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► To cite this version:

Claude Yugma, Stephane Dauzere-Peres, Christian Artigues, Alexandre Derreumaux, Olivier Sibille. Batching, Scheduling, Disjunctive graph, Local search, Simulated Annealing, Wafer fabrication. International Journal of Production Research, 2011, 10.1080/00207543.2011.575090 . hal-00714553

HAL Id: hal-00714553

<https://hal.science/hal-00714553>

Submitted on 5 Jul 2012

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Journal:	<i>International Journal of Production Research</i>
Manuscript ID:	TPRS-2010-IJPR-0566.R1
Manuscript Type:	Original Manuscript
Date Submitted by the Author:	11-Jan-2011
Complete List of Authors:	Yugma, Claude; Ecole des Mines de Saint-Etienne, CMPGC Dauzere-Peres, Stephane; Ecole des Mines de Saint-Etienne, CMP Georges Charpak Artigues, Christian; Université de Toulouse, LAAS-CNRS Derreumaux, Alexandre; Ecole des Mines de Saint-Etienne, CMP Georges Charpak Sibille, Olivier; Zone industrielle d'ATMEL
Keywords:	BATCH SCHEDULING, SCHEDULING, HEURISTICS, SEMICONDUCTOR MANUFACTURE, SIMULATED ANNEALING
Keywords (user):	

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Manuscripts

International Journal of Production Research
Vol. 00, No. 00, 00 Month 200x, 1–21

RESEARCH ARTICLE

A Batching and Scheduling Algorithm for the Diffusion Area in Semiconductor Manufacturing

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(Received 00 Month 200x; final version received 00 Month 200x)

This paper proposes an efficient heuristic algorithm for solving a complex batching and scheduling problem in a diffusion area of a semiconductor plant. Diffusion is frequently bottleneck in the plant and also one of the most complex areas in terms of number of machines, constraints to satisfy and the large number of lots to manage. The purpose of this study is to investigate an approach to group lots in batches and to schedule these batches on machines. The problem is modeled and solved using a disjunctive graph representation. A constructive algorithm is proposed and improvement procedures based on iterative sampling and Simulated Annealing are developed. Computational experiments, carried out on actual industrial problem instances, show the ability of the iterative sampling algorithms to significantly improve the initial solution, and that Simulated Annealing enhances the results. Furthermore, our algorithm compares favorably to an algorithm of the literature on a simplified version of our problem. The constructive algorithm has been embedded in a software and is currently being used in a semiconductor plant.

Keywords: Batching, Scheduling, Disjunctive graph, Local search, Simulated Annealing, Wafer fabrication

1. Introduction

Semiconductor wafer fabrication can be described as a multistage process with re-entrant flows. The processing is done layer by layer. Each layer requires several steps of process-

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ing such as chemical-mechanical polishing, diffusion, film deposition, photolithography, implant (doping) and etching. For each of the product types, and depending on the technology, a wafer goes through more than 400 process steps over a period of a few weeks. Wafer fabrication planning and scheduling is a complex task due to the large number of products and machines involved. It is further complicated by additional constraints such as re-entrant flow of operations (see (Kumar 1994)), setup issues, preventive maintenances and random machine breakdowns (see (Ovacik and Uzsoy 2007) and (Sze 2001)). The importance of scheduling on the performance of semiconductor wafer fabrication facilities (fabs) is known for many years (see (Wein 1988) and (Varadarajan and Sarin 2006)).

In this paper, we focus on an important part of the manufacturing process. Among the complex operations involved in the fabrication of a wafer, the diffusion phase is of critical importance since the batching decisions that are involved may affect the performance of the entire wafer fab (see for instance (Ibrahim *et al.* 2003) and (Monch and Habenicht 2003)). The processing time of the operations in the diffusion area can be large (10 hours) compared to other operations in the fab. (Mehta and Uzsoy 1998) state that optimizing batching operations results in good performance measures of the whole production process. Lots regularly arrive in the diffusion area and the diffusion phase is primarily used to alter the type and level of conductivity of semiconductor materials.

The purpose of this article is to develop efficient methods to partition lots in batches and to schedule batches on machines in the diffusion area while taking into account numerous constraints and optimizing three main production criteria: maximizing the number of operations (moves), maximizing the batch sizes and minimizing the total tardiness.

The remaining sections of this paper are organized as follows. In Section 2, we provide some background on existing related batching and scheduling problems. In Section 3, the problem is stated. We present in Section 4 a disjunctive graph representation of the problem, which supports our solving procedures. The method for computing an initial solution and improvement procedures based on iterative sampling and Simulated Annealing are described in Section 5. Experimental results on real problem instances and comparison with an algorithm of the literature are given and discussed in Section 6. Section 7 concludes the paper with recommendations for further research.

2. Previous related work

The operations of batching and scheduling jobs are a common practice in manufacturing systems, especially in semiconductor manufacturing systems, see (Mathirajan and Sivakumar 2006a) for more details. Reasons for batching are the reduction of setups, the ability of machines to process several jobs simultaneously, etc. Using the classification of (Mathirajan and Sivakumar 2006a), we notice that there is not much literature on batch scheduling problems taking into account the re-entrance features of the system, see for examples (Cigolini *et al.* 2002), (Mason and Oey 2003) and (Oey and Mason 2001). (Mönch *et al.* 2009) present a survey on scheduling problems in semiconductor manufacturing, where typical batching problems are described. For a general introduction on scheduling problems, the reader can for instance refer to (Blazewicz *et al.* 2007).

The problem addressed in this paper deals with the following characteristics:

- Multiple non-identical machines at each stage. (Mehta and Uzsoy 1998) present a total tardiness minimization problem on a batch processing machine with incompatible

job families. They propose a dynamic programming algorithm to solve the problem. (Balasubramanian *et al.* 2004) extend the approach of (Mehta and Uzsoy 1998) to a batching problem with incompatible jobs on parallel machines aiming at minimizing the weighted total tardiness. The main focus of interest in (Kim *et al.* 2010) is the scheduling of lots on diffusion workstations in a fab. There are multiple identical machines, and each of them can process a limited number of lots at a time. The scheduling problem involves multiple job families on identical parallel batch-processing machines.

- Multiple stages. Jobs have to be processed on a cleaning machine in a first stage, and then on furnaces in a second stage. The second stage is actually a multi-stage process, since jobs may have up to three different consecutive operations on furnaces. Moreover, the sequence of operations can differ from one job to another depending of the type of operations that the jobs must undergo. For example, the same furnace can be used for the last furnace operation for a job in a batch and for the first furnace operation for another job in another batch. Our problem is thus different from a flexible flow-shop scheduling problem (see (Kis and Pesch 2005)), where the processing order is the same for all jobs. In the literature, the number of stages usually does not exceed two. (Su 2003) considers an hybrid two-stage flow-shop scheduling problem with a batch processor in Stage 1 and a single processor in Stage 2. This is also the case in (Sung and Min 2001) and (Sung and Kim 2003) where a batching problem on two stages is considered. (Oulamara *et al.* 2009) study a two-machine flow-shop scheduling problem with conventional and batching machines in the first and second stage, respectively, and arbitrary job compatibilities.
- Multiple criteria. The goal of the paper is to simultaneously optimize three indicators. These indicators are the number of wafers going through the line (to maximize), the average number of lots in batches (to maximize) and the waiting time of lots (to minimize). Generally, related studies in the literature tackle scheduling problems by considering one single indicator to optimize. (Uzsoy 1995) tackles the problem with the objective of minimizing the completion time of jobs, and (Hung 1998) the objective of maximizing the batch processing machine utilization. The minimization of the total weighted tardiness on a single machine is considered in (Perez *et al.* 2005) while, in (Mathirajan and Sivakumar 2006b), the authors focus on the minimization of the total weighted tardiness on heterogeneous batch processing machines under dynamic arrival of jobs, incompatible job families and non-identical job sizes. Few articles deal with different criteria simultaneously. In (Pfund *et al.* 2008), the authors adapt the Shifting Bottleneck Heuristic to facilitate the multi-criteria optimization of makespan, cycle time and total weighted tardiness using a desirability function.

