NP-hard and combinatorial [8].

Reference [9] defines two types of FJSP. Type I FJSP refers to the case in which jobs can be characterized by alternative operation sequences and alternative identical or non-identical machines for each operation: the problem, here, is to select an operation sequence for each job and then determine job processing orders on machines. In type II FJSPs, instead, jobs have fixed operation sequences but alternative identical or non-identical machines for each operation. The problem is to assign jobs to the machines according to their operation sequence constraints in order to optimize the objective function.

3. A MILP model for materials assignment

Each available item of raw material (a *wet blue leather skin*) can be classified, according to the ISO11457 standard (see [24]), into one of five well-defined *grades*, namely: A, B, C, D and E grade.

Each grade is characterized by the following main aspects:

- maximum percentage of defective surface,
- zones where defects are allowed,
- type of accepted defects

A LP approach is used to address the former sub-problem. Each order i is characterized by:

- a required quantity q_i
- a due date t_i
- an estimated overall processing time p_i

The estimated processing time is a rough approximation of the actual processing time, that can be better estimated only once the exact scheduling is defined. At this level it is only used to evaluate a "do not start production later than" time, defined as $T_i = t_i - p_i$

Each raw material j is characterized by:

- quantities arriving at specific times d_{jt}
- quantities of material j already available is modeled as d_{jt} with $t = 1$
- a set of orders it can serve I_j (consequently defining the J_i sets of raw materials that can be used for each order i)
- the cost the firm incurs for using material j for each order $i \in I_j$ (namely c_{ij})

The following parameters characterize the quality management aspects:

- GR_i is the quality grade required by order i (grades A, B, C, D, E are translated for the mathematical model as 1, 2, 3, 4, 5);
- G_i is the quality grade of a batch of hides of material j;
- λ^+ is the maximum difference between the assigned class and the required class, when the assigned class is better than required
- λ^- is the maximum difference between the assigned class and the required class, when the assigned class is worse than required
- π^+ is the weight to be minimized when the assigned class is better than required
- π^- is the weight to be minimized when the assigned class is worse than required

The decision to be made at this stage is determining the quantity of order i to be fulfilled using material batch j at time t. Hence the non-negative decision variables x_{ijt} are defined, for each order i, for each batch material $j \in J_i$ and for each time t.

At the same time, this choice establishes the quality grade of the batch assigned to a given order. The quality-related aspects require the definition of further decision variables to be able to pursue the objective to maximize the match between the quality requirements in the orders and the quality of the raw materials selected to serve each order. An exact match, indeed, though desirable, is highly unlikely to happen in real cases, due to actual availability of raw materials:

- e_i non-negative variables that represent the sum of the positive surplus (equal or worse quality assignments) of the quality grade associated with the amount of material assigned to order i;
- ℓ_i non-negative variables that represent the sum of negative gap (equal or better quality assignments) of the quality grade associated with the amount of material assigned to order i;

Furthemore, in order to pursue the minimization of delays, auxiliary the non-negative decision variables y_{ij} can be defined (for each order i and for each material $j \in J_i$) to take into account the quantity of order i served by material j after time T_i.

The following ILP model is hence defined:

$$Obj_1: min \sum_{j \in J_i} \sum_{i \in I} (\pi^+ e_i + \pi^- l_i) \quad (1)$$
$$Obj_2: min \sum_i \sum_{j \in J_i} y_{ij} \quad (2)$$

$$\sum_{i \in I_j} x_{ijt} \leq d_{jt} \qquad \forall j, t \quad (3)$$
$$y_{ij} = \sum_{t > T_i} x_{ijt} \qquad \forall i, \forall j \in J_i \quad (4)$$
$$\sum_{j \in J_i} \sum_t x_{ijt} = q_i \qquad \forall i \quad (5)$$

$$e_i \geq \sum_{j \in J_i^+} \sum_t x_{ijt}(G_j - GR_i) \qquad \forall i, \quad J_i^+ = \{j \in J_i : 0 \leq G_j - GR_i \leq \lambda^+\} \quad (6)$$
$$l_i \geq \sum_{j \in J_i^-} \sum_t x_{ijt}(GR_i - G_j) \qquad \forall i \quad J_i^- = \{j \in J_i : 0 \leq GR_i - G_j \leq \lambda^-\} \quad (7)$$
$$e_i \geq 0 \quad \forall i \quad (8)$$
$$l_i \geq 0 \quad \forall i \quad (9)$$
$$x_{ijt} \geq 0 \qquad \forall i, \forall j \in J_i, \forall t \quad (10)$$
$$y_{ij} \geq 0 \qquad \forall i, \forall j \in J_i \quad (11)$$

The objective function (1) minimizes the overall gap of quality between the required quality grade and the assigned quality grade. The objective function (2) minimizes the overall quantities served with delay. Actually, in the test case, a more refined objective was pursued, in order to take into account not only how much of the orders is served late, but also how much is this lateness and weighing it with the size of each order. Here we prefer to provide an easier, more readable version of the objective.

