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Iterated search methods for earliness and tardiness minimization in hybrid flowshops with due windows

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Abstract

In practice due dates usually behave more like intervals rather than specific points in time. This paper studies hybrid flowshops where jobs, if completed inside a due window, are considered on time. The objective is therefore the minimization of the weighted earliness and tardiness from the due window. This objective has seldom been studied and there are almost no previous works for hybrid flowshops. We present methods based on the simple concepts of iterated greedy and iterated local search. We introduce some novel operators and characteristics, like an optimal idle time insertion procedure and a two stage local search where, in the second stage, a limited local search on a exact representation is carried out. We also present a comprehensive computational campaign, including the reimplementation and comparison of 9 competing procedures. A thorough evaluation of all methods with more than 3000 instances shows that our presented approaches yield superior results which are also demonstrated to be statistically significant. Experiments also show the contribution of the new operators in the presented methods.

Keywords: hybrid flowshop, due date window, heuristics, iterated local search, iterated greedy

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1. Introduction

Production scheduling is a very important step for manufacturing industries. Production schedules obtained by manual methods or without optimization techniques are known to have ample room for improvement as commented in Framinan et al. (2014). Therefore, using optimization methods results in large gains (McKay et al., 2002; Pinedo, 2012, among others). As a result, scheduling is a very active field inside operations research. Since the mid-fifties, thousands of papers have been published. However, the application of such research developments in real industry remains rare, or at least the proportion of papers tackling with realistic production settings is much lower that those papers dealing with simplified problem settings (MacCarthy and Liu, 1993; McKay et al., 2002; Ruiz and Maroto, 2006).

Among the different types of scheduling problems, we are interested in what is probably the most commonly found situation in many industries, which is the combination of the parallel machines and flowshop problems. The addition of the two is usually referred to as hybrid flowshop and can be defined as follows: There is a set M of $m \geq 2$ production stages where $M = \{1, \ldots, m\}$. The stages are disposed in series. At each stage i, $i \in M$ we have a set M_i of m_i identical parallel machines where $M_i = \{1, \ldots, m_i\}$ and $m_i \geq 1, \forall i \in M$ and $\exists i \in M, m_i > 1$. A set N of n jobs has to be processed on the stages. More precisely, each job j, $j \in N$ visits first stage 1, then stage 2 and so on until stage m. At each stage i, each job is to be processed by exactly one of the available m_i parallel machines. As a result, a job is made up of m different tasks, one per stage. The processing time of any job j at any stage i is a positive integer denoted by p_{ij}. Jobs are processed without interruptions.

The hybrid flowshop or HFS in short has attracted a lot of interest in the literature, given its potential practical applications. As such, there are several reviews published. Some of them are Linn and Zhang (1999), Vignier et al. (1999), Wang (2005), Quadt and Kuhn (2007) and more recently Ribas et al. (2010) and Ruiz and Vázquez-Rodríguez (2010). According to these last two most recent hybrid flowshop reviews, by far the most commonly studied optimization criterion is the minimization of the makespan or ($C_{\max}$), defined as $C_{\max} = \max_{j=1}^{n} C_j$ where C_j is the time at which job j is finished at stage m. C_j is commonly referred to as the completion time of job j. The HFS with makespan criterion can be represented as $((PM^{(i)})_{i=1}^{m})//C_{\max}$, following the well known and accepted three field notation of Graham et al. (1979) and

the extension for hybrid flowshops proposed by Vignier et al. (1999). Note that there are further assumptions stemming from the flowshop nature of the problem, these are well known and are detailed elsewhere, for example in Naderi et al. (2010) or in Framinan et al. (2014). In the HFS for each job and stage we have to decide to which machine the job is assigned. Then, for each machine at each stage, a sequence for the processing of the assigned jobs has to be determined. The simplest possible HFS with only two stages where one stage has one single machine and the other has just two parallel machines was shown to be $\mathcal{NP}$-Hard by Gupta (1988). As a result, the best state-of-the-art exact techniques can only cope with small problems with few stages, machines and jobs. For real-sized problems metaheuristics are currently the most promising solution approach.

While makespan minimization is the most studied objective in the scheduling literature, accounting for more than 60% of the published papers in the HFS according to the study of Ruiz and Vázquez-Rodríguez (2010), it is not the most appropriate objective to study nowadays. As explained in Framinan et al. (2014), makespan minimization increases machine utilization, which made sense in the early days of manufacturing where costs had to be minimized and production used to be the bottleneck. Presently, service level objectives are much more important. We define by d_j the due date of job j, $j \in J$. If $C_j > d_j$ then job j is tardy by $C_j - d_j$ units of time. The tardiness of job j is $T_j = \max\{C_j - d_j, 0\}$ and the total tardiness objective is $TT = \sum_{j=1}^{n} T_j$. About 6% of the published research in HFS considers this objective. Additionally, not all jobs are equally important. Therefore, we can use a weighted tardiness version by defining w_j as the weight of job j, $j \in J$ and the total weighted tardiness objective as $TWT = \sum_{j=1}^{n} w_j T_j$. About 2% of the reviewed literature in Ruiz and Vázquez-Rodríguez (2010) consider this objective. Note that when $C_j < d_j$ the tardiness is always 0 regardless of how small C_j is. In real problems, finishing products early results in tied up inventory and financial burden. A possibility is to account for the earliness as well, defined as $E_j = \max\{d_j - C_j, 0\}$ or $TWE = \sum_{j=1}^{n} w'_j E_j$ with weights. Note the different weight for earliness w'_j and tardiness w_j. Minimizing earliness only potentially negates the tardiness and the solution is to minimize the total earliness and tardiness or $TWET = \sum_{j=1}^{n} \left(w'_j E_j + w_j T_j\right)$. Only 1% of the reviewed literature reviewed in Ruiz and Vázquez-Rodríguez (2010) deal with this objective and most of the time without weights. Furthermore, the introduction of earliness into the objective results in a non-regular function

with enormous implications as the objective function value can be improved by arbitrarily delaying the start or completion time of jobs at machines and semi-active schedules no longer contain the optimal solution.

Due dates that represent a specific point in time are not realistic (Sabuncuoglu and Lejmi, 1999). Real due dates are actually due windows. Within the window the job is considered to be delivered on time. Therefore, we define job's j due window as $\left[d_j^-, d_j^+\right]$. Earliness and tardiness are redefined to consider this window as $T_j^{dw} = \max\{C_j - d_j^+, 0\}$ and $E_j^{dw} = \max\{d_j^- - C_j, 0\}$, respectively. The objective function that we consider is therefore the minimization of the weighted earliness and tardiness from a distinct due date window for each job, with different weights for earliness and tardiness or $TWET^{dw} = \sum_{j=1}^{n} \left(w'_j E_j^{dw} + w_j T_j^{dw}\right)$. The full problem studied is then denoted as $((PM^{(i)})_{i=1}^{m})//TWET^{dw}$ and we will refer to it as HFSDW in short. The result is a more realistic problem that might capture more easily industrial practice with the consideration of a more real objective function where not only the tardiness is considered but also earliness to avoid stocking product way before due dates. Distinct due dates for each job and different weights for earliness and tardiness allow practitioners to transfer to the objective priorities, rush orders and many other situations. Additionally, the important consideration of due windows also captures the reality where some jobs might have a tight due window of only one morning during the week whereas other jobs might be finished without penalties in longer time frames of several days. From the complexity hierarchies of objective functions given in Pinedo (2012) we conclude that the studied problem in this paper is $\mathcal{NP}$-Hard since the makespan version already belongs to this complexity class. Note that we could reach the same conclusion by considering that single machine problems with due-windows are already $\mathcal{NP}$-Hard. To the best of our knowledge, the problem studied in this paper with the $TWET^{dw}$ objective function has not been considered in the literature to this date. In this paper we propose simple methods based on Iterated Local Search and on Iterated Greedy for solving the problem. The choice of simple methods is mainly due to reasons: First, simple methods are easier to understand, implement and extend to other problem variants. They have fewer parameters and the results are easy to replicate. Second, recent studies in many different scheduling problems (Urlings et al., 2010b; Naderi et al., 2010; Framinan et al., 2014) indicate that simple methods give state-of-the-art results when compared to more complex approaches. As a result, these simple methods are easily transferable

to industries.