Furthermore, in our problem, there are setup times (corresponding to loading and unloading lots from the machine), which do not depend on the sequence, and the complexity is increased by the presence of maximum times lags between batching operations.

Our problem can be viewed as a complex variant of the flexible job-shop scheduling problem (see for instance (Dauzère-Pérès and Paulli 1997)). These types of problems have been addressed by several authors, as in (Mason *et al.* 2002) and (Ovacik and Uzsoy 2007). These problems are frequently solved using a method known as the Shifting Bottleneck (SB) procedure originally designed for the standard job-shop scheduling problem (see (Adams *et al.* 1988) and (Dauzère-Pérès and Lasserre 1993)). Several aspects, like identifying appropriate subproblem solution procedures, can be found in (Demirkol and Uzsoy 2000) and (Uzsoy and Wang 2000). In (Mason *et al.* 2002), a scheduling problem in semiconductor manufacturing close to the one tackled in this paper is solved by a modified Shifting Bottleneck heuristic. We model the considered batching and scheduling

problem through a variant of the disjunctive graph described in (Mason *et al.* 2002), and we use it to propose different solving procedures.

3. Problem description

The diffusion area defines a batching and scheduling problem of wafer lots on two types of equipment: cleaning machines and furnaces. These resources are able to perform several lots simultaneously. Each lot requires one or more consecutive operations in the diffusion area, and each operation has a recipe¹ which determines its duration and the set of machines that are able to process the lot. On a 24-hour basis, each operation has to be assigned to a machine and included into a batch, i.e. a set of operations of the same recipe that are simultaneously processed by the machine. Lots usually have to be processed on one cleaning machine and then on one or more furnaces. Constraints in the diffusion area are divided into three types: Equipment constraints, process constraints and line management constraints.

3.1. Constraints

Some of these constraints are common to the two types of resources while others are dedicated to furnaces.

3.1.1. Equipment constraints

- **Common constraints**

Dedicated equipment: Any machine is able to process a limited set of recipes.

Maximum batch size: Any machine defines a maximum batch size corresponding to its capacity.

Loading and unloading times: A time may be needed to load and unload a batch on the machine.

Unavailability periods: The machine may be unavailable during some periods (defined by time windows) due to qualification, repair, maintenance, etc.

In process jobs: The machine may be occupied at the beginning of the time horizon by in-process operations that have to be completed before the machine becomes available.

- **Specific furnace constraints**

Minimum time between two batches on an furnace: Furnaces must be inspected after completing each batch.

3.1.2. Process constraints

- **Common constraints**

Precedence: Operations must be performed following the manufacturing process of the lot. The operations of a lot are chained and no operation can start before the end of its predecessor, except for the first operation of each lot.

Minimum time lag: There is a fixed handling and transport time between every two successive operations of a lot.

Release dates: They correspond to the arrival times of lots at the cleaning machines and furnaces. A lot cannot be scheduled before its release date. Because the diffusion

¹Specifications on a process on how it should be executed on a tool; This pertains to requirements of maintaining proper temperature, pressure, and metal composition, among others.

area is a stage of the complex global production process, release dates are estimated by a simulation tool.

Fixed recipe: Each operation of a lot is associated with a recipe, i.e. the lot should be processed on resources that are qualified for the corresponding recipe. This implies that all lots in the same batch must be processed with the same recipe.

Process time: The process time of a batch on a machine depends on the recipe.

maximum time lag: A time limit is given for two successive operations x and y of a lot. The difference between the starting time of y and the completion time of x cannot exceed this limit. The maximum time lag depends on the operations x and y and corresponds, for instance, to the maximum time allowed between a cleaning operation and the first operation on a furnace.

3.1.3. Line management constraints

- **Specific furnace constraints**

Minimum time between two batches of the same recipe: There is a minimum time between the beginning of two batches of the same recipe on two different furnaces.

3.2. Objective

In semiconductor fabs, several indicators are used to measure the performance. The interested reader can refer to (Montoya-Torres 2006) for more details. Jointly with managers of the fab, we identified three relevant indicators for our study, that are described below.

- *Number of moves* (to maximize). It corresponds to the number of completed operations on the planning horizon, which can be compared to the target number fixed by the production managers.
- *Batching coefficient* (to maximize). Defined on the planning horizon, it is calculated as the number of moves divided by the sum of the number of batches performed on each machine, times the maximum capacity of that machine. Note that the denominator is the number of lots that could be performed if the machine was loaded up to its maximum capacity.
- *X-factor* (to minimize). This indicator is used to evaluate the waiting times of lots in the diffusion area in order to reduce cycle times. For a given lot, this factor is calculated as the total time of the lot in the diffusion area over its processing time.

It must be noted that these indicators are not always antagonist, e.g. increasing the batching coefficient usually leads to increasing the number of moves. However, each indicator shows a different aspect of a proposed schedule to managers. Depending on the situation in the fab, it might be preferable to prioritize the maximization of the batching coefficient, which may lead to an increased X-factor, since some lots might wait for other lots of the same family to arrive in the diffusion area to create a larger batch.

In the literature, although other indicators are used to evaluate the quality of a solution, we can show that they are equivalent to ours. The *Work-In-Process* (WIP) is defined as the number of wafers being in the fab at a given period, either in a production state or in a non-production state (e.g. transport and waiting). Little's law (Little 1961) establishes that, if a system is stable and stationary, then the average WIP is proportional to the average cycle time. The WIP indicator is linked to the *X-factor*. The *throughput*, defined as the outgoing number of wafers of the fab per unit of time, is linked to the *number of moves*. The evolution of the throughput in time makes it possible to know if the system is stable, i.e. to know if there is no accumulation of lots in the fab or if the

system evolves according to forecasts. (Glassey and Resende 1988) observe that there is a relation between the increase of the throughput and the output of a fab. The cycle time drastically increases when the throughput is close to the maximal capacity of the fab. Hence, to consider both WIP and throughput, our indicators are adequate.

The goal is to optimize the various performance measures, while taking into account the numerous complex constraints. The next section describes the mathematical formulation of the problem.

3.3. Mathematical formulation of the problem

The scheduling problem can be formulated as follows. For sake of clarity, the above-described *Unavailability periods*, *In-process jobs* and *Minimum distance between batches of the same recipe* constraints are not included. In Section 4, we describe how we tackle these characteristics.

