A Two-Phase Approach to Solve the Synchronized Bin-Forklift Scheduling Problem

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Abstract

In this paper, we propose a two-phase approach to solve a combined routing and scheduling problem that occurs in the textile industry: fabrics are dyed by dye-jets and transported by forklifts. The objective is to minimize the cost of the unproductive activities, i.e., the dye-jet setup times and the forklift waiting time. The first phase solves an integer linear program to assign jobs (fabrics) to dye-jets while minimizing the setup cost; we compare an arc-based and a path-based formulation. The second phase uses a mixed-integer linear program for the dye-jet scheduling and both the routing and scheduling of forklifts. Experiments are performed on real data provided by a major multinational company, and larger test problems are randomly generated to assess the algorithm. The tests were conducted using Cplex 12.6.0 and a column generation solver. The numerical results show that our approach is efficient in terms of both solution quality and computational time.

Keywords: Scheduling, Column Generation, Mixed-Integer Programming, Textile Industry.

1 Introduction

The textile industry is primarily concerned with the design and manufacture of clothing and the distribution and use of textiles. This industry occupies an important place in the economy of countries such as China, India, Turkey, and Morocco. In Morocco, it is one of the leading sectors, and its production represents about 15% of the total value of the processing industries. Morocco benefits from a qualified workforce, competitive wage rates, and proximity to the European markets, which increases its efficiency and responsiveness. Ready-made garments (shirts, skirts, jackets, etc.) and knitwear production are the most dynamic subsectors. They represent 43% of the total production and more than 70% of the total Moroccan exports. Morocco manufactures for well-known brands such as GAP, Banana Republic, Levi Strauss, and Marks & Spencer. Our industrial partner is a major player in this field.

Textile operations consist of activities such as spinning, weaving, dyeing, drying, and printing. The dyeing section in our partner's plant can be broken down into four primary processes as follows: (1) dyeing, (2) wringing, (3) drying, and (4) compacting. Dyeing is the process of coloring fabrics using computerized jet dyeing equipment. After they are dyed, the fabrics are transported to the PAD machine to be wrung. It is also necessary to dewater the fabric, to apply softener to it in order to maintain good color, and to overstretch it. It is then preshrunk to the required finished width and dried. Finally, it goes through compactors that carefully fix it so that it can maintain the required width when in use. Most companies have automated jet dyeing tanks. These rotate the fabric automatically through the dyeing process for a specified period depending on the color. There are several operational challenges, especially in the dyeing process. Our partner wishes to develop optimized production schedules for the dyeing and finishing operations.

Textile firms must optimize their operations because of global competition and customer demand for improved quality, customization, and shorter delivery lead times. To remain competitive, decision makers and managers must optimize the entire flow of the materials in the supply chain.

Currently, most companies manually generate a color sequence on each dye-jet and perform a manual routing and scheduling of the forklifts. These solutions are generally inefficient since they generate large (unproductive) setup and waiting times, and more powerful solution methods are therefore needed. The aim of this study is to present a two-phase approach that considers the synchronization of the forklift routing and scheduling and the dye-jet scheduling.

The paper is organized as follows. Section 2 presents a literature review focusing on the scheduling problem encountered in the dyeing house. Sections 3 and 4 present respectively the synchronized bin-forklift scheduling problem and our solution approach. The experimental setting is described in Section 5, where our computational results are also reported. Section 6 provides concluding remarks.

2 Literature Review

Several models have been developed in the literature to address production planning and scheduling in a dyehouse.