The remainder of this paper is organized as follows. In the next section we briefly review the related literature. Sections 3 and 4 describe in detail the proposed methods, which are later comprehensively tested in Section 5. Finally, section 6 gives some concluding remarks and further research.

2. Literature review

Only 1% of the papers reviewed by Ruiz and Vázquez-Rodríguez (2010) dealt with hybrid flowshop problems and earliness tardiness objectives (not considering due windows). This includes Chang and Liao (1994) and Liu and Chang (2000) where a $TWET$ objective is considered in a linear combination with other objectives. Janiak et al. (2007) also combine earliness and tardiness (ET) with other functions. Finke et al. (2007) presented Tabu Search methods to solve the HFS problem with ET objectives in a simplified setting where job to machine assignments are given. Khalouli et al. (2010) presented an Ant Colony Optimization (ACO) method for the HFS with $TWET$ objective. Behnamian et al. (2010a) presented a complex hybrid of population based methods, ACO, Simulated Annealing and Variable Neighborhood Search for the same problem but with the addition of sequence dependent setup times. A similar work is that of Behnamian et al. (2010b) where in this case Particle Swarm Optimization is used for a related problem of group scheduling. More recently, Behnamian and Zandieh (2013) have included learning effects into the problem. To the best of our knowledge, no other studies deal with ET in HFS. Other less closely related works are those of Jolai et al. (2009) where a no-wait hybrid flowshop with a common due date window is studied with maximization of the profit for processing jobs. Sheikh (2013) adds the earliness-tardiness criterion to the previous problem. Lastly, Pan et al. (2013) studies a real problem in the steelmaking industry considering, among other things, earliness an tardiness criterion. Most existing research in the hybrid flowshop literature considers, as mentioned, makespan or tardiness objectives, as in Jun and Park (2015) but not earliness-tardiness.

As regards due windows, most existing research has been carried out on single machine problems. Starting with the work of Cheng (1988) where the single machine with a common due window for all jobs is studied. Two machine flowshop problems with common due windows are studied in Yeung et al. (2004). The combination of hybrid flowshops and due windows, as stated previously is almost non-existent in the literature. We only find recent related

papers, the first one by Huang and Yu (2013) which study a two stage hybrid flowshop with distinct due windows and an objective function which is a linear combination of makespan, ET without weights. In the second paper, the same authors Huang et al. (2014) introduce reentry of jobs into the problem. These two papers disregard different weights for the jobs and for the earliness and tardiness and only consider two stages in the hybrid flowshop. Therefore and as we can see, the general hybrid flowshop with m stages and $TWET^{dw}$ objective has not been yet considered in the literature.

3. Iterated Local Search method

Iterated Local Search (ILS) is, as the name implies, an iterative method that, starting from an initial solution, applies a local search to obtain a local optimum. Then a perturbation is applied to escape from it. The process iterates with the application of local search again to obtain a new local optimum. The procedure is simple to code. This is ideal for scheduling problems as there are many potential variations and objectives. ILS is a natural choice for scheduling problems given its past achievements. For example, for the flowshop problem with makespan criterion, the ILS of Stützle (1998) is one of the best methods according to the evaluation of Ruiz and Maroto (2005) and as detailed in Lourenço et al. (2010) for problems like the single machine with total weighted tardiness criterion, parallel machines, jobshop, graph bipartitioning and MAX-SAT, etc. Lastly, Naderi et al. (2010) obtained the best results for a type of HFS problem with a variant of ILS. As a result, ILS is a promising approach to be applied to the HFSDW problem studied in this paper. We choose the simplest memory-less ILS variant, outlined in Figure 1. Basically all we need is a way to represent a solution for the

procedure ILS
 π_0 := GenerateInitialSolution
 π := LocalSearch(π_0)
 while (termination criterion not satisfied) **do**
  π' := Perturbation(π)
  π'' := LocalSearch(π')
  π := AcceptanceCriterion(π'', π)
 endwhile
end

Figure 1: Iterated Local Search (ILS) method (Lourenço et al., 2010).

HFSDW problem, an initialization procedure, local search, perturbation and acceptance criterion. These components are detailed in the following sections.

3.1. Solution representation

As discussed in Ruiz and Maroto (2006) there are several possible solution representations for the HFS. The most direct representation would be to have a list of jobs for every machine at each stage and then to decide the start and completion times of each job at each machine. Of course, such an exact representation would result in a very large search space and more compact approaches are desirable. Different representations for complex HFS problems were explored by Urlings and Ruiz (2007) and by Urlings et al. (2010a) where it was demonstrated that the more detailed the representation, the worse the results. Indirect representations employ surrogate heuristics as decoding procedures for completing the solution and the outcome is usually a much better solution than with a direct representation. As a result, the vast majority of the literature uses an indirect permutation representation. This job permutation indicates the order in which the jobs are going to be processed in the first stage of the HFS. The machine assignment decision is left for a dispatching rule. Many rules are proposed in Urlings et al. (2010a), however, for the HFS with identical parallel machines, the most common is the well known First Available Machine of FAM. Let us suppose we have a solution represented by a permutation of jobs $\pi = (\pi_1, \pi_2, \ldots, \pi_n)$, where π_j denotes the job occupying position j in the permutation. At the first stage we have to decide to which machine we assign job π_1. Since all machines are free, we assign it to machine 1 at the first stage. Then jobs π_2 through π_n are assigned to the machine that is available at the earliest time. When all jobs have been completed at stage 1 we proceed with stage 2 through stage m. Note that jobs can finish at different times so instead of using permutation π to decide the launch order of jobs for the remaining stages we order the jobs according to their completion times at the previous stage. Therefore, $\pi^{(i)} = \left(\pi_1^{(i)}, \pi_2^{(i)}, \ldots, \pi_n^{(i)}\right)$ is the permutation that indicates the order in which the jobs will be processed at stage i. This order is obtained by sorting the jobs in ascending completion times at stage $i-1$, where $\pi^{(1)} = \pi$. After the jobs are sorted, the FAM rule is applied again for machine assignment. It is important to note that during sorting, ties might occur with jobs having the same completion time at a given stage. To break ties, we favor the job with the smallest slack in the due date: $d_j^+ - C_{i-1,j}$. The computational complexity of this decoding method is $\mathcal{O}(n\sum_{i=1}^{m} m_i + m\log(n))$. Note that $\sum_{i=1}^{m} m_i > m$ or otherwise we would not have a HFS problem so the complexity is then $\mathcal{O}(n\sum_{i=1}^{m} m_i)$.

Let us give an example of the decoding method. We have a HFSDW problem with five jobs and two stages, where each stage contains two machines. The processing times, due windows and earliness and tardiness weights are the following:

$$(p_{i,j})_{2\times 5} = \begin{pmatrix} 4 & 3 & 6 & 2 & 1 \\ 5 & 4 & 1 & 1 & 4 \end{pmatrix}, \begin{pmatrix} d_j^- \\ d_j^+ \end{pmatrix}_{1\times 5} = \begin{pmatrix} 8 & 7 & 10 & 7 & 9 \\ 10 & 9 & 11 & 10 & 11 \end{pmatrix},$$
$$\begin{pmatrix} w'_j \\ w_j \end{pmatrix}_{1\times 5} = \begin{pmatrix} 1 & 2 & 1 & 3 & 1 \\ 2 & 1 & 2 & 1 & 3 \end{pmatrix}$$

Now let us decode solution $\pi = (1, 2, 3, 4, 5)$. At the first stage job 1 is assigned to machine 1 with completion time $C_{1,1} = 4$, job 2 to machine 2 with $C_{1,2} = 3$. Job 3 is assigned to the first available machine (2), so $C_{1,3} = 3 + 6 = 9$. For job 4 the first available machine is 1 and $C_{1,4} = 4 + 2 = 6$. For job 5 we have $C_{1,5} = 6 + 1 = 7$. For the second stage jobs do not finish in the same order in which they were launched and after ordering the jobs by increasing completion times the permutation is $\pi^{(2)} = (2, 1, 4, 5, 3)$. Applying the same process and considering the completion times at the previous stage, job 2 is assigned to machine 1 with $C_{2,2} = 7$, job 1 to machine 2 ($C_{2,1} = 9$), job 4 to machine 1 ($C_{2,4} = 8$), job 5 to machine 1 ($C_{2,5} = 12$) and job 3 to machine 1 ($C_{2,3} = 10$). We calculate the earliness and tardiness with the job completion times ($C_1 = 9$, $C_2 = 7$, $C_3 = 10$, $C_4 = 8$ and $C_5 = 12$). Jobs 1 through 4 complete within their respective due windows and the only tardy job is 5 with one unit of tardiness. Given that $w_5 = 3$ the objective function value for this solution π is $\sum_{j=1}^{n} \left(w'_j E_j^{dw} + w_j T_j^{dw} \right) = 3$. The Gantt chart for this solution is given in Figure 2.