A set of jobs (lots) $\mathcal{J} = \{J_i | i = 1, \dots, n\}$ has to be processed on a horizon T by a set of machines $\mathcal{M} = \{M_k | k = 1, \dots, m\}$. Each job J_i is made of n_i operations such that each operation O_{ij} has a duration $p_{ij} > 0$ and a set $\mathcal{M}_{ij} \subseteq \mathcal{M}$ of machines (the furnaces or the cleaning machines) able to process it. Let $\mathcal{O}_k = \{O_{ij} \in \mathcal{O} | M_k \in \mathcal{M}_{ij}\}$ denote the set of operations that can be assigned to machine M_k . The value of p_{ij} and the elements of the set \mathcal{M}_{ij} are determined by the recipe of operation O_{ij} denoted ρ_{ij} . In general we have $\mathcal{M}_{ij} \subset \mathcal{M}$ since each machine cannot be configured for all recipes. Each operation O_{ij} has to be included in a batch on a resource $k \in \mathcal{M}_{ij}$. Each machine has a finite capacity R_k which gives the maximal number of lots in the same batch. On each machine k , S_k denotes the setup time needed before starting a new batch, D_k denotes the removal time needed after the completion of a batch and s_k denotes the constant setup time needed between two different batches. s_k^0 denotes the initial setup time on machine k , depending on the state of the resource at time 0. Two consecutive operations O_{ij} and $O_{i(j+1)}$ of the same job are linked by minimum and maximum time lags. Once the batch of O_{ij} is completed and removed from k , the setup for the batch of $O_{i(j+1)}$ cannot start before a minimum time lag τ_{ij}^{\min} and has to start before a maximum time lag τ_{ij}^{\max} . Let $\mathcal{O} = \{O_{ij} | i = 1, \dots, n; j = 1, \dots, n_i\}$ denote the set of all operations. Each job J_i has a relative priority c_i ($c_i < c_j$ means that J_i is more urgent than J_j). Each job corresponds to a number w_i of wafers produced when the job is completed. Table 1 summarizes the notations.

Finding a feasible solution for the problem lies in making four types of decisions:

- D1 - Partition the operations into batches,
- D2 - Select a resource to process each batch,
- D3 - Order the batches on each resource,
- D4 - Assign a start time to each batch.

Decisions D1-D3 can all be represented by a family of batches $\mathcal{B} = \{B_{kq}\}_{k \in \{1, \dots, m\}, q \in \{1, \dots, \nu_k\}}$ where B_{kq} is the batch sequenced at position q on machine M_k . $\nu_k \in \{0, \dots, |\mathcal{O}_k|\}$ denotes the number of batches assigned to machine M_k . Decision D4 leads to a family of start times $\mathcal{T} = \{t_{ij}\}_{O_{ij} \in \mathcal{O}}$ assigned to the operations. Once a solution $\{\mathcal{B}, \mathcal{T}\}$ is determined, we have a machine assignment $\{m_{ij}\}_{O_{ij} \in \mathcal{O}}$ where m_{ij} denotes the machine O_{ij} is assigned to, i.e. verifying that $\exists q \in \{1, \dots, \nu_k\}$ such that $O_{ij} \in B_{m_{ij}q}$. To be feasible, a solution $\{\mathcal{B}, \mathcal{T}\}$ and its corresponding assignment $\{m_{ij}\}_{O_{ij} \in \mathcal{O}}$ have to satisfy the following constraints. The operations of the same batch

Notation	Description
$\mathcal{J} = \{J_i i = 1, \dots, n\}$	Set of jobs (lots)
T	Horizon length
$\mathcal{M} = \{M_k k = 1, \dots, m\}$	Set of machines
n_i	Number of operations of lot J_i
$\mathcal{O} = \{O_{ij} i = 1, \dots, n; j = 1, \dots, n_i\}$	Set of operations
O_{ij}	Operation j of lot J_i
p_{ij}	Duration of operation O_{ij}
\mathcal{M}_{ij}	Qualified machines to process O_{ij}
\mathcal{O}_k	Operations processable on machine M_k
ρ_{ij}	Recipe of O_{ij}
R_k	Capacity of machine M_k (batch max. size)
S_k	Setup before the operation on machine M_k
D_k	Setup after the operation on machine M_k
s_k	Inter batch delay
s_k^0	Initial setup time
τ_{ij}^{\min}	Min. delay between O_{ij} and $O_{i(j+1)}$
τ_{ij}^{\max}	Max delay between O_{ij} and $O_{i(j+1)}$
c_i	Priority of lot J_i
w_i	Number of wafers of J_i
$\mathcal{B} = \{B_{kq} k \in \{1, \dots, m\}, q \in \{1, \dots, \nu_k\}\}$	Batch at position q on machine M_k
ν_k	Number of batches on machine M_k
$\mathcal{T} = \{t_{ij} O_{ij} \in \mathcal{O}\}$	Set of start times
m_{ij}	Machine which processes O_{ij}
θ_{ij}	Completion ratio of O_{ij}
\mathcal{B}^T	Batches started before T
Z_k	Number of qualified recipes on machine M_k
$N = \sum_{i=1}^n n_i$	Total number of operations

Table 1. Summary of notations used to formalize the problem

must have the same recipe, i.e.

$$\rho_{ij} = \rho_{xy} \quad \forall B \in \mathcal{B}, \forall O_{ij}, O_{xy} \in B \tag{1}$$

Each operation must be assigned to a machine able to process its recipe:

$$m_{ij} \in \mathcal{M}_{ij} \quad \forall O_{ij} \in \mathcal{O} \tag{2}$$

The batch capacity cannot be exceeded and each batch includes at least one operation:

$$1 \leq |B_{kq}| \leq R_k \quad \forall B_{kq} \in \mathcal{B} \tag{3}$$

An operation appears in only one batch, i.e.

$$B \cap B' = \emptyset \quad \forall B, B' \in \mathcal{B}, B \neq B' \tag{4}$$

All operations are included in a batch:

$$\cup_{B \in \mathcal{B}} B = \mathcal{O} \quad (5)$$

The start time of the first operation of each lot cannot exceed the lot release date:

$$t_{i1} \geq r_i \quad \forall J_i \in \mathcal{J} \quad (6)$$

Each operation O_{ij} , $j > 1$, cannot start before a minimum time lag after the end of its preceding operation $O_{i(j-1)}$, which takes into account the removal time of the batch of $O_{i(j-1)}$, the minimum time lag $\tau_{i(j-1)}^{\min}$ and the setup time of the batch of O_{ij} :

$$t_{ij} - t_{i(j-1)} \geq D_{m_{i(j-1)}} + p_{i(j-1)} + \tau_{i(j-1)}^{\min} + S_{m_{ij}} \quad \forall i \in \{1, \dots, n\}, \forall j \in \{2, \dots, n_i\} \quad (7)$$

Each operation O_{ij} , $j > 1$, has to start before a maximum time lag after the end of its preceding operation $O_{i(j-1)}$, which takes into account the removal time of the batch of $O_{i(j-1)}$, the maximum time lag $\tau_{i(j-1)}^{\max}$ and the setup time of the batch of O_{ij} :

$$t_{ij} - t_{i(j-1)} \leq D_{m_{i(j-1)}} + p_{i(j-1)} + \tau_{i(j-1)}^{\max} + S_{m_{ij}} \quad \forall i \in \{1, \dots, n\}, \forall j \in \{2, \dots, n_i\} \quad (8)$$

The start times of two operations of the same batch must be equal:

$$t_{ij} = t_{xy} \quad \forall B \in \mathcal{B}, \forall O_{ij}, O_{xy} \in B \quad (9)$$