[Morales *et al.* (1996)] and [Maldonado *et al.* (2000)] study models to determine a color sequence that minimizes the setup (cleaning) time between two colors. [Nara Lace Co. Ltd. (2003)] has developed a decision support system (DSS) called *Asprova* for the scheduling of the dyeing process. The manager's manual scheduling takes three to four hours, whereas *Asprova* reduces this to half an hour. It eliminates the need to write instructions, efficiently handles customer due dates, and increases the accuracy of the scheduling. [Saydam and Cooper (2002)] report the development and implementation of a DSS for scheduling jobs on multi-port dyeing machines. They present a two-phase approach. In the first phase, they use a linear programming model to maximize machine utilization when allocating dye-orders to dye machines. In the second phase, they develop a heuristic approach to sequence fabric rolls while minimizing the manual operations on the plant floor. [Laoboonlur *et al.* (2006)] discuss a detailed production schedule for dyeing and finishing operations. They consider a flexible job shop with sequence-dependent setups, and they minimize the maximum lateness (completion time − due date). [Zhou *et al.* (2010)] present a short-term scheduling MILP model, based on continuous time, for the printing and dyeing industry; they solve it using the ILOG-CPLEX solver. For more details about scheduling dyeing operations, see [Cho, 2004].

The problem addressed in this study is similar to many problems encountered in manufacturing contexts such as the navigation of autonomous mobile robots and the use of automatic guided vehicles (AGV). Many research groups have investigated the use of autonomous mobile robots in flexible manufacturing (see [Giralt and Chatila (1987)]). [Hu and Gu (2000)] propose a navigation algorithm that simultaneously locates the robots and updates the landmarks in a manufacturing environment. Current research into mobility in the context of flexible manufacturing systems involves the use of AGVs for the internal and external transport of materials. Some researchers have investigated the operational issues of dispatching, routing, and scheduling AGVs. For example, [Singh *et al.* (2009)] present the scheduling of AGVs for efficient and uniform material distribution from a truck-dock to machining units. They introduce the notion of zones with comparable demands for AGVs, and they assign one AGV to each zone so that each AGV can operate independently. [Confessore *et al.* (2011)] consider AGV dispatching, modeling the problem as a minimum-cost network flow problem. For more details see [Vis (2006)].

A few researchers have focused on the transportation problems encountered in the textile industry. [Brahmadeep and Thomassey (2014)] present a model in which all the processes are simulated. They minimize the costs and delays by considering all the parameters and constraints that explain the production flow and the distribution logic of bobbins for the rewinding process in a yarn dyeing factory. Surprisingly, the synchronization issue has received little attention in the literature. To the best of our knowledge, [El Hachemi *et al.* (2013)] is the first study to synchronize dye-jets and forklifts in the textile sector.

The goal of this project is to build a model in which all the processes can be simulated and all the parameters and constraints are considered.

3 The Synchronized Bin-Forklift Scheduling Problem

We consider a set J of jobs (fabrics), a set D of dye-jets, and a set F of forklifts. Each job $j \in J$ is characterized by its color c_j and its size w_j expressed in terms of bins (one bin is 529 lbs of fabric). Each dye-jet $d \in D$ has a specified capacity Q_d. We must generate an optimal plan where each fabric is dyed on a dye-jet and transported by a forklift to the wringing section. Each day, the forklifts must begin and finish their work at the dyeing section. They can carry only one bin of a fabric at a time, traveling back and forth between the dye-jets and the wringing section.

The synchronized bin-forklift scheduling problem (SBFSP) consists in constructing a schedule for the dye-jets and a transportation plan for the forklifts such that all the jobs are dyed and transported to the wringing section at a minimum total cost, and the dye-jet capacity constraints are respected. In the context of the textile industry, the various sections (dyeing, wringing, drying, and compacting) of the plant are not large, and the distances between the dye-jet pads are similar. Consequently, the transportation costs are independent of the scheduling decisions. The objective function minimizes the unproductive activities (setup and waiting times) of the dye-jets and forklifts.

The SBFSP is closely related to routing problems encountered in other industries, in particular, the so-called *pick-up and delivery problems*. For general surveys of the vehicle routing problem (VRP) and the pick-up and delivery problem with time windows (PDPTW), see the book edited by [Toth and Vigo (2001)].

4 Solution Approach

We develop a two-phase approach to the SBFSP. The first phase determines the sequence of jobs to assign to each dye-jet while minimizing the total setup (cleaning) times of the dye-jets. The second phase schedules the jobs and the transportation while minimizing the total waiting times (associated with jobs).

4.1 First phase: Assigning jobs to dye-jets

In this phase we assign jobs to dye-jets while respecting the capacity constraints and the planning horizon. We have developed both a column generation method and a mixed integer program (MIP).