3.2. Idle time insertion method

After decoding, jobs are scheduled as soon as possible in all machines in a semi-active schedule and many jobs will potentially complete way before their due windows, resulting in high earliness penalties. Therefore, a procedure to schedule the different tasks closer to their due windows is needed. The insertion of idle times is common in the earliness-tardiness literature. However, as we have seen from Section 2, little has been done in the HFS in this regard. We present an idle time insertion procedure that is applied after the decoding method. We will show that the proposed procedure results in optimal completion times once the sequence of jobs for each machine is given. Note that there are other exact methods to insert idle time in scheduling

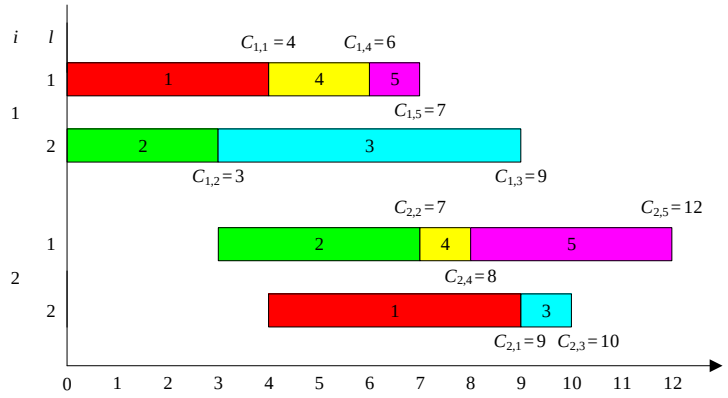


Figure 2: Gantt chart for permutation $\pi = (1, 2, 3, 4, 5)$ in the example.

problems with earliness and tardiness, most notably the one proposed by Hendel and Sourd (2007). This kind of methods are commonly referred to as timing algorithms (Sakuraba et al., 2009). However, most of these methods are not fast enough to be used for solution decoding. The procedure is loosely inspired by the Net Benefit of Movement (NBM) by Tseng and Liao (2008) on a type of flowshop lot-streaming problem and is an extension of the right sub-block move of Kedad-Sidhoum and Sourd (2010) that was initially proposed for the single machine earliness-tardiness minimization problem without due windows.

The procedure is applied to all machines in the last stage of the hybrid flowshop. Since jobs have been scheduled as soon as possible, only by forward movements or by right shifting we can improve the objective function, i.e., by the insertion of idle time before starting jobs. Given any machine in the last stage we will have jobs or blocks of consecutive jobs separated by idle times. Let us refer to any of these blocks of jobs as S_M. Now we divide the jobs in S_M into three different subsets: Jobs that are early or $S_E = \{j|E_j > 0, j \in S_M\}$, jobs that are tardy or $S_T = \{j|T_j \geq 0, j \in S_M\}$ and jobs that are on time, finishing within the due window or $S_D = \left\{j|C_j \geq d_j^-, C_j < d_j^+, j \in S_M\right\}$. Note that the minimum idle time insertion is one unit, that is why a job j with $C_j = d_j^+$ while on time and not tardy, is included in S_T since it would be tardy after inserting just one unit of idle time. Now if all the jobs in S_M are moved forward one unit, the earliness will decrease by $\sum_{j \in S_E} w'_j$. At the same time, the tardiness will increase by $\sum_{j \in S_T} w_j$. Therefore, we have a simple way of deciding if idle time should be inserted before S_M which is if the gains in earliness are greater than looses in tardiness, i.e., $\sum_{j \in S_E} w'_j > \sum_{j \in S_T} w_j$.

Actually we can keep inserting idle time until either the sets S_E or S_T change. Instead of inserting units one by one we can calculate the maximum possible idle time insertion for S_M as $\Delta_1 = \min\left\{\min_{j\in S_E}\{E_j\}, \min_{j\in S_D}\left\{d_j^+ - C_j\right\}\right\}$. Insertion of more than Δ_1 units of idle time results in either a job moving from S_D to S_T and/or a job moving from S_E to S_D. Additionally, there might be another block of jobs after S_M so we denote by Δ_2 the idle time in between both blocks. Considering all of the above, the maximum idle time insertion before a block S_M is $\Delta = \min\{\Delta_1, \Delta_2\}$. This procedure is applied to all blocks of jobs at all machines in the last stage, starting from the last job and considering one job at a time. Let us now formalize it. We denote n_l to the number of jobs assigned to machine l inside the last stage m. Also, $\gamma_l = \{\gamma_{1,l}, \gamma_{2,l}, \ldots, \gamma_{n_l,l}\}$ is the partial permutation of the jobs assigned to machine l. The pseudocode of the idle time insertion procedure is given in Figure 3. While the procedure looks intricate, it is actually very efficient.

procedure IdleTimeInsertion(π)
 for $l := 1$ **to** m_m **do**
  $j := n_l$
  while $j > 0$ **do**
   Construct a block of jobs S_M starting from job $\gamma_{j,l}$
   if there is a job to the right of S_M **then** Calculate idle time Δ_2
   else $\Delta_2 := +\infty$
   Generate S_E, S_D and S_T from S_M
   if $\sum_{j\in S_E} w'_j > \sum_{j\in S_T} w_j$ **then**
    Calculate $\Delta_1 = \min\left\{\min_{j\in S_E}\{E_j\}, \min_{j\in S_D}\left\{d_j^+ - C_j\right\}\right\}$
    Insert $\Delta = \min\{\Delta_1, \Delta_2\}$ time units before S_M
    Set $C_{m,k} = C_{m,k} + \Delta, \forall k \in S_M$
    Set $E_k = E_k - \Delta, \forall k \in S_E$
    Set $T_k = T_k + \Delta, \forall k \in S_T$
   else $j := j - 1$
  endwhile
 endfor
end

Figure 3: Idle time insertion procedure.

The outer loop goes for all machines in the last stage and the inner loop for all jobs assigned to each machine. In total there are n jobs assigned to the different machines. The calculation of Δ_1 also requires traversing all jobs so in the worst case the computational complexity of the idle time insertion heuristic is $\mathcal{O}(n^2)$.

The previous procedure can be trivially extended to insert idle times into all stages. However, for simplicity and as this would not improve the objective

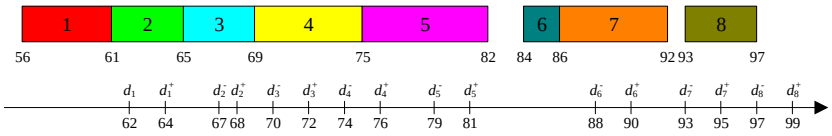
function value and would increase the computational times, it is not carried out in this paper. This idle time insertion procedure is a significant extension to parallel machines and due windows of the Net Benefit of Movement (NBM) of Tseng and Liao (2008). The authors proved NBM to be optimal for inserting idle time in the last machine of a lot-streaming flowshop. Since we apply the same principle to all machines in the last stage of the HFS, it follows that it is also optimal. We proceed now with an example with eight jobs focused on only one machine among the m_m parallel machines at the last stage m:

$$
\begin{aligned}
&(C_j)_{1\times 8} = (61, 65, 69, 75, 82, 86, 92, 97)\,,\\
&\begin{pmatrix} d_j^- \\ d_j^+ \end{pmatrix}_{1\times 8} = \begin{pmatrix} 62 & 67 & 70 & 74 & 79 & 88 & 93 & 97 \\ 64 & 68 & 72 & 76 & 81 & 90 & 95 & 99 \end{pmatrix},\\
&\begin{pmatrix} w'_j \\ w_j \end{pmatrix}_{1\times 8} = \begin{pmatrix} 1 & 2 & 1 & 3 & 1 & 2 & 1 & 4 \\ 2 & 1 & 2 & 1 & 2 & 1 & 2 & 3 \end{pmatrix}
\end{aligned}
$$