An operation of a batch which is not at the first position on its machine cannot start before the end of the preceding batch on the machine, plus the necessary removal time of the preceding batch, plus the minimum setup time on the machine between two batches, plus the necessary setup time for the next batch.

$$t_{ij} - t_{xy} \geq p_{xy} + D_k + s_k + S_k \quad \forall B_{kq}, q > 1 \in \mathcal{B}, \forall O_{ij} \in B_{kq}, \forall O_{xy} \in B_{k(q-1)} \quad (10)$$

An operation of a batch in the first position on its machine cannot start before the initial setup time for this batch (we assume $S_k^0 \leq S_k + D_k + s_k, \forall M_k \in \mathcal{M}$):

$$t_{ij} \geq s_{m_{ij}}^0 \quad \forall O_{ij} \in \mathcal{O} \quad (11)$$

By definition, a feasible solution includes each operation inside a batch. In our problem, the scheduling horizon is limited to T . Hence, only those batches released in the interval $[0, T]$ must be taken into account. Several criteria are used to measure the quality of a feasible solution. The number of moves is the number of wafers produced in $[0, T]$:

$$f_{\text{mov}} = \sum_{O_{ij} \in \mathcal{O}} w_i \theta_{ij} \quad (12)$$

where w_i is the number of wafers in job i ($w_i \leq 25$ in practice), and $\theta_{ij} \in [0, 1]$ denotes the completion ratio of operation O_{ij} before time T , i.e.

$$\theta_{ij} = \begin{cases} \frac{\min(t_{ij} + p_{ij}, T) - t_{ij}}{p_{ij}} & \text{if } t_{ij} \leq T \\ 0 & \text{Otherwise.} \end{cases}$$

The batching coefficient is the average ratio of the actual size of each batch divided by its maximal size. Let $\mathcal{B}^T = \{B \in \mathcal{B} | t_{ij} < T, \forall O_{ij} \in B\}$ denote the set of batches started before time T .

$$\text{Batching coefficient} = \frac{\sum_k \sum_{B_{kq} \in \mathcal{B}^T} |B_{kq}| / R_k}{|\mathcal{B}^T|} \quad (13)$$

$$f_{\text{batch}} = \frac{\sum_k \sum_{B_{kq} \in \mathcal{B}^T} |B_{kq}| / (R_k + \frac{Z_k}{100})}{|\mathcal{B}^T|} \quad (14)$$

where Z_k is the total number of qualified recipes on machine M_k .

The weighting of the batching coefficient by the number of qualified recipes on the concerned machine makes it possible to use the least general-purpose machines preferably.

The average X-factor is the average of the X-factor of each job weighted by the job priority. All the jobs do not have the same priority. Some jobs are more important than others (important customers, tests to be carried out quickly, delay to catch up with, etc). Thus, a weight c_i is assigned to each job J_i to reflect its priority. Let $\mathcal{J}^T = \{J_i \in \mathcal{J} | t_{in_i} + p_{in_i} \leq T\}$ denote the set of jobs completed before T .

$$\text{X-fac} = \frac{\sum_{J_i \in \mathcal{J}^T} (t_{in_i} + p_{in_i} - r_i) / p_{in_i}}{|\mathcal{J}^T|} \quad (15)$$

$$f_{\text{X-fac}} = \frac{\sum_{J_i \in \mathcal{J}^T} c_i (t_{in_i} + p_{in_i} - r_i) / p_{in_i}}{|\mathcal{J}^T|} \quad (16)$$

The choice made together with the decision makers of the production unit is to combine these different objectives into a single one by maximizing the following weighted sum:

$$f = \alpha f_{\text{mov}} + \beta f_{\text{batch}} - \gamma f_{\text{X-fac}} \quad (17)$$

where α , β and γ are adjustable weights allocated to each objective function. The objective functions have been designed to integrate some requests of managers. In the calculation of $f_{\text{X-fac}}$, the delay of each lot is multiplied by its priority, in order to accelerate the urgent lots. In the calculation of the total batching coefficient, the batching coefficient of each machine is multiplied according to the number of qualified recipes on this machine. This leads to choosing in priority the machines that are able to process less recipes, and thus to maintain the availability of the most flexible machine.

The objective of the problem is to determine a feasible selection $\{\mathcal{B}, \mathcal{T}\}$ such that f is maximized. Note that, given a (feasible) solution $\{\mathcal{B}, \mathcal{T}\}$, f can be computed in $O(N)$ time where $N = \sum_{i=1}^n n_i$ is the total number of operations.

4. The disjunctive graph representation

The considered problem can be seen as an extension of the flexible job-shop scheduling problem and, consequently, the disjunctive graph model can be used for this batching and scheduling problem as proposed in (Mason *et al.* 2002). In their article, the authors consider a different objective function (total weighted tardiness). Sequence-dependent setup times and reentrant flows are also considered but there are no maximum time lags. Unfortunately, these constraints considerably increase the difficulty of the problem (see (Gentner *et al.* 2004)). Let us explain how the problem is modeled using disjunctive graphs.

We define the disjunctive graph $G = (V, C, E)$ as follows.

- V is a set of nodes where there is one node per operation, denoted V_{ij} , plus a dummy start node denoted 0.
- C is the set of conjunctive arcs representing the release dates and minimum and maximum time lags. There is an arc from node 0 to node V_{i1} of each job J_i . There is an arc from V_{ij} to $V_{i(j+1)}$ and an arc from $V_{i(j+1)}$ to V_{ij} , for pair of each consecutive operations O_{ij} and $O_{i(j+1)}$ of each job J_i .
- E is the set of disjunctive arcs which represent the decisions of the problem. There are two opposite conjunctive arcs $(V_{ij}, V_{xy})^k$ and $(V_{xy}, V_{ij})^k$ for any machine $k \in \mathcal{M}$ and for any pair of operations $O_{ij}, O_{xy} \in \mathcal{O}_k$, $O_{ij} \neq O_{xy}$. These arcs represent the sequencing or the batching decision concerning O_{ij} and O_{xy} on machine k .

Let \mathcal{B} denote a partial or complete batching for the problem satisfying at least Constraints (1) through (4). \mathcal{B} is a complete batching if Constraint (5) is also verified, otherwise it is a partial batching. Recall that \mathcal{B} also defines the machine assignment m_{ij} , for all $O_{ij} \in \cup_{B \in \mathcal{B}} B$. We assume $m_{ij} = 0$ if O_{ij} is not batched in \mathcal{B} , i.e. if $O_{ij} \notin \cup_{B \in \mathcal{B}} B$.

\mathcal{B} unambiguously defines a selection \mathcal{S} as follows. For each distinct operations O_{ij} and O_{xy} such that $m_{ij} = m_{xy} = k \neq 0$, select arc $(V_{xy}, V_{ij})^k$ if O_{xy} is in a batch sequenced before the batch of O_{ij} , select arc $(V_{ij}, V_{xy})^k$ if O_{ij} is in a batch sequenced before the batch of O_{xy} , and select both arcs $(V_{ij}, V_{xy})^k$ and $(V_{xy}, V_{ij})^k$ if O_{ij} and O_{xy} are assigned to the same batch.