4.1.1 Branch and Price Approach

The problem of determining the sequence of jobs to assign to each dye-jet is equivalent to solving a VRP, where the vehicles and customers are dye-jets and jobs, respectively.

Let $G = (N, A)$ be a network where the set N of nodes consists of the start of the sequence (node s), the end of the sequence (node p), and all the jobs, i.e., $N = \{s\} \cup \{d_j, j \in J\} \cup \{p\}$. For each arc $(i, j) \in A$, we define a cost c_{ij} as well as a cleaning time t_{ij} when jobs i and j are sequentially treated by the same dye-jet. If the nodes i and j ($\in$ N) correspond respectively to jobs i and j, then $c_{ij} = r_j + t_{ij}$ where r_j represents the treatment duration of job j. Finally, we define $c_{si} = 0$ and $c_{ip} = r_i$.

Let L represent the set of types of dye-jets. For each $l \in L$, M_l represents the number of available dye-jets of type l. We denote by S^l the set of feasible sequences for dye-jets of type l (on graph G). A sequence of jobs is feasible for a dye-jet l if (1) it starts at source s and ends at sink p, (2) the size of each job in the sequence is less than the capacity of the associated dye-jet, and (3) the total working time (processing and cleaning times) for the sequence does not exceed the length of the given horizon H. For each dye-jet type $l \in L$ and each feasible sequence $s \in S^l$, we define a binary variable x_{sl} that equals 1 if sequence s is chosen for dye-jet type l, and 0 otherwise. We also define for each $s \in S^l$ and each job $j \in J$ a parameter a_{sj} such that $a_{sj} = 1$ if sequence s contains job j, and $a_{sj} = 0$ otherwise. Finally, c_{sl} is the total cost of the cleaning time.

$$\text{Min} \sum_{l \in L} \sum_{s \in S^l} c_{sl} x_{sl} \quad (1)$$

$$\text{subject to:} \quad \sum_{l \in L} \sum_{s \in S^l} a_{sj} x_{sl} = 1, \qquad \forall j \in J \quad (2)$$

$$\sum_{s \in S^l} x_{sl} \leq M_l, \qquad \forall l \in L \quad (3)$$

$$x_{sl} \in \{0, 1\}, \qquad \forall l \in L \ \ \forall s \in S^l \quad (4)$$

The objective function (1) minimizes the total cleaning time of the dye-jets. Constraints (2) ensure that each job is assigned to one dye-jet (or one sequence). Constraints (3) limit the number of available dye-jets of each type. Finally, constraints (4) are integrality constraints.

Column generation (CG) is an iterative method that can be used to solve the linear relaxation of model (1)–(4), which is called the master problem. It iterates between a restricted master problem (RMP) and several subproblems. The RMP is derived from the master problem by considering a subset of its variables that is updated at each iteration. The RMP is solved by a linear programming solver. Given an optimal dual solution for the current RMP, the role of the subproblems is to identify negative-reduced-cost columns (variables) to be added to the RMP before starting another iteration. If no such columns exist, the solution process stops, and the optimal primal solution of the current RMP is also optimal for the master problem. The subproblems correspond to resource-constrained shortest path problems that are solved by dynamic programming. All the constraints related to sequences are managed at the subproblem level via the network structure that uses resource variables. For SBFSP, there is only one resource constraint: it computes the total working time of a dye-jet.

A subproblem is generally a shortest path problem with a number of resource constraints defined on a network that implicitly represents all the feasible columns. A resource is a quantity that varies along a path and whose value is restricted to fall within a given interval, called a resource window, at each node. Such subproblems can be solved by a label-setting algorithm (see [Desrosiers (1995)], [Irnich and Desaulniers (2005)]). Every feasible column corresponds to a path from the source to the sink node in this network. The feasibility rules are treated during the path construction in the label-setting algorithm via the use of constrained resource variables.