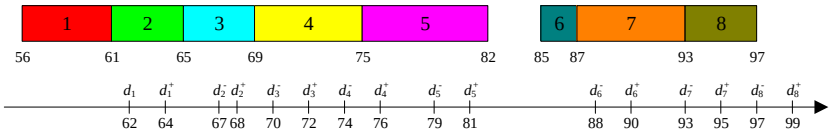
The initial schedule is shown in Figure 4a where $\pi = (1, 2, 3, 4, 5, 6, 7, 8)$. Jobs 1, 2, 3, 6 and 7 are early ($E_1 = 1$, $E_2 = 2$, $E_3 = 1$, $E_6 = 2$, $E_7 = 1$). Jobs 4 and 8 finish on time and job 5 is tardy ($T_5 = 1$). Therefore, $TWET^{dw} = 13$. The procedure starts with the last job. Job 8 finishes on time, therefore $j := j - 1$ and job 7 is considered. Job 8 is to the right of this S_M and the idle time is $\Delta_2 = 1$. Job 7 is early so we insert one unit of idle time before it. S_M is recalculated. Jobs 7 and 8 form a block and $S_M = \{7, 8\}$. Now both jobs 7 and 8 are on time. Job 6 is now considered. It is 2 units early. $\Delta_2 = 1$ due to jobs 7 and 8. After inserting one unit of idle time before job 6 we recalculate completion times, earliness and tardiness. The resulting schedule is shown in Figure 4b with an improvement in the $TWET^{dw}$ of 3 units. Now S_M has changed to $S_M = \{6, 7, 8\}$. There is no job/block to the right of this S_M so $\Delta_2 = +\infty$. From the jobs in S_M, $S_E = \{6\}$ and $S_D = \{7, 8\}$ and there are no tardy jobs. $\Delta_1 = \min\{\min\{1\}, \min\{95 - 93, 99 - 97\}\} = 1$, so $\Delta = 1$ which is what we insert before job 6, resulting in the schedule shown in Figure 4c. The solution is further improved by 2 units. After this all three jobs in the block are on time. Then we consider job 5, which is late. The next job is 4, forming a block with 5. As job 4 is on time, delaying this block is not advisable. We deal with job 3, forming a block with 4 and 5. Now $S_M = \{3, 4, 5\}$, $S_E = \{3\}$, $S_D = \{4\}$ and $S_T = \{5\}$ so we calculate if inserting idle time is profitable: $\sum_{j\in S_E} w'_j = 1$ and $\sum_{j\in S_T} w_j = 2$ so there is no gain. We include job 2 in the block which is early and its earliness weight is 2 so,

together with job 3 makes the movement advisable. The procedure continues in a similar way until all jobs are considered.

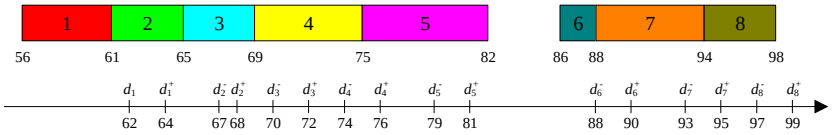
The final schedule is given in Figure 4d.



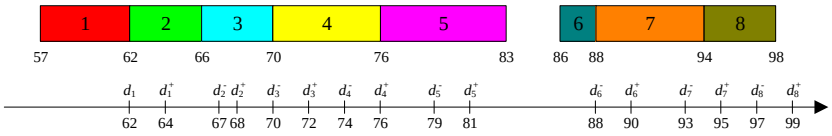
(a) Initial schedule. $TWET^{dw} = 13$.



(b) Insertion of 1 unit of idle time before job 7 and then 6. $TWET^{dw} = 10$.



(c) After inserting 1 unit of idle time before jobs 6, 7 and 8. $TWET^{dw} = 8$.



(d) After inserting 1 unit of idle time before jobs 1 to 5. $TWET^{dw} = 6$.

Figure 4: Gantt charts for the example application of the idle time insertion procedure.

3.3. Initialization

We select quick and reasonable heuristics for the initialization of the proposed methods. For problems with earliness and tardiness criterion, three dispatching rules are commonly used. The first one is the well known Earliest Due Date or EDD where jobs are simply sorted in increasing order of their due dates, i.e., the EDD produces a permutation of jobs $\pi = \{\pi_1, \pi_2, \ldots \pi_n\}$ so that $d^+_{\pi_{(j)}} \leq d^+_{\pi_{(j+1)}}, j = 1 \ldots, n-1$ where $\pi_{(j)}$ denotes the job occupying the j-th position in the permutation. The second dispatching rule is the smallest slack on the last machine or LSL. Here we consider the processing times of the jobs at the last stage and sort them according to $d^+_{\pi_{(j)}} - p_{m,\pi_{(j)}} \leq d^+_{\pi_{(j)}} - p_{m,\pi_{(j+1)}}, j =$

$1 \ldots, n-1$. The third and last rule is the overal slack time or OSL. It is a generalization of the previous rule in which the slack is calculated with respect to the processing times at all stages, i.e., $d^+_{\pi_{(j)}} - \sum_{i=1}^{m} p_{i,\pi_{(j)}} \leq d^+_{\pi_{(j)}} - \sum_{i=1}^{m} p_{i,\pi_{(j+1)}}, j = 1 \ldots, n-1$. All these heuristics are very fast needing only $\mathcal{O}(n \log n)$ steps. We calculate all three given permutations and after decoding and idle time insertion we keep the best solution as an initial schedule for the proposed methods.

3.4. Local Search

After initialization (and also after the perturbation phase inside the main loop, which is explained in next Section), a local search is carried out. We apply a two stage local search. The first one works over the indirect representation of a solution in the insertion and interchange neighborhoods. These two neighborhoods are explored inside a simple Variable Neighborhood Descent (VND) method. The application of VND with these two neighborhoods has produced state-of-the-art performance in a number of flowshop and hybrid flowshop problems as detailed in Tasgetiren et al. (2007) and Naderi and Ruiz (2010). The procedure is simple, we take a solution π and apply a single insertion movement, i.e., a job is randomly selected, extracted from its position and inserted in another random position in the sequence. The new permutation is decoded and the idle time insertion procedure is applied. If the solution is not improved, in the next iteration a random interchange of jobs is carried out. If improvements are found we go back to the insertion movement as depicted in the simple VND procedure of Figure 5. Note that we

```
procedure VND(π, loop_max)
 loop := 1
 while loop < loop_max do
  N_counter := 1
  while N_counter < 3 do
   if N_counter = 1 then π' =InsertionMovement(π)
   if N_counter = 2 then π' =InterchangeMovement(π)
   if TWET^dw(π') < TWET^dw(π) then
    π = π'
    N_counter := 1
   else N_counter := N_counter + 1
  endwhile
  loop := loop + 1
 endwhile
end
```

Figure 5: Variable Neighborhood Descent sampling local search in the permutation space.

do not explore the whole insertion and interchange neighborhoods, as doing so, together with the solution decoding and idle time insertion procedure, would result in a very slow local search mechanism. Alternatively, both neighborhoods are iteratively explored until no improvements are found for $loop_{\max}$ iterations, this being a parameter of the local search.

As we mentioned in Section 3.1, an indirect representation gives better results. Still, with an indirect representation some potentially good solutions are left unexplored. This fact was examined by Urlings and Ruiz (2007) in their shifting representation search method. For our research, instead of changing the representation we propose a second stage local search procedure that works in the exact or complete representation. A similar local search was presented by Pan et al. (2014) but for a problem with makespan criterion and no due windows.