Once a selection is computed, we define a graph $G(\mathcal{S}) = (V, C \cup \mathcal{S})$ where arcs $C \cup \mathcal{S}$ are valued as follows (we assume $s_0^0 = s_0 = S_0 = D_0 = 0$):

- Each arc from 0 to the first operation O_{i1} is valued by $\max(r_i, S_{m_{i1}}^0)$, the maximal value between the release date of job i and the initial setup time for machine m_{i1} .
- Each arc from V_{ij} and $V_{i(j+1)}$ is valued by $D_{m_{ij}} + p_{ij} + \tau_{ij}^{\min} + S_{m_{i(j+1)}}$, the value of the minimum time lag between O_{ij} and $O_{i(j+1)}$ plus the setup and removal times linked to the assignment of the operations.
- Each arc from $O_{i(j+1)}$ and O_{ij} is valued by $-(D_{m_{ij}} + p_{ij} + \tau_{ij}^{\max} + S_{m_{i(j+1)}})$, the (negative) value of the maximum time lag between O_{ij} and $O_{i(j+1)}$ plus the necessary setup and removal times.
- Each arc $(V_{ij}, V_{xy})^k$ is valued either by $p_{ij} + D_k + s_k + S_k$ if the opposite arc is not selected or by 0 if the opposite arc is selected. Indeed, in the first case, this arc represents the decision to sequence O_{xy} after O_{ij} on machine k whereas, in the second case, both arcs $(V_{ij}, V_{xy})^k$ and $(V_{xy}, V_{ij})^k$ represent the synchronization of the operations included in the same batch.

We can state that the (partial) solution represented by the (partial) batching \mathcal{B} and its selection \mathcal{S} is feasible if and only if all longest path problems from node 0 to each node V_{ij}

in $G(\mathcal{S})$ have a solution. If this is the case and if \mathcal{B} is complete, a feasible schedule \mathcal{T} can be obtained by setting t_{ij} to the length of the longest path from 0 to V_{ij} . Furthermore, \mathcal{T} is the best schedule compatible with \mathcal{B} one can obtain when the objective is to maximize f .

The problem can be formulated as follows: Find the batching \mathcal{B} verifying Constraints (1) through (5) such that the corresponding selection \mathcal{S} is feasible and maximizes f .

As stated in the previous sections, the actual data issued from the fab have other characteristics that have been tackled, such as in-process jobs and machine down times. Thanks to the disjunctive graph representation, we can model these two characteristics by operations with fixed start times on the machines. A start time t can be fixed by linking the node with node 0 by two opposite arcs valued by t and $-t$. As stated in Section 3, the actual problem also includes an important line management constraint: A minimum time between the start time of two batches of the same recipe scheduled on two different batches has to be respected. This can also be tackled through the disjunctive graph representation. A fictitious machine can be associated to each recipe, and disjunctive arcs linking two operations of the same recipe can be defined. Then, whenever the two operations are batched on two different machines (furnaces), the disjunctive arc has to be oriented. Once oriented, the arc is valued by the minimum required distance.

The disjunctive graph is extensively used in the solution methods proposed in the following section. The graph is necessary to determine feasible solutions in the constructive algorithms, to evaluate solutions and also to move from one solution to another in the neighborhood of the Simulated Annealing algorithm.

5. Solution Methods

We propose a two-phase heuristic method and a metaheuristic to solve the problem. The first phase of the heuristic is a constructive heuristic based on successive job insertions. The second phase is a local search method which aims at improving the initial solution. Both phases are based on the evaluation of a (complete or partial) selection through the orientation of arcs and longest path calculations in the disjunctive graph. For the metaheuristic, we propose a Simulated Annealing algorithm with a neighborhood based on the graph representation.

5.1. Evaluation of a partial or complete batching

Any partial or complete batching \mathcal{B} and its selection \mathcal{S} can be evaluated through the calculation of start times t_{ij} , equal to the longest path from 0 to V_{ij} in $G(\mathcal{S})$ of each operation O_{ij} . To compute such longest paths, since the graph includes arcs with negative weights, we use the Bellman-Ford algorithm which has a $O(N|\mathcal{S} \cup \mathcal{C}|)$ time complexity. If the algorithm finds a path of positive length, then the partial or complete solution is unfeasible. Otherwise the algorithm returns the start times t_{ij} , and the objective function value f can be determined.

5.2. Computing an initial solution by a priority rule-based constructive heuristic

The initial solution (selection) is computed by a job insertion method. The jobs are first sorted in a list L according to the order: Jobs with increasing maximum time lags first,

then increasing release dates, then job priorities.

The method starts with an empty batching. Then, the jobs are taken in the order given by the list and inserted one by one in the current batching. The insertion of J_i is made as follows. Let $\mathcal{B} = \{B_{kq}\}_{k \in \mathcal{M}, q \in 1, \dots, \nu_k}$ denote the current batching including jobs located before J_i in \mathcal{L} . For each operation O_{ij} of J_i and for each resource $k \in \mathcal{M}_{ij}$, there are $2\nu_k + 1$ insertion positions of O_{ij} in the batch sequence of machine M_k : Indeed, for each batch B_{kq} , we may insert O_{ij} inside batch B_{kq} or create a new batch at any position. Each of these insertion positions is evaluated with the algorithm described in the previous section and the one that maximizes f is kept to update \mathcal{B} . If none of the insertion positions is feasible for an operation O_{ij} , then all these partial solutions violate a maximum time lag and there exist insertion positions that violate only the maximum time lag between $O_{i(j-1)}$ and O_{ij} (the last position on each resource of \mathcal{M}_{ij} , for instance). Hence, $O_{i(j-1)}$, the previous operation of job J_i , has to be removed from \mathcal{B} and inserted at a later position. If this is not feasible, $O_{i(j-1)}$ and O_{ij} are not scheduled and are deleted from the list of operations. We use the disjunctive graph for the sequence of operations and time lags (conjunctive arcs), batching (disjunctive arcs are created between jobs of the same batch) and batch sequences on the same tool. Bellman's algorithm is used to calculate the start dates of operations and to detect infeasible solutions. Note that at most $\sum_{j=1}^{n_i} \sum_{k \in \mathcal{M}_{ij}} 2\nu_k + 1$ insertion positions are tested per inserted lot. Thereafter, the algorithm described above will be called Priority-rule Based Insertion Algorithm (PBIA).

5.3. Improving the initial solution by iterative sampling

As shown in the previous section, a solution can be computed with PBIA based on a list of jobs. Our first iterative sampling algorithm, called Pseudo-Random Iterative Algorithm by Priority-rule Based Insertion (PRIA-PBIA), consists in applying PBIA on a list that is only moderately changed compared to the list used in Section 5.2. This will be done by, when the list is constructed, randomly selecting a job in the set of jobs not already selected that are close regarding the ranking criteria (minimum maximum time lag remaining, minimum release date and maximum job priority). The goal is to only allow limited perturbations of the initial list.

On the contrary, in our second iterative sampling algorithm called Random Iterative Algorithm by Priority-rule Based Insertion (RIA-PBIA), PBIA is applied on a list of jobs that is entirely randomly constructed. Hence, any list of jobs can be generated. The interest of RIA-PBIA is that very different solutions can be attained. Numerical experiments in Section 6 show that, as expected, the quality of the solutions obtained with RIA-PBIA is very variable. However, better solutions than the ones obtained with PRIA-PBIA can sometimes be obtained.