In our case, testing optimality implies computing the reduced costs of all the feasible sequences in S. The reduced cost associated with sequence $s \in S^l, l \in L$ is given by:

$$\bar{c_{sl}} = c_{sl} - \sum_{j \in J} a_{sj}\mu_j^* - \Pi_l^*,$$

where $(\mu_j^*)_{j\in J}$ and $(\Pi_l^*)_{l\in L}$ are the optimal values of the dual variables associated with constraints (2) and (3), respectively. A series of subproblems, one for each dye-jet type $l \in L$, is defined as follows:

$$(SP^l) : \max \qquad \bar{c_{sl}} = c_{sl} - \sum_{j \in J} a_{sj}\mu_j^* - \Pi_l^* \tag{5}$$

$$\text{s.t.} \qquad s \in S_l. \tag{6}$$

If the optimal solution of each $(SP^l), l \in L$ yields a nonpositive objective value, then the current solution is optimal and the LP relaxation is solved. Otherwise, sequences (yielded by different subproblems) with positive reduced costs are identified and added to the RMP and the process continues.

Let $G^l = (N^l, A^l)$ be the network associated with subproblem (SP^l). Each node $i \in N^l$ represents one job. Each arc $((i,j) \in A)$ means that jobs i and j are performed sequentially. An example of a network is given in Figure 1. This network contains three types of nodes: the *source*, the *sink*, and the *job*. There is a single source node and a single sink node to represent the start and the end of the sequence, respectively. The network has three arc types: *start of the sequence*, *end of the sequence*, and *cleaning-time arcs*. The source and the sink nodes are linked to each job node. Cleaning-time arcs link each pair of jobs together. In Figure 1, we give an example of a network for a given type of dye-jet where we consider 8 jobs, j-1 to j-8.

4.1.2 The MIP Formulation

We now present an integer programming approach for the problem of assigning jobs to dye-jets. We denote by H the planning horizon, and we let C represent