An exact or complete representation is an ordered list of jobs for each machine at each stage. The neighborhood to explore is the result of extracting a job from a position at a given machine and inserting it into all other positions of that machine and all positions of the other machines in the same stage. In total this means there are $\prod_{i=1}^{m} n(n-1)(m_i-1)$ neighbors of a given solution considering all stages, which is challenging to explore effectively. Instead we focus on a characteristic of the HFS problem at hand. Let us picture the schedule given for the example in Figure 2. Machine 1 at stage 2 completes job 2 at time 7 ($C_{2,2} = 7$). The decoding procedure schedules job 4 afterwards since that machine is free before machine 2 (which is processing job 1) and also because jobs are selected according to the completion times at the previous stage, i.e., $\pi^{(2)} = (2, 1, 4, 5, 3)$. However, we observe that at time 7, when we schedule job 4 according to $\pi^{(2)}$, job 5 was already finished at the first stage and could have been scheduled as well. If we had done so, job 5 would have been scheduled after job 2 on machine 1 of stage 2, with a completion time of $C_{2,5} = 11$. Then jobs 4 and 3 are assigned, following the decoding procedure, to machine 2 of stage 2 with completion times $C_{2,4} = 10$ and $C_{2,3} = 11$, respectively. This schedule does not generate any idle time (which would cause problems in downstream stages) and considering these new completion times all jobs finish within their due windows and $TWET^{dw} = 0$. Therefore, the idea to exploit is not to examine the complete neighborhood, but only these situations where several jobs are ready to be scheduled and different solutions can be obtained by making different choices of which job should be scheduled first, without incurring in additional idle times. Let us now define

procedure FindLimitedNeighbors$(i, \pi^{(i)})$
$M := \varnothing$
for $j := 1$ **to** $n - 1$ **do**
Find first available machine $l^* = \underset{l=1}{\overset{m}{\operatorname{argmin}}} \{\varepsilon_l\}$ at stage i
$h := j + 1$
while $C_{i-1,\pi_h^{(i)}} \leq \varepsilon_{l^*}$ **do**
$\delta^{(i)} :=$ exchange jobs $\pi_j^{(i)}$ and $\pi_h^{(i)}$in permutation $\pi^{(i)}$
$M := M \cup \left\{\delta^{(i)}\right\}$
$h := h + 1$
endwhile
Assign job $\pi_j^{(i)}$ to machine l^*
$C_{i,\pi_j^{(i)}} = \max\left\{\varepsilon_{l^*}, C_{i-1,\pi_j^{(i)}} + p_{i,\pi_j^{(i)}}\right\}$
$\varepsilon_{l^*} = C_{i,\pi_j^{(i)}}$
endfor
end

Figure 6: Procedure to find limited neighbors used in the decoding.

this limited neighborhood structure. As stated, $\pi^{(i)} = \left(\pi_1^{(i)}, \pi_2^{(i)}, \ldots, \pi_n^{(i)}\right)$ is the job permutation generated for stage i after sorting the jobs by their completion times at stage $i - 1$, where $i \geq 2$. Recall that the decoding procedure will assign jobs to the first available machine at stage i following permutation $\pi^{(i)}$. We define by ε_l the availability time of machine l inside stage i (the time at which it completed its last assigned job). Therefore, the machine with the earliest availability time is $l^* = \underset{l=1}{\overset{m}{\operatorname{argmin}}} \{\varepsilon_l\}$. Let us assume that from this permutation and at the earliest availability time among all machines, jobs $\pi_j^{(i)}, \pi_{j+1}^{(i)}, \ldots, \pi_{j+k}^{(i)}$ were completed in stage $i - 1$ before ε_{l^*}, i.e., $C_{i-1,\pi_h^{(i)}} \leq \varepsilon_{l^*}, \forall h \in j, j+1, \ldots, j+k$. Then a neighboring solution of $\pi^{(i)}$ is the one that results from exchanging jobs $\pi_j^{(i)}$ and $\pi_{j+k}^{(i)}, \forall j \in 1, \ldots, k$ in the permutation $\pi^{(i)}$. All these neighbors can be extracted easily during the decoding method by using the algorithm depicted in Figure 6. The second stage local search based on this neighborhood consists of extracting and evaluating all M neighbors stage by stage. The complete procedure is detailed in Figure 7. The limited local search is applied only once after the VND search has obtained a complete solution. At every step, the idle time insertion procedure is applied. The local search step given in the pseudocode of Figure 1 is just the consecutive application of the VND given in Figure 5 and the local search based on the limited exact representation of Figure 7.

procedure LimitedLocalSearch(π)
 for $i := 2$ **to** m **do**
  $M :=$FindLimitedNeighbors$(i, \pi^{(i)})$
  while $|M| > 0$ **do**
   $\delta^{(i)} :=$ extract permutation from M
   Schedule stage i according to $\delta^{(i)}$
   Schedule stages $i+1, i+2, \ldots, m$ using the decoding method
   if $TWET^{dw}(\delta^{(i)}) < TWET^{dw}(\pi)$ **then** $\pi^{(i)} = \delta^{(i)}$
  endwhile
 endfor
end

Figure 7: Second stage local search based on the limited exact representation space.

3.5. Perturbation

The perturbation step is central to the ILS procedure (Lourenço et al., 2010). The perturbation disrupts the solution, moving it away in the solution space, to a new region, with the hope of finding a higher quality solution. We combine the simplicity of the random movements presented in Stützle (1998) with the enhancements given in Naderi et al. (2010). More precisely, we carry out a random number ω of job insertions and interchanges in the permutation of a given solution. As a result, the new perturbed solution is usually worse than the original solution. In order to avoid this problem we direct the perturbation. The previous operator is performed ϖ times, henceforth obtaining ϖ different solutions. All of them are decoded and the idle time insertion procedure is applied. The perturbed solution with the best $TWET^{dw}$ value is chosen for the next iteration. As shown in Naderi et al. (2010), this perturbation operator resulted in a much more effective algorithm. Increasing the value of ϖ too far has a strong effect on computational time. Furthermore, it is expected that ϖ will interact with the number of movements ω. Therefore, both factors will be calibrated in later sections.

3.6. Acceptance Criterion

At each loop the incumbent solution is perturbed and improved by a local search. This improved solution, referred to as π'' in Figure 1, might be better or worse than the incumbent solution π. Accepting only better solutions results in algorithms that get easily stuck in strong local optima. The simplest acceptance criterion for ILS is the one presented in Stützle (1998) where worse solutions are accepted according to a simplified constant temperature simulated annealing-like function. This temperature depends on the processing

times and number of machines as follows: $Temp = T\frac{\sum_{j=1}^{n}\sum_{i=1}^{m} p_{ij}}{10\cdot\sum_{i=1}^{m} m_i}$ where T is a parameter to calibrate. Many studies, like Stützle (1998) or more recently Pan and Ruiz (2014) have demonstrated in statistical experiments, the robustness of the T parameter for different scheduling problems.

We introduce a new improved operator. The importance of the acceptance criterion should not be underrated. After a number of improvement moves, every iterative method spends a large percentage of the CPU time with non-improving solutions. The new operator is based on tournament selection. We keep a list of historical solutions which at first contains the initial one (after local search). Then if π'' is better than the best solution found so far, the list is cleared. If π'' is worse than the incumbent π, it is appended at the end of the list. Then, using a parameter θ we randomly select, without repetition, θ solutions from this list and carry out a θ-tournament for selecting the incumbent solution for the next iteration, i.e., the best solution among the θ randomly picked ones from the historical list is selected. As we can see, the value of θ is a direct parameter for controlling the intensification since a very large value of θ is similar to only accepting better solutions. If at a given moment the list of historical solutions contains less than θ elements, the selection operator always results in the best solution found so far. As with the other parameters, the value of θ will be calibrated.

4. Iterated Greedy approach

In this paper we also propose an adaptation of the Iterated Greedy (IG) method of Ruiz and Stützle (2007) for the problem studied. Very few studies, apart from Urlings and Ruiz (2007), Urlings et al. (2010a) and a few more have studied IG as a methodology for solving HFS problems. IG is similar to ILS. The main difference is that instead of a perturbation operation, IG has a destruction and reconstruction operator. Therefore, it suffices to explain in detail just this difference, as all other steps are identical to those of ILS. In the destruction a complete solution has some of its elements removed. In the reconstruction, these elements are reintroduced, one at a time, following a high performance greedy heuristic, back into the solution. All other steps are identical to ILS. IG has been successfully applied to many different scheduling problems, often resulting in state-of-the-art performance. Apart from the already cited results in the permutation flowshop with makespan criterion of Ruiz and Stützle (2007) and complex hybrid flowshops of Urlings and

Ruiz (2007) and Urlings et al. (2010a), IG has also demonstrated excellent performance in parallel machines problems (Fanjul-Peyro and Ruiz, 2010), flowshops with blocking (Ribas et al., 2011), no-wait (Pan et al., 2008) amongst others. In this paper we propose a straightforward IG procedure. In the destruction operator, d jobs from the permutation are randomly selected and removed form the sequence. In the reconstruction, removed jobs are considered in the order in which they were eliminated and are reinserted, one by one, into all possible positions in the sequence. For each position the partial sequence is evaluated (and idle time inserted) and each removed job is finally placed in the position resulting in the lowest $TWET^{dw}$ value. The procedure ends when all jobs have been reinserted into the sequence.

5. Computational evaluations

We proceed with the details of the generated benchmark and the experimental setting for the computational evaluation. We will detail the competing methods that have been reimplemented and adapted to the HFSDW problem. All algorithms (proposed and competing) are calibrated and then evaluated in a complete computational campaign.

5.1. Benchmark, competing methods and experimental setting

While there exist benchmarks for HFS problems, the special feature of the HFSDW problem considered in this paper (the due windows) calls for special attention as regards due dates. Therefore, we have generated a large benchmark with four sets of instances. The first two are the small and large instance sets. The last two are the corresponding small and large calibration instances. We separate between test and calibration in order to avoid bias in the calibration. We control five factors in the instance generation: number of jobs n, number of stages m, number of identical parallel machines per stage m_i, Tardiness Factor (T), Due Date Range (R) and the width of the due window with respect to the due date (W). Processing times are uniformly distributed in the range $U[1, 99]$ and earliness and tardiness weights in the range $U[1, 9]$ as it is common in the scheduling literature. Following Potts and Van Wassenhove (1982), the due dates are generated with a random uniform distribution as $d_j = \max\left(0, U\left[\lfloor P(1-T-R/2)\rceil, \lfloor P(1-T+R/2)\rceil\right]\right)$ where, $\lfloor x\rceil$ indicates that x is rounded to the nearest integer. This procedure is common in the scheduling literature with due date based criteria, as shown in Vallada et al.

(2008). Depending on the values of T and R, the generated due dates range from easy to satisfy to hard to meet. P is a makespan lower bound. We have used the existing state-of-the-art bounds for the HFS, which are proposed by Hidri and Haouari (2011). In that paper the authors review and compare all effective bounds for the HFS and propose new ones. We use all these bounds for generating the makespan lower bound, i.e., $LB^1, LB^2, \ldots, LB^7$, LB_{VHHL} and LB_{RER}. Note that this last bound uses a complex revisited energetic reasoning procedure which needs a substantial CPU time in the large instances. The final lower bound is the maximum among these 9. With the due date we generate the due window as: $d_j^- = \max(0, \lfloor d_j - d_j \cdot H/100 \rceil)$ and $d_j^+ = \max(0, \lfloor d_j + d_j \cdot H/100 \rceil)$ where $H = U[1, W]$, i.e., the due window is centered around d_j and has a maximum width that is $W\%$ the d_j.

The combinations of the factors used for the small instances set are: $n = \{10, 15, 20\}$, $m = \{2, 3, 4\}$, $m_i = \{2, 3\}$, $T = \{0.2, 0.4, 0.6\}$, $R = \{0.2, 0.6, 1.0\}$ and $W = \{10, 20\}$. We generate 5 replicates per combination with different seeds resulting in a total of $3 \cdot 3 \cdot 2 \cdot 3 \cdot 3 \cdot 2 \cdot 5 = 1620$ small instances. For the large instances, the factors T, R and W are used with the same combinations, however, the values of the other three factors are changed as: $n = \{50, 100, 150, 200\}$, $m = \{5, 10\}$ and $m_i = \{5, 10\}$. with 5 replicates so the total number of large instances is $4 \cdot 2 \cdot 2 \cdot 3 \cdot 3 \cdot 2 \cdot 5 = 1440$.

The calibration benchmarks are simply generated by selecting, at random, one value of n, m, T, R and W from the sets of values above and creating a new different instance. This is repeated 10% of times the size of each set. Therefore, there are 162 small calibration instances and 144 large calibration instances. All instances, along with the best complete solutions found in this paper and makespan bounds are available to download at `http://soa.iti.es`.

From the literature on HFS we have selected the best 9 existing algorithms: 1) the Artificial Immune System of Engin and Döyen (2004) (AIS), 2) the Genetic Algorithm of Ruiz and Maroto (2006) (GA_R), 3) the Ant Colony Optimization of Alaykýran et al. (2007) (ACO), 4) the Genetic Algorithm of Kahraman et al. (2008) (GA_K), 5) The Improved Simulated Annealing of Naderi et al. (2009) (HSA), 6) Ant Colony Optimization of Khalouli et al. (2010) (ACO_K), the 7) the Iterated Local Search of Naderi et al. (2010) (ILS_N), 8) The Discrete Colonial Competitive Algorithm of Behnamian and Zandieh (2011) (DCCA) and 9) The Artificial Bee Colony of Pan et al. (2013) (ABC_P). The selection of these methods has several motivations. First of all they are all recent and competitive methods. Second, they represent the best performance from different and varied techniques. Lastly, they have not

been compared (at least not all of them) before. All these methods have been carefully reimplemented. They have been adapted to the HFSDW problem. It is important to note that all methods include the proposed idle time insertion procedure. Together with these methods we will test the proposed ILS and IG procedures in two versions: the ones with the existing acceptance criterion (ILS and IG) and the ones with the θ-tournament alternative (ILST and IGT).

All methods are coded in C++ and compiled with Visual Studio 2013. The methods share most important functions in the code. The calibration experiments in this paper are performed on Virtual Windows XP machines with 1 virtual processor and 1 GByte of RAM memory. A virtualization server composed of 30 blades is employed. Each blade runs two Intel XEON E5420 processors running at 2.5 GHz. and 16 GBytes of RAM memory. For the final experiments where the calibrated methods are compared, we switched to Virtual Windows 7 machines with 1 virtual processor and 2 GBytes of RAM memory. An updated virtualization server of 8 blades, each one with four AMD Opteron Abu Dhabi 6344 processors running at 2.6 GHz. and 256 GBytes or RAM is used. The reason behind this machine change is just a migration of servers while this research was being carried out.

5.2. Calibration of the proposed and competing methods

The 9 competing methods and the 4 proposed algorithms are calibrated. For the proposed ILS, ILST, IG and IGT the common factors to calibrate are the maximum number of iterations in the VND local search $loop_{\max}$ tested at 3 levels $\{100, 200, 300\}$ and the usage of the second stage local search. We call this second factor 2LS and it is tested at 2 variants, yes and no. ILS and ILST share the factors ω at 3 levels $\{100, 200, 300\}$ and ϖ at 4 levels $\{1, 10, 30, 50\}$. On the other hand, IG and IGT share only the number of destructed jobs d which is tested at 4 levels $\{1, 2, 3, 4\}$. Finally, the proposed methods with the usual temperature based acceptance criterion (ILS and IG) share T tested at levels $\{1, 3, 5, 7\}$ and the two methods with the tournament acceptance (ILST and IGT) share θ at 4 levels $\{2, 3, 4, 5\}$. Therefore, ILS and ILST have 288 combinations and IG and IGT 96. We employ the Design of Experiments (DOE) methodology. The setting is four full factorial experiments, one per algorithm. We separate the results for the small and large calibration sets so there are 8 experiments in total. The instance factors (n, m, T, R and W) are not controlled in order to have an overall picture of performance and to avoid instance-specific calibration. We

run each treatment five different times with each instance. The total number of results is therefore $288 \cdot (162 + 144) \cdot 5 = 440,640$ for ILS and ILST and $96 \cdot (162 + 144) \cdot 5 = 146,880$. The grand total of results is $1,175,040$ among all four proposed methods.

The response variable is the Relative Deviation Index (RDI) calculated as $\frac{Method_{sol} - Best_{sol}}{Worst_{sol} - Best_{sol}} \cdot 100$, where $Best_{sol}$ and $Worst_{sol}$ are the best and the worst solutions obtained throughout the calibrations for any instance respectively, and $Method_{sol}$ is the solution given by a particular combination of parameters of an algorithm. An RDI between 0 and 100 is obtained. If there is a case where $Worst_{sol} = Best_{sol}$ then RDI is replaced by 0 since it means that all methods in all replicates resulted in the same value. All results are examined with the Analysis of Variance (ANOVA) procedure which is a powerful parametric statistical tool. As such, all hypotheses were checked and met. ANOVA has been extensively used in the last 10 years in the scheduling literature to calibrate methods with success. Finally, even though ANOVA is a powerful technique and we are using a large number of results, the process is by no means a fine calibration. After all, a full factorial is no more than a type of screening design. Far more exhaustive techniques for algorithm calibration are explained in Bartz-Beielstein et al. (2010).

All methods included in this paper need a stopping criterion. While many authors stop algorithms after a number of iterations have elapsed (also generations, or solution evaluations) we think it is much more precise to stop after a predefined CPU time has elapsed. After all, the CPU time is the budget that a method has for spending. Stating that a given algorithm or configuration A is better than B if at the same time A needs much more CPU time is at best, inconclusive. The real question is, if given the same CPU time, is A still better than B? Therefore, we stop the methods in the calibration after a predefined CPU time that is equal to $t = 30nm$ milliseconds. Note that this CPU time also adjusts with the instance size so that larger instances have more time than smaller ones. We will not show the full ANOVA tables due to space constraints. The full calibration details of the proposed methods are available as on-line materials. Some means plots with 95% Tukey's Honest Significant Difference (HSD) confidence intervals are shown in Figure 8 for the large instances. Overlapping confidence intervals indicate statistical insignificance in the observed differences of the response variable among the overlapped averages. As we expected, the number of perturbations ω strongly interacts with the number of solutions generated and perturbed (ϖ). We see that small perturbations of $\omega = 1$ or large perturbations of $\omega = 3$ do not yield good

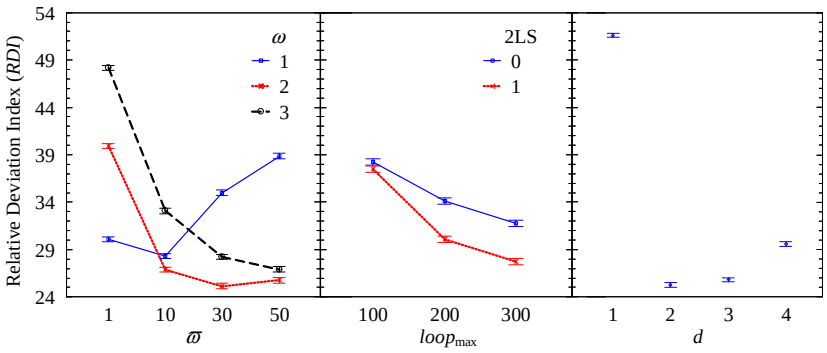


Figure 8: Means plot for the ANOVA large calibration experiment. All means have Tukey's Honest Significant Difference (HSD) 95% confidence intervals. To the left the interaction between ω and ϖ for ILST. At the center the interaction between 2LS and $loop_{\max}$ for IG and to the right the factor d for IGT.

results. Also, we see that when $\omega = 1$ generating many perturbed solutions ($\varpi = 30$) only wastes CPU time. The best is a combination of two movements and generating 30 perturbed solutions to explore around the current solution. The plot is very similar for ILS. Also we see in the middle plot of Figure 8 how the second stage local search (2LS= 1 or "yes") improves solutions considerably. However, it needs a large $loop_{\max}$ value of 200 or 300 since for a value of 100 the effect of the second stage local search is small. The fine local search is expensive and should only be applied to solutions that have already been improved by the VND procedure. From these plots we see that the improved perturbation for the ILS and the two stage local search, provide very good results. Lastly, the plot on the right of Figure 8 shows that destroying only one element in the IG methods results in bad performance. A value of $d = 2$ seems better, which is in line with the perturbation value in the ILS. Similar to most related studies (Ruiz and Stützle, 2007), the factor T is not statistically significant. As a final note, the selected factor levels after the calibration are for ILS: $\omega = 2/2$, $\varpi = 10/30$, $loop_{\max} = 100/300$, 2LS=yes/yes and $T = 7/7$ where the / separates the selected values for small and large bechmarks, respectively. The sets of values for ILST, IG and IGT are ($\omega = 2/2$, $\varpi = 10/30$, $loop_{\max} = 100/300$, 2LS=yes/yes and $\theta = 4/3$), ($loop_{\max} = 100/300$, 2LS=yes/yes, $T = 7/7$, $d = 4/3$) and ($loop_{\max} = 100/300$, 2LS=yes/yes, $d = 4/2$, $\theta = 4/2$), respectively.

As for the competing methods we have comprehensively calibrated each one of them following an identical procedure. However, no details are given

here due to space considerations. Instead, we have put together the results of the calibration as on-line materials. In these materials all experiments and results are detailed. For example, the GA_R of Ruiz and Maroto (2006) was calibrated with a full factorial design of 240 treatments and the GA_K of Kahraman et al. (2008) with 192. In total, also considering the proposed methods, we have tested 1,236 treatments for small and the same number for the large calibration benchmark. All this required a total of almost 342 CPU days of computation.

5.3. Evaluation of results and statistical analyses

For the final evaluation we use the test benchmark with 1620 small and 1440 large instances. All 13 methods are run 10 different times with different random seeds with each instance. In order to have a broader picture of performance, we use three different stopping times as ρnm milliseconds where $\rho = \{30, 60, 90\}$. This translates into 0.6 seconds in the smallest instances of 10 jobs and 2 stages when $\rho = 30$ to 180 seconds for the largest instances of 200 jobs and 10 stages if $\rho = 90$. To avoid self-correlation in the results, for each stopping time each method is run independently from the beginning. All methods have been coded in the same programming language, share identical operating environments and most important functions, like objective function evaluation and idle insertion and are run for the same CPU time on the same computer. As a result, the comparison is fair and the results completely comparable.

Considering that each one of the 13 test methods is run with 1620 small and 1440 large instances, 10 different times and with 3 different CPU time limits we have a total of $13 \cdot (1620 + 1440) \cdot 10 \cdot 3 = 1,193,400$ experimental results. Very strong conclusions can be drawn from such a large dataset. The CPU time needed for all experimentation was almost 387 CPU days. The average relative deviation index, grouped by CPU time ρ, number of jobs n and number of stages m is given in Table 1 for the small instances. The same table but for the large instances is given in Table 2. In both tables each cell is the average RDI over 1,800 results (combinations of m_i, T, R, W, instance replicate and 10 replicates per algorithm). The complete spreadsheets with all detailed results are available upon request from the authors.

Some of the adapted methods do not produce good results, despite calibration and insertion of idle times. This is the case for ACO and ACO_K. DCCA and AIS are also far from the best results. GA_R, despite being among the oldest methods tested, shows a relatively good performance. The recent

ρ	n	m	ABC_P	ACO	ACO_K	AIS	DCCA	GA_K	GA_R	HSA	ILS_N	IG	IGT	ILS	ILST
30	10	2	1.67	85.18	25.91	3.26	4.59	2.86	1.95	1.60	1.59	**0.76**	**0.76**	0.82	0.81
		3	2.60	83.06	43.40	5.05	5.81	4.10	3.00	2.50	2.43	**1.11**	**1.11**	1.14	**1.11**
		4	1.54	70.72	58.98	3.78	4.68	3.18	2.02	1.61	1.46	0.70	0.70	**0.69**	0.70
	15	2	1.56	87.81	39.85	4.19	6.33	2.81	2.36	1.00	0.95	**0.36**	**0.36**	**0.36**	0.38
		3	1.71	77.19	68.32	4.90	6.96	3.53	2.57	1.03	1.00	0.42	**0.41**	**0.41**	0.42
		4	1.36	57.73	80.72	4.38	5.69	3.23	2.35	0.81	0.80	0.32	0.30	0.32	**0.29**
	20	2	2.54	89.78	46.27	5.99	7.82	3.68	2.87	0.84	0.83	0.44	**0.41**	0.46	0.46
		3	2.31	76.57	72.80	5.85	7.09	3.82	3.01	1.02	1.06	0.57	**0.55**	0.63	0.59
		4	2.04	52.98	84.34	5.15	5.76	3.15	2.91	0.91	0.96	0.54	**0.51**	0.57	0.54
60	10	2	1.66	83.74	22.35	3.14	4.26	2.72	1.82	1.55	1.55	**0.70**	0.73	0.74	0.72
		3	2.57	82.01	37.10	4.88	5.48	4.16	2.78	2.46	2.43	**1.05**	1.06	1.07	1.08
		4	1.51	69.32	51.91	3.54	4.37	3.04	1.86	1.52	1.45	**0.63**	**0.63**	0.65	0.65
	15	2	1.32	87.23	36.26	3.58	5.70	2.66	2.06	0.86	0.86	0.25	0.26	**0.23**	0.25
		3	1.48	76.65	63.30	4.30	6.72	3.27	2.23	0.96	0.92	0.31	**0.30**	**0.30**	0.31
		4	1.18	57.16	74.97	3.87	5.50	2.99	2.01	0.72	0.71	0.21	0.22	**0.20**	**0.20**
	20	2	1.95	89.37	43.00	5.01	6.40	3.09	2.33	0.65	0.64	0.27	**0.26**	0.27	0.29
		3	1.87	76.21	68.30	5.09	6.54	3.27	2.53	0.81	0.84	0.39	**0.36**	0.42	0.40
		4	1.68	52.49	79.27	4.42	5.45	2.66	2.51	0.75	0.79	0.39	**0.36**	0.40	0.39
90	10	2	1.65	83.11	20.54	3.01	4.14	2.77	1.82	1.52	1.54	**0.67**	0.68	0.70	0.68
		3	2.53	81.27	34.02	4.72	5.35	4.07	2.73	2.43	2.43	**1.02**	1.04	1.03	1.06
		4	1.50	68.54	47.69	3.42	4.28	3.08	1.79	1.49	1.45	**0.58**	0.59	0.61	0.60
	15	2	1.23	86.70	34.40	3.32	5.61	2.47	1.88	0.81	0.82	0.21	0.22	**0.19**	**0.19**
		3	1.36	76.23	60.56	4.10	6.64	3.16	2.09	0.92	0.89	**0.24**	0.25	0.25	0.25
		4	1.11	56.78	72.04	3.71	5.43	2.72	1.87	0.69	0.68	0.17	0.19	**0.16**	0.17
	20	2	1.68	89.11	41.41	4.57	6.18	2.90	2.10	0.57	0.58	0.21	**0.20**	**0.20**	0.23
		3	1.66	75.93	65.79	4.67	6.41	2.97	2.32	0.73	0.77	0.31	**0.29**	0.33	0.32
		4	1.53	52.28	76.87	4.11	5.37	2.45	2.34	0.68	0.72	0.31	**0.30**	0.32	0.32
Average			1.73	75.01	53.72	4.30	5.72	3.14	2.30	1.16	1.15	0.49	**0.48**	0.50	0.50

Table 1: Average Relative Deviation Index (RDI) for small instances. Best results in bold.

methods ABC_P, HSA and ILS_N show good results. We see that the four proposed approaches clearly dominate all other proposals in the small instances and also dominate all other methods, except possibly HSA in the large instances. Looking at average results for the large instances, the best proposed method is ILST with an overall *RDI* of 0.31. The closest competing method is HSA with 0.41, this means that ILST is approximately 32% better than HSA. Furthermore, the ILST approach is much simpler and has less calibration parameters than HSA. Finally, from the 43,200 results given in the large instances (1440 instances, 3 termination criteria and 10 replicates) ILST gives a better solution than HSA in 28,040 cases, HSA is better than ILST in 15,129 and both tie in 31 cases.

ρ	n	m	ABC_P	ACO	ACO_K	AIS	DCCA	GA_K	GA_R	HSA	ILS_N	IG	IGT	ILS	ILST
30	50	5	2.54	22.75	92.21	15.34	5.55	3.28	2.54	0.85	0.99	0.65	0.73	0.69	**0.64**
		10	1.38	6.54	94.88	5.31	2.15	1.35	1.23	0.43	0.50	0.37	0.38	0.39	**0.35**
	100	5	2.93	14.93	94.58	12.53	4.39	3.25	1.86	0.65	0.75	0.61	0.64	0.52	**0.51**
		10	1.26	4.66	96.84	4.18	1.63	1.14	0.88	0.25	0.29	0.25	0.27	0.26	**0.24**
	150	5	2.85	12.22	95.78	11.08	4.09	3.65	1.65	0.80	0.89	0.78	0.77	0.60	**0.59**
		10	1.11	4.00	97.64	3.82	1.53	1.17	0.72	**0.21**	0.24	0.27	0.29	0.25	0.24
	200	5	2.63	10.92	96.44	10.02	4.10	3.96	1.53	0.96	1.07	0.75	0.76	**0.60**	**0.60**
		10	1.04	3.68	97.97	3.55	1.55	1.27	0.67	**0.25**	0.28	0.35	0.36	0.30	0.29
60	50	5	1.83	22.67	88.91	14.44	5.30	2.47	2.21	0.71	0.86	0.47	0.50	0.53	**0.46**
		10	1.07	6.53	92.85	5.07	2.05	1.04	1.12	0.37	0.45	0.29	0.27	0.31	**0.26**
	100	5	2.04	14.89	92.24	12.01	4.24	2.24	1.61	0.42	0.50	0.41	0.41	0.36	**0.33**
		10	0.93	4.65	95.57	4.03	1.57	0.85	0.80	0.20	0.23	0.18	0.17	0.19	**0.16**
	150	5	2.20	12.18	94.11	10.87	3.99	2.49	1.42	0.45	0.55	0.56	0.55	0.39	**0.36**
		10	0.86	3.99	96.63	3.75	1.47	0.84	0.65	**0.14**	0.17	0.18	0.18	0.17	0.15
	200	5	2.11	10.89	95.03	9.87	4.01	2.74	1.26	0.56	0.64	0.57	0.56	0.40	**0.39**
		10	0.83	3.67	97.12	3.49	1.50	0.89	0.60	**0.14**	0.17	0.25	0.26	0.20	0.19
90	50	5	1.57	22.60	87.14	13.98	5.03	2.17	2.06	0.65	0.79	0.40	0.40	0.45	**0.39**
		10	0.93	6.52	91.56	4.93	1.95	0.93	1.07	0.34	0.42	0.25	**0.22**	0.27	**0.22**
	100	5	1.59	14.87	91.05	11.70	4.08	1.82	1.51	0.34	0.41	0.31	0.29	0.28	**0.24**
		10	0.77	4.65	94.81	3.95	1.51	0.73	0.76	0.17	0.21	0.14	**0.13**	0.16	**0.13**
	150	5	1.82	12.16	93.06	10.77	3.87	1.96	1.31	0.31	0.39	0.44	0.42	0.29	**0.25**
		10	0.72	3.99	96.06	3.70	1.42	0.70	0.62	**0.11**	0.14	0.14	0.14	0.14	0.12
	200	5	1.80	10.87	94.17	9.78	3.89	2.15	1.15	0.36	0.44	0.46	0.45	0.30	**0.28**
		10	0.71	3.67	96.67	3.46	1.45	0.72	0.56	**0.10**	0.13	0.20	0.20	0.16	0.14
Average			1.56	9.94	94.31	7.98	3.01	1.83	1.24	0.41	0.48	0.39	0.39	0.34	**0.31**

Table 2: Average Relative Deviation Index (*RDI*) for large instances. Best results in bold.

Finally, we mention the effect of the proposed θ-tournament operator. The versions with this operator (IGT and ILST) seem to either give the same results, or, in the case of the large instance and ILST, better results than those with the regular temperature based acceptance criterion (IG and ILS) but the difference is not large. This needs careful examination. We are going

to check for statistical relevance of