5.4. Simulated Annealing

Simulated annealing (SA) belongs to the class of randomized local search algorithms and has been developed by (Kirkpatrick *et al.* 1983) to handle hard combinatorial problems. The use of simulated annealing supposes the definition of a neighborhood. Our neighborhood is based on the disjunctive graph representation and is defined by the following moves:

- (1) "Batch move". A batch is randomly moved (both the machine and the position can change),

- (2) "Operation move". An operation is randomly moved in an existing batch or a new batch is created (both the machine and the position can change),
- (3) "Operation switch". Two batches with the same recipe are randomly selected, and two randomly selected operations are switched.

In our implementation, 50% of the considered moves are batch moves, 25% are operation moves and 25% are operation switches. According to randomly generated moves, we proceed as follows. All random selections are made according to the uniform law. If a move is impossible due to a constraint violation, we restore the previous solution and try another move. Each neighbor solution is evaluated by means of the longest path computations discussed in Section 5.1.

The algorithm starts with an initial solution s_0 , and then tries to find better solutions by searching in its neighborhood (obtained by the moves described above) and applying a stochastic acceptance criterion. When a neighbor (a new solution s) of s_0 is selected, the difference $\Delta f = f(s) - f(s_0)$ is calculated. If Δf is negative, the neighbor s replaces the current solution s_0 . Otherwise, the neighbor s is accepted with a probability based on the Boltzmann distribution $P_{accept}(\Delta f) \approx \exp(\frac{-\Delta f}{kT})$, where k is a constant and the temperature T is a control parameter. This temperature is gradually lowered following a geometrical function $g(T)$: $g(T) = \alpha T$ with $\alpha < 1$.

6. Computational experiments

We coded the proposed algorithms in Java and we tested them on a 1 GigaOctet RAM and 3.4 GigaHertz processor computer. We conducted two types of experiments. The first type corresponds to actual fab data and consists in comparing the constructive initial solution obtained by PBIA with the solutions determined with the pseudo and random lists and Simulated Annealing (SA). In the second type of experiments, we compare a slightly modified version of PBIA to an algorithm of the literature for scheduling jobs on parallel batch machines with incompatible job families and unequal ready times proposed in (Mönch *et al.* 2005), as this problem is close to the one tackled in this paper.

6.1. Experimental tests on actual fab data

These tests have been performed on actual instances issued for two months of production: Month A and Month B. There are 700 jobs yielding a total of 1400 operations with about 50 different recipes to schedule on 70 furnaces and 12 cleaning machines. Each furnace has a capacity of 4 or 6 lots and each cleaning machine of 2 or 4 lots. The time needed to load and unload a batch varies between 10 and 30 minutes. The minimum and maximum time lags vary from 10 minutes to 4 hours. The target time horizon is 24 hours. The weights of the components of the objective function have been defined both to normalize the different indicators and to take account of the user preferences. For the experiments, we selected $\alpha = 601$, $\beta = 1500001$ and $\gamma = 41$.

The number of replications is 5 for the simulated annealing algorithm and 20 for the pseudo and random lists. The computational time of the simulated annealing algorithm for one instance does not exceed 5 minutes and is limited to 1 minute for the constructive heuristic and the random and pseudo lists. The percentage is calculated on the average relative improvement brought by the considered method over the reference solution obtained by the initial constructive heuristic (initial), i.e. $\frac{\text{Method solution} - \text{Initial solution}}{\text{Initial solution}}$.

In Tables 2 and 3, we display the objective function solution values (obj), the number of moves (f_{mov}), the batching coefficient (f_{batch}) and the X-factor (f_{X-fac}) obtained from the three methods: Simulated Annealing (SA), Pseudo (PRIA-PBIA) and Random (RIA-PBIA) algorithms on the basis of solutions obtained by PBIA (Initial). It is important to note that the Simulated Annealing algorithm starts from the best solution of (PRIA-PBIA) and (RIA-PBIA). The best values obtained on each line when comparing f_{mov} (maximum), f_{batch} (maximum), f_{X-fac} (minimum) and Obj. (maximum) for Simulated Annealing (SA), Pseudo-Random (PRIA-PBIA), Random (RIA-PBIA) and Initial solution (Initial) are also highlighted in bold.

The results obtained with the iterative sampling algorithms PRIA-PBIA (Pseudo-Random) and RIA-PBIA (Random) are rather disappointing for the two considered months (Months A and B). The indicators are most often worse on average, and are rarely improved when analyzing in details the various instances. This shows that the ranking of the jobs in the initial list used in PBIA is relevant, and helps to provide quite good results. On the other hand, in most of the cases, we are able to substantially improve the initial solution with the simulated annealing algorithm. An improvement of 47.05% on the number of moves f_{mov} is obtained for Month A (resp. 6.6% for Month B), of 33.04% on the batching coefficient f_{batch} (resp. 4.15% for Month B), f_{X-fac} increases by 41% (resp. by 4.07% for Month B) and the objective function (Obj.) is improved by 11.13% (resp. 12.61% for Month B).

The primary objective of this study was to develop and propose an efficient scheduling algorithm to support fabrication operators and improve the main indicators in the diffusion area. The comparison has been done before and after applying our algorithm (PBIA) on the data for the two months. For confidential reasons, we are not allowed to provide the real values of the fab. This is why we give results in percentages on two types of machines. Two indicators are presented: The X-factor and the batching coefficient. For the first month, the X-factor on the Type 1 machines is improved by 26% and by 17% for the Type 2 machines. The batching coefficient is also improved by 20% for the Type 1 machines and 29% for the Type 2 machines. For the second month, the X-factor is improved by 36% for the Type 1 machines and 23% for the Type 2 machines. On the other hand, the batching coefficient is deteriorated by 6% for the Type 1 machines and an improvement of 2% is obtained on the Type 2 machines. Our algorithm has been implemented and is currently running. Substantial productivity improvements have been achieved in the diffusion area of the plant thanks to the Priority-based Insertion algorithm (PBIA).

6.2. Experimental tests on data from (Mönch et al. 2005)

We compare our algorithm (PBIA) to an algorithm proposed in (Mönch et al. 2005) for a simplified version of our problem, namely the scheduling problem of jobs on parallel batch processing machines with incompatible job families and unequal ready times. We show through experimental tests that our constructive heuristic PBIA, designed for the specific problem of batching and scheduling in a diffusion area, outperforms the heuristic described in (Mönch et al. 2005) on many instances for the problem of minimizing the Total Weighted Tardiness.

The problem studied in (Mönch et al. 2005) has the following characteristics:

- Jobs of the same family have the same processing time,
- All the batch processing machines are identical in nature,
- Once a machine is started, it cannot be interrupted, i.e. no preemption is allowed.