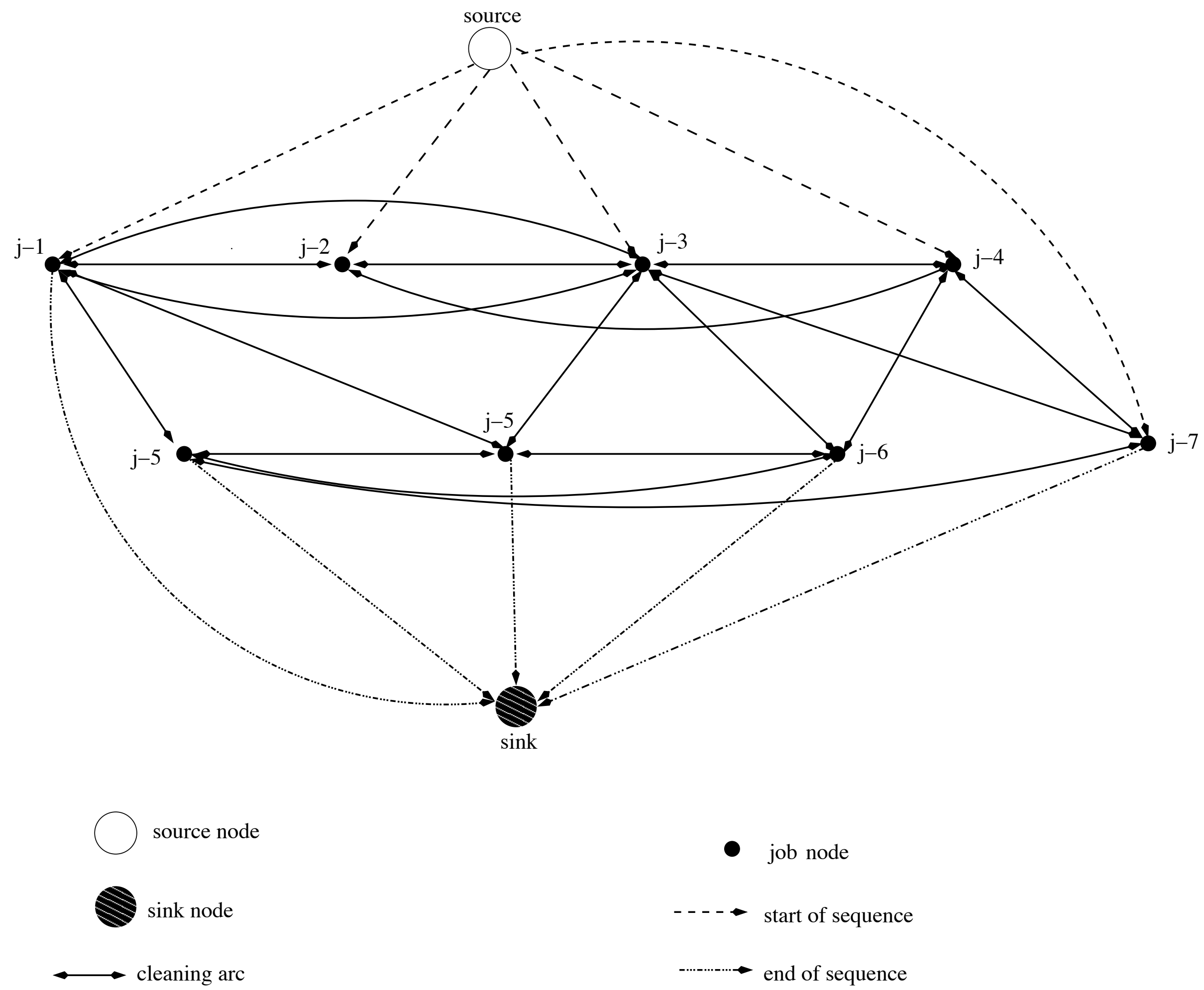

Figure 1: Example of a network for a given type of dye-jet

the set of colors of all the jobs. We define a binary parameter b_{jc} that equals 1 if c is the color of job j, and 0 otherwise. Δ represents the setup (cleaning) time when two consecutive jobs of different colors are processed on the same dye-jet, and M is a large constant. We introduce three groups of decision variables. Y_{cd} represents a binary variable that equals 1 if color c is treated by dye-jet d, and 0 otherwise. Z_{jd} is a binary variable that equals 1 if job j is assigned to dye-jet d, and 0 otherwise. Finally, W_d is an integer variable that represents the minimum number of setup times associated with dye-jet d.

$$\text{Min} \sum_{d \in D} W_d \tag{7}$$

$$\text{subject to:} \quad \sum_{d \in D} Z_{jd} = 1, \quad \forall j \in J \tag{8}$$

$$w_j Z_{jd} \leq Q_d, \quad \forall j \in J \;\; \forall d \in D \tag{9}$$

$$\sum_{j \in J} b_{jc} Z_{jd} \leq M.Y_{cd}, \quad \forall c \in C \;\; \forall d \in D \tag{10}$$

$$\sum_{j \in J} t_j Z_{jd} \leq H - \Delta W_d, \quad \forall d \in D \tag{11}$$

$$\sum_{c \in C} Y_{cd} \leq W_d + 1, \quad \forall d \in D \tag{12}$$

$$Y_{cd} \in \{0, 1\}, \quad \forall c \in C \;\; \forall d \in D \tag{13}$$

$$Z_{jd} \in \{0, 1\}, \quad \forall j \in J \;\; \forall d \in D \tag{14}$$

$$W_d \in \mathbb{N}, \quad \forall d \in D \tag{15}$$

The objective function (7) minimizes the total cleaning time of the dye-jets. Constraints (8) ensure that each job is assigned to one dye-jet. Constraints (9) express the fact that each dye-jet has a limited capacity. Constraints (10) ensure that color c is treated by dye-jet d only if there is a job of color c dyed by d. Constraints (11) ensure that the total working time (processing and cleaning times) does not exceed the length of the horizon H. Constraints (12) compute the minimum number of setups when a set of colors is processed by a dye-jet. Finally, constraints (13), (14), and (15) are integrality constraints.