Constraints (3) guarantee that at most the total quantity d_{jt} of material j that becomes available at time t is consumed by the orders that use it. It is important to notice that we are not considering, here, the quantities available at any possible time t, but only the arrivals of new quantities at specific times. In other words, for the sake of this first optimization step, the system is considered as if it had infinite capacity in terms of production resources. Hence, new materials are *consumed* as soon as they arrive, meaning that they are *assigned* to a specific order at arrival time: it is the next scheduling step that actually decides when the assigned materials will be used by the orders they are assigned to.

Constraints (4) define the link among x and y variables. In this case, y variables may be omitted and more complex expressions using only the x variables may be used: and this is what we actually implemented but using y variables provides a better readability of the model.

Constraints (5) guarantee that all orders are, sooner or later, satisfied. This could not be the case in actual instances of the problem. In order to always obtain a feasible problem, it is sufficient to introduce *fake* arrivals for all materials in a sufficiently far future, so that all orders can be fulfilled. Objective (2) will be responsible for using such arrivals as little as possible. A reasonable time in the future to be chosen can be estimated considering the typical lead time needed to receive new materials after ordering them.

Constraints (6) define the link among e and x variables. They represent the upper bound of overall surplus: the non-zero contribution is given by all possible assignments in which the numerical value of the assigned class is higher than the value of the requested class.

Constraints (7) define the link among l and x variables. They represent the upper bound of overall gap: the non-zero contribution is given by all possible assignments in which the numerical value of the requested class is higher than the value of the assigned class.

Expressions (8) - (11) introduce the non-negative decision variables.

Once the model is solved to optimality with the objective (1), using a standard simplex-based approach the achieved solution serves as a starting point for a second model in which the pursued objective is the minimization of the overall cost delays, objective (2), while accepting a user defined acceptable deterioration of the former objective function.

4. Detailed scheduling

The addressed problem encompasses several aspects. The orders to be planned are characterized by a required quantity, a release date and a due date. The raw material items to be used for each order are the ones defined by the MILP model at the former step, hence the release date for each order, given by the arrival date of the raw material items to be used.

Actually, the material assignment step might decide to serve an order using different materials, or even different quantities of a same material due to arrive at different dates. In this case, the order is split into different sub-orders, each requiring the quantity defined at the former step and having the release date defined by the specific material arrival to be used. The due date is common among all sub-orders deriving from a same actual order.

Each order is characterized by a production cycle, i.e. it has undergo a sequence of operations. Since the different quality grades and the specific location of defects on each item influence both the production cycle to be used (the steps through the shopfloor) and the processing times, this information is used when defining the tasks to be scheduled for each order.

Each operation can be processed by any capable machine from a given subset, so it provides a case of the FJSP introduced in section 1, with all the implied complexity issues discussed in the introduction. We propose an approach that models the scheduling problem as a COP (Constraint Optimization Problem), which is solved using the IBM ILOG CP Optimizer tool, currently one of the leading CP (Constraint Programming) solvers available on the market. We will not examine all the syntactic details needed to define the problem in all its aspects, but we will better introduce the main variables and constraints used to model the most relevant ones.

For each order, an *interval* decision variable is defined, i.e. a CP-specific type of decision variables that includes a start, an end, a length and a size to be decided by the model. The assignment of each operation that is required by each order is modeled through another set of interval variables: an optional interval variable is defined for each operation and for each machine that can process it. Optionality foir these variables means that the CP solver can decide not to consider them in the solution schedule and, more specifically, an *alternative* constraint forces the solver to consider exactly one interval for each operation to be performed, hence implicitly assigning it to the machine that will execute it. *Span* constraints, which ensure one interval variable to cover the intervals in a set of intervals, are used to establish the correct logical link between the order and the operation interval variables of a same order. The impossibility for more orders to be processed on a same machine at once is achieved through the use of *noOverlap* constraints, which ensure that positions of intervals in the solution are disjointed in time. Finally, order relations between *startOf* and *endOf* intervals are used to define the correct temporal constraints among the operations within each order.

Pure CP is designed to find a solution to a problem through constraint propagation algorithms. The IBM ILOG CP Solver, however, as well as other commercial solutions, allow the definition of objectives to be pursued through various approaches while still exploiting the constraint propagation techniques. The objective considered in our model is the minimization of the overall delay, weighted by the quantities being shipped after their due dates.