Inst.	Simulated Annealing			Pseudo-Random (PRIA-PBIA)			Random (RIA-PBIA)			Initial		
	f_{mov}	f_{batch}	f_{X-fac}	Obj.	f_{mov}	f_{batch}	f_{X-fac}	Obj.	f_{mov}	f_{batch}	f_{X-fac}	Obj.
M1D1	18812	0.75	2.48	0.86	14248	0.79	2.56	0.79	14102	0.75	2.49	0.80
M1D2	13910	0.69	2.13	0.85	13571	0.65	2.26	0.76	13227	0.68	2.30	0.74
M1D3	14659	0.72	2.59	0.80	14233	0.72	2.71	0.74	14622	0.73	2.72	0.76
M1D4	18068	0.79	2.49	1.06	17509	0.77	2.58	0.99	16930	0.76	2.64	0.92
M1D5	16941	0.77	2.78	0.92	16291	0.74	2.99	0.80	16463	0.75	2.98	0.81
M1D6	17861	0.78	2.54	1.04	17091	0.75	2.72	0.92	17352	0.76	2.64	0.96
M1D7	18812	0.79	2.41	1.12	17466	0.77	2.46	1.02	17318	0.77	2.61	0.95
M1D8	17919	0.78	2.86	0.95	17177	0.77	2.94	0.88	16643	0.79	3.06	0.85
M1D9	18759	0.80	3.04	0.98	18334	0.79	3.22	0.89	17534	0.78	3.27	0.81
M1D10	16296	0.79	2.82	0.89	15670	0.77	2.96	0.81	15191	0.78	3.03	0.74
M1D11	16016	0.76	2.78	0.86	14986	0.73	2.86	0.75	15085	0.76	2.90	0.75
M1D12	16554	0.79	3.01	0.87	15853	0.76	3.05	0.77	15652	0.77	3.06	0.76
M1D13	16899	0.82	2.66	0.99	15933	0.78	2.72	0.86	15779	0.78	2.74	0.86
M1D14	16540	0.75	2.45	0.97	15891	0.73	2.54	0.87	15276	0.72	2.54	0.71
M1D15	16839	0.81	2.75	0.96	15886	0.77	2.89	0.84	15693	0.78	2.88	0.82
M1D16	14132	0.69	2.31	0.82	13399	0.67	2.44	0.73	13253	0.68	2.55	0.69
M1D17	15994	0.76	2.36	0.97	15047	0.74	2.42	0.87	15103	0.74	2.48	0.86
M1D18	15138	0.77	2.51	0.90	13991	0.74	2.72	0.76	14347	0.76	2.72	0.77
M1D19	15846	0.79	2.67	0.91	14766	0.74	2.81	0.78	14735	0.79	2.83	0.77
M1D20	17563	0.81	2.87	0.96	16223	0.78	3.00	0.80	15890	0.77	3.15	0.75
M1D21	17264	0.80	2.43	1.05	16389	0.76	2.51	0.94	16019	0.75	2.54	0.86
M1D22	17248	0.76	2.45	1.00	16402	0.73	2.53	0.90	16859	0.74	2.55	0.92
M1D23	17083	0.80	2.44	1.04	16287	0.75	2.52	0.93	16024	0.78	2.62	0.90
M1D24	14153	0.77	2.56	0.83	13506	0.74	2.78	0.71	13257	0.76	2.77	0.72
M1D25	14998	0.75	2.47	0.88	14381	0.70	2.60	0.76	14262	0.72	2.57	0.77
M1D26	15972	0.78	3.05	0.81	14485	0.74	3.05	0.69	14685	0.77	3.19	0.64
M1D27	17326	0.82	2.56	1.04	16203	0.77	2.76	0.88	16576	0.80	2.76	0.89
M1D28	18231	0.81	2.89	0.99	17556	0.78	2.94	0.90	16658	0.79	3.00	0.84
M1D29	17627	0.81	3.39	0.83	15770	0.76	3.52	0.65	15779	0.79	3.64	0.65
M1D30	17187	0.79	3.16	0.86	16574	0.76	3.36	0.74	16577	0.79	3.34	0.78
M1D31	17395	0.80	3.50	0.79	16183	0.77	3.60	0.68	16648	0.79	3.56	0.70
Avg.	16573	0.78	2.69	0.93	15719	0.75	2.81	0.82	15598	0.76	2.84	0.80

Table 2. Results on actual fab instances of month A

To solve this NP-hard problem, the authors propose two different decomposition ap-

	Simulated Annealing					Pseudo-Random (PRJA-PBIA)					Random (RIA-PBIA)					Initial				
	Inst.	f_{mov}	f_{batch}	f_{X-fac}	Obj.	f_{mov}	f_{batch}	f_{X-fac}	Obj.	f_{mov}	f_{batch}	f_{X-fac}	Obj.	f_{mov}	f_{Batch}	f_{X-fac}	Obj.			
M2D1	16059	0.79	0.79	2.57	0.94	14878	0.79	2.63	0.85	14205	0.78	2.68	0.78	15414	0.77	2.60	0.90			
M2D2	16650	0.79	0.79	2.31	1.05	15534	0.76	2.49	0.90	15189	0.76	2.42	0.87	16176	0.75	2.41	0.96			
M2D3	16681	0.78	0.78	2.36	0.98	15165	0.76	2.42	0.89	14954	0.78	2.50	0.84	15015	0.73	2.43	0.88			
M2D4	15407	0.81	0.81	2.61	0.92	14283	0.78	2.63	0.83	13676	0.79	2.72	0.75	14583	0.77	2.58	0.86			
M2D5	15432	0.78	0.78	2.21	1.00	14286	0.75	2.32	0.86	14607	0.77	2.26	0.92	14360	0.73	2.31	0.88			
M2D6	12754	0.75	0.75	2.57	0.74	11241	0.71	2.75	0.57	11601	0.71	2.66	0.58	10992	0.73	2.67	0.61			
M2D7	16313	0.80	0.80	2.60	0.96	15189	0.77	2.78	0.83	14660	0.79	2.78	0.80	15582	0.76	2.76	0.86			
M2D8	16659	0.83	0.83	2.74	0.99	15402	0.82	2.85	0.86	14294	0.79	2.89	0.73	15787	0.80	2.81	0.90			
M2D9	16453	0.79	0.79	2.46	0.99	14809	0.75	2.53	0.86	13795	0.76	2.53	0.76	15428	0.75	2.52	0.90			
M2D10	15893	0.78	0.78	2.80	0.88	14907	0.76	2.88	0.76	13777	0.76	3.00	0.68	15251	0.76	2.91	0.80			
M2D11	13123	0.74	0.74	2.62	0.74	12039	0.74	2.70	0.63	12512	0.73	2.65	0.62	12225	0.72	2.71	0.66			
M2D12	13142	0.77	0.77	2.66	0.75	11253	0.75	2.65	0.65	11573	0.75	2.63	0.62	12451	0.75	2.85	0.67			
M2D13	14496	0.82	0.82	3.06	0.77	13683	0.79	3.15	0.68	12913	0.79	2.84	0.66	13810	0.79	3.11	0.70			
M2D14	14430	0.82	0.82	2.80	0.84	13149	0.79	2.78	0.74	13238	0.82	3.04	0.67	13586	0.78	2.88	0.75			
M2D15	12341	0.75	0.75	2.61	0.71	11349	0.71	2.84	0.57	11774	0.73	2.78	0.59	11504	0.71	2.80	0.59			
M2D16	14213	0.76	0.76	2.53	0.83	12949	0.71	2.61	0.70	12827	0.74	2.63	0.69	13269	0.72	2.61	0.73			
M2D17	13400	0.72	0.72	2.54	0.76	12403	0.70	2.66	0.66	12371	0.69	2.83	0.57	12600	0.70	2.67	0.67			
M2D18	13566	0.75	0.75	2.35	0.84	12231	0.70	2.44	0.70	12725	0.72	2.54	0.68	12255	0.70	2.43	0.71			
M2D19	12153	0.76	0.76	2.80	0.66	11553	0.74	2.98	0.57	11672	0.74	2.92	0.58	11578	0.73	3.01	0.56			
M2D20	11663	0.75	0.75	2.69	0.66	10940	0.73	2.82	0.57	11165	0.75	2.95	0.53	10939	0.73	2.82	0.58			
M2D21	13457	0.74	0.74	2.41	0.81	12872	0.73	2.47	0.74	12650	0.71	2.65	0.66	12672	0.73	2.51	0.74			
M2D22	13477	0.69	0.69	2.61	0.71	13392	0.67	2.83	0.63	12819	0.68	2.87	0.60	12734	0.64	2.82	0.58			
M2D23	13647	0.69	0.69	2.80	0.67	13427	0.66	2.75	0.64	13844	0.67	2.80	0.64	13341	0.65	2.79	0.62			
M2D24	13761	0.69	0.69	2.44	0.76	13234	0.68	2.46	0.70	13328	0.67	2.46	0.71	13211	0.67	2.45	0.72			
M2D25	12721	0.68	0.68	2.33	0.73	12480	0.66	2.60	0.64	12384	0.67	2.59	0.63	12379	0.66	2.63	0.63			
M2D26	13428	0.69	0.69	2.20	0.81	12232	0.65	2.34	0.67	12600	0.65	2.36	0.68	12382	0.65	2.35	0.69			
M2D27	12270	0.67	0.67	2.45	0.68	11846	0.67	2.69	0.59	11379	0.66	2.81	0.51	11449	0.65	2.72	0.54			
M2D28	14153	0.73	0.73	2.72	0.75	13277	0.71	2.84	0.66	13474	0.70	2.89	0.63	13252	0.712	2.86	0.66			
M2D29	12795	0.71	0.71	2.74	0.67	12495	0.68	2.74	0.62	12289	0.69	2.90	0.55	12712	0.68	2.74	0.64			
M2D30	13182	0.68	0.68	2.45	0.72	12314	0.66	2.66	0.60	12136	0.66	2.69	0.57	12311	0.66	2.67	0.61			
M2D31	14244	0.74	0.74	2.57	0.80	13649	0.70	2.51	0.72	13488	0.70	2.70	0.67	13126	0.70	2.59	0.71			
Avg.	14108	0.75	0.75	2.57	0.81	13176	0.73	2.67	0.70	13030	0.73	2.71	0.67	13302	0.72	2.68	0.72			