4.2 Second phase: Transporting and scheduling jobs from dye-jets to pads

We present in this subsection a mixed integer linear model that combines the transportation of the fabrics from dye-jets to pads with the scheduling of the dyeing and trip tasks. We define three parameters for each job j: d_j represents the time to dye the job; t_j represents the total time to transport the bins of job j by a forklift (one bin at a time) from the dyeing house to a pad, ensuring that the forklift returns at the end of its trip to the dyeing section; and Ω_j represents the maximum time that job j can wait before being processed on a pad. For each dye-jet $d \in D$, we denote by J_d the set of jobs performed on dye-jet d according to the first step (in the solution of the first phase). For each $i, j \in J$, we define f_{ij} to be equal to 1 if the two jobs have different colors, and 0 otherwise. Finally, M' is a large constant. We introduce three families of decision variables. X_{jd} represents the start time of dyeing job j on dye-jet d. V_{jf} represents the start time of the transportation of job j by forklift $f \in F$ where F is the set of forklifts. If forklift f is not transporting job j then V_{jf} will be equal to 0. Finally, R_{jf} is a binary variable that equals 1 if job j is transported by forklift f, and 0 otherwise.

$$\text{Min} \sum_{j \in J} \sum_{f \in F} V_{jf} \ - \sum_{j \in J} \sum_{d \in D} X_{jd} \tag{16}$$

$$\begin{aligned}
\text{subject to:} \sum_{f \in F} R_{jf} = 1, & \qquad \forall j \in J & (17)\\
V_{jf} \leq (H - t_j) R_{jf}, & \qquad \forall j \in J, \forall f \in F & (18)\\
\sum_{f \in F} V_{jf} \geq d_j \ + X_{jd}, & \qquad \forall d \in D, \forall j \in J & (19)\\
X_{jd} \geq X_{j'd} + d_{j'} - M Z_{jj'} + f_{jj'} \Delta, & \qquad \forall d \in D, \forall j, j' \in J_d & (20)\\
X_{j'd} \geq X_{jd} + d_j - M(1 - Z_{jj'}) + f_{jj'} \Delta, & \qquad \forall d \in D, \forall j, j' \in J_d & (21)\\
V_{jf} \geq V_{j'f} + t_{j'} R_{j'f} - M Z'_{jj'f} - M'(1 - R_{jf}), & \qquad \forall j, j' \in J, \forall f \in F & (22)\\
V_{j'f} \geq V_{jf} + t_j R_{jf} - M(1 - Z'_{jj'f}) - M'(1 - R_{j'f}), & \qquad \forall j, j' \in J, \forall f \in F & (23)\\
\sum_{f \in F} V_{jf} + t_j - d_j - X_{jd} \leq \Omega_j, & \qquad \forall d \in D, \forall j \in J_d & (24)\\
R_{jf} \in \{0, 1\}, & \qquad \forall j \in J \ \ \forall f \in F & (25)\\
Z_{jj'} \in \{0, 1\}, & \qquad \forall j, j' \in J \ \ \forall f \in F & (26)\\
Z'_{jj'f} \in \{0, 1\}, & \qquad \forall j, j' \in J \ \ \forall d \in D & (27)\\
X_{jd} \geq 0, & \qquad \forall j \in J, \ \forall d \in D & (28)\\
V_{jf} \geq 0, & \qquad \forall j \in J, \ \forall f \in F & (29)
\end{aligned}$$

In this step, the objective function (16) minimizes the overall waiting time (where the waiting time of a job is the time between the end of the dyeing task and the start of the transportation task). Constraints (17) ensure that each job is transported by one forklift. Constraints (18) ensure that the planning horizon is respected. Constraints (19) ensure that transportation by a forklift starts only if the dyeing process is finished. To schedule jobs on dye-jets or on forklifts, we have to add disjunctive constraints. Thus, constraints (20) and (21) ensure that when two jobs j and j' are performed on the same dye-jet d, one job precedes the other. Similarly, the disjunctive constraints (22) and (23) apply to two jobs j and j' transported by the same forklift f. For quality reasons, we add constraints (24) ensuring that the waiting time of job j does not exceed Ω_j. Constraints (25)–(27) are the integrality constraints. It should be noted that for each disjunctive constraint we define a binary variable. Finally, constraints (28) and (29) ensure that variables X_{jd} and V_{jf} are nonnegative.