5. Test case

The proposed approach was tested within a DSS (Decision Support System) being developed for an Italian tannery. Tests and tuning are still in progress at the time of writing. A massive test was made planning an entire quarter of production activity: 627 orders were considered, requiring a total of 10428 operations (14 operations required for each order on average). The orders required 84 different finished materials, while the number of different available raw materials or materials due to arrive within the considered planning horizon was 272; each finished material could be obtained from at least two to at most five different raw materials. The problem was solved in less than a minute on a 2.8 GHz Intel i7 PC.

Table 1 and Table 2 summarize the results of the first step of the approach. Table 1 reports, in percentage for each requested class, the corresponding assigned classes. For example, the requests of class A are satisfied with a perfect match for the 60,4% of the order quantities and the remaining 39,6% are assigned to materials of class B.

Table 1 Assigned Class vs Requested Class

	Assigned Class					
Requested Class	**A**	**B**	**C**	**D**	**E**	**Tot**
A	60,4%	39,6%	0%	0%	0%	100
B	9,4%	64,8%	25,8%	0%	0%	100
C	3,1%	9,3%	77,3%	10,3%	0%	100
D	4,4%	5,3%	18,9%	52,3	19,3%	100
E	2,5%	6,6%	19,8%	19,0%	52,1%	100

Table 2 highlights the results in terms of class gap. Gap 0 indicates the perfect match between request and assignment, gap 1 indicates that there is only one class of difference between request and assignment, and so on. This report shows that:

- Almost 60% of orders obtain a perfect match for the required quality class;
- Gaps 0 and 1 together cover most of the orders (90%).

Table 2 Class Gap

Class Gap	A	B	C	D	E	TOT
0	**5,1%**	**13,2%**	**12,0%**	**19,0%**	**10,0%**	**59,3%**
1	**1,9%**	**4,8%**	**12,1%**	**5,3%**	**7,0%**	**31,1%**
2	0,5%	1,9%	3,8%	0%	0%	**6,2%**
3	1,6%	1,3%	0%	0%	0%	**2,87%**
4	0,5%	0%	0%	0%	0%	**0,55**
TOT	9,6%	21,1%	27,9%	24,3%	17%	**100%**

The results of the second step of the approach are presented to the user through a familiar Gantt chart representation showing all the planned operations on all machines. Given the extremely high number of operations, the user has the possibility to filter the Gantt on a specific order or on a specific set of machines. Figure 1 shows an example of a Gantt chart filtered on a single production line: this representation shows the scheduling of activities on the same production line and at the same time highlights the workload assigned to the same resource.

The solver had to run for 5 minutes in order to obtain a first solution, than it was allowed one hour of processing time to improve it. Unfortunately, unlike branch and bound approaches, with CP there is no theoretical bound allowing to have a quantitative idea of the still possible improvement to the solution.

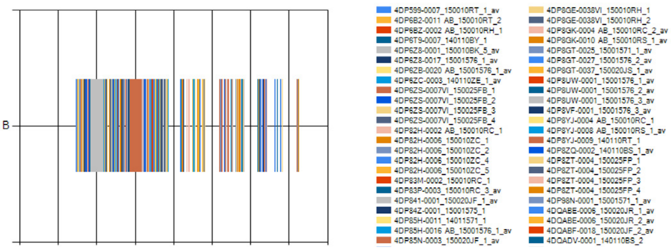

Figure 1 Gantt of production line

Table 3 resumes the delay performance for each assigned quality class of provided by scheduling models:

- **AvgDelayOBJ1**: days of average delay of the scheduling model, using the material assignment defined by (1) – (11).
- **AvgDelayOBJ2**: days of average delay of the scheduling model, using the material assignment defined by (2) – (11). In this case the only objective function is given by (2).

Table 3 Delays

Class	Avg DelayOBJ1	AvgDelayOBJ2
A	14,3	6,92
B	7,8	8,96
C	8,2	7,5
D	11,6	8,4
E	14,6	7,5
TOT	**10,94**	**7,97**

It is possible to observe that the maximization of customer satisfaction in terms of material quality requirements can lead to an increase in order lead times and therefore in average delays; however, it can be observed that this delay worsening remains limited due to the use of the secondary objective function (2) in the materials assignment module.

6. Conclusion

We investigated a viable way to take advantage of the specific and extremely detailed quality-related aspects that are made available by an Industry 4.0 compliant tannery within the production planning and scheduling of the firm. We used a mixed MILP/CP approach to model and solve the complex problem and reported some preliminary results derived from the usage of the proposed approach in an actual case from a leather tannery industry involved in the publicly funded M2H project.

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