Table 3. Results on actual fab instances of month B

proaches. The first approach constructs fixed batches, then assigns these batches to the

Average standard deviations				
Simulated Annealing				
	f_{mov}	f_{batch}	f_{X-fac}	Obj
Month A	0.51%	0.62%	0.62%	1.01%
Month B	0.93%	0.50%	1.09%	1.44%
Pseudo-Random (PRIA-PBIA)				
	f_{mov}	f_{batch}	f_{X-fac}	Obj
Month A	1.76%	0.58%	1.05%	2.52%
Month B	1.73%	0.60%	0.99%	2.21%
Random (RIA-PBIA)				
	f_{mov}	f_{batch}	f_{X-fac}	Obj
Month A	3.93%	1.60%	2.26%	5.76%
Month B	4.21%	1.74%	2.57%	6.33%

Table 4. Average standard deviations for Months A and B

machines using a genetic algorithm (GA) and, finally, sequences batches on each machine. The second approach first assigns jobs to machines using a GA, then constructs the batches on each machine for its assigned jobs and, finally, sequences the batches. (Mönch *et al.* 2005) show in their experiments that the algorithm GA 2 BATC-II, which belongs to the second type of approach, provides better results on average. We conducted experiments on the (randomly generated) 162 instances with the same computer than the experiments in Section 6.1.

Let us recall that, in this section, the objective function is the Total Weighted Tardiness and that the goal is to compare the Total Weighted Tardiness obtained with our heuristic (PBIA) to the algorithm GA 2 BATC-II proposed in (Mönch *et al.* 2005). Since the input of PBIA is a list and the calculation for one list is fast, we kept the best solution obtained with the two following lists. In the first list, jobs are ordered by increasing order of their due dates and, in the second list, jobs are ordered by decreasing order of their priorities. Starting from the best solution, we apply some local improvements (see Section 5.3). Table 5 shows our results and compares them with the ones obtained with GA 2 BATC-II.

	GA 2 BATC II		PBIA		Nb. of times PBIA outperforms GA 2 BATC-II
	Avg. Obj. func.	Time (sec.)	Avg. Obj. func.	Time (sec.)	
Machines					
m=3	412.23	34210	411.14	218	29/54
m=4	300.13	28241	278.08	168	43/54
m=5	230.61	19198	206.13	149	46/54
Batch size					
B=4	389.08	17303	367.57	140	59/81
B=8	239.57	37129	229.33	216	59/81

Table 5. Comparison between our proposed algorithm and one of the best algorithms of (Mönch *et al.* 2005)

From Table 5, we notice that, on average as well as for the case of $m = 3$, $m = 4$ and $m = 5$, our heuristic (PBIA) performs better in terms of objective function and

computational times. The computational times of our heuristic are more than 100 times smaller than those of GA 2 BATC-II. Among the 162 tested instances, PBIA outperforms GA 2 BATC-II on 118 instances (29 out of 54 for $m = 3$, 43 out of 54 for $m = 4$ and 46 out of 54 for $m = 5$). Furthermore, for a batch size of 4, PBIA outperforms GA 2 BATC-II for 59 instances out of 81 and, for a batch size of 8, also on 59 instances out of 81.

7. Concluding remarks

We proposed a model and methods based on a disjunctive graph representation for a batching and scheduling problem in a semiconductor manufacturing factory while taking into account complex constraints and optimizing multiple measures. A constructive algorithm has been proposed to solve the problem, local search improvements based on the disjunctive graph representation have been defined and a simulated annealing algorithm has been developed. The computational tests made on real instances of the factory showed that good solutions are obtained fast. For the industry, very substantial productivity improvements have been achieved in the diffusion area and also on the overall fab thanks to the use of the proposed algorithm named Priority rule-Based Insertion algorithm (PBIA).

With adjustments, PBIA has been embedded in a software used by the industry. The use of a disjunctive graph brings significant improvements for interactive scheduling at the fab level. A prototype software includes the off-line batching and scheduling phase, and also an interactive module with a graphical user interface that allows decision-makers to test modifications and validate options on the proposed plan.

The simulated annealing algorithm significantly improves the different criteria (number of moves, batching coefficient and X-factor) in comparison with the initial constructive algorithm. We also compared our approach to an algorithm designed for the problem of scheduling jobs on parallel batch machines with incompatible job families and unequal ready times. The computational tests showed that, for more than half of the instances, our heuristic outperforms the best algorithm in (Mönch *et al.* 2005).

This research can be extended in many ways. Other types of moves such as the simultaneous move of two jobs linked by a maximum time lag could be tested. The maximum time lags are currently hard constraints. However, in practice, some of them can be relaxed and treated as soft constraints or objectives. Another important issue would be to perform a more thorough multicriteria analysis. Computing several Pareto optimal solutions may be useful, particularly when the situation frequently changes as it is often the case in semiconductor manufacturing.

Acknowledgments

This work was part of the MEDEA+ European project HYMNE (High Yield driven MaNufacturing Excellence in sub 65 nm CMOS), partly funded by the “Ministère de l’Économie, de l’Industrie et de l’Emploi” (French Ministry of Economy, Industry and Employment).

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