5 Experimental Results

We were provided with two case studies by our industrial partner. Case I_1 involves 18 dye-jets, 2 forklifts, and 33 fabrics to dye with 11 different colors, with a one-day horizon. Case I_2 is the same except that there are 40 fabrics. Our partner also provided approximate processing times for each operation: the dyeing time varies between three and six hours depending on the color of the fabric. Each forklift takes about 2 min to move between the dye-jet and the PAD areas, whether it is loaded or unloaded. The time to clean a dye-jet is about 8 min. A fabric must not wait more than 2 h between the end of the dyeing process and the end of the transportation process. The sizes of the fabrics range from 1 to 12 bins, and the capacities of the dye-jets range from 2 to 12 bins. From instance I_1 we randomly generated four instances, two ($I_1^{20\%,1}$ and $I_1^{20\%,2}$) with 20% more fabrics and two ($I_1^{40\%,1}$ and $I_1^{40\%,2}$) with 40% more fabrics. We note that the added fabrics are randomly selected from the fabrics of the real instance, and the horizon is set to 30 h for the random instances. We set the discretization step to be equal to a back-and-forth trip between the dye-jet and the pad areas, i.e., 4 min. The tests were run on a cluster of Itanium II 1.5 Ghz processors.

As noted, we developed two models for the first phase. We solve the column generation model using a CG solver and the MIP model using Cplex 12.6.0. The optimal solution does not have any setup (cleaning) time since each dye-jet processes fabrics of the same color. To assess the two approaches, we report in Table

1 the gap, the number of branching nodes, and the computational time. Table 1 shows that the MIP is much faster than the CG approach, especially for large instances. This is because the daily instances processed by the company are easy to solve (Cplex finds the optimal solution at node 0). However, the manager's manual solution contains setup (cleaning) time. We believe that the CG solver will provide good solutions compared to those of the MIP solver for fairly large instances.

We solved the MIP model of the second phase using Cplex 12.6.0; Table 2 gives the computational time. The overall waiting time (as defined in Section 4) of the fabrics is equal to zero, except for instance I_2, for which the value is 144 min.

For the transportation planning, the manager did not have a complete view of the horizon. Sometime, different dye-jets finished larger fabrics almost simultaneously, and as a result, the two forklifts were unable to transport all the orders on time. The company plans to adopt our algorithm to solve its scheduling problems.

Criterion	Approach	Instances					
		I_1	I_2	$I_1^{20\%,1}$	$I_1^{20\%,2}$	$I_1^{40\%,1}$	$I_1^{40\%,2}$
Gap (%)	MIP	0	0	0	0	0	0
	CG	0	0	0	0	0	0
CPU (s)	MIP	0.04	0.16	0.06	0.05	0.07	0.16
	CG	6	7	10	8	29	1406
# of nodes	MIP	0	0	0	0	0	4
	CG	5	2	4	2	16	56

Table 1: Comparison of the first-phase approaches

Instance	CPU (s)	Total waiting time (min)
I_1	0.48	0
I_2	3.07	144
$I_1^{20\%,1}$	0.71	0
$I_1^{20\%,2}$	0.61	0
$I_1^{40\%,1}$	0.89	0
$I_1^{40\%,2}$	1.42	0

Table 2: Second-phase results

6 Conclusion

We have described a two-phase approach for the SBFSP. The first phase determines the optimal assignment of fabrics to dye-jets so as to minimize the overall cleaning time. We developed two models for this phase. For the second phase we presented an MIP model that combines the transportation of fabrics from dye-jets to PADs and the scheduling of the dyeing and the forklift trips.

Future research will focus on solving the problem in a single phase using an integrated MIP model; dealing with additional constraints related to the PAD area; and producing robust solutions by including stochasticity in the machine operations and the forklift travel times. We plan to make initial decisions based on the deterministic context and to observe the outcomes on a continuous, rolling-horizon basis. If stochastic information becomes available or an unexpected event (machine breakdown) occurs, it is important to use this information in dynamic planning. We believe that doing so would solve the assignment problems in most cases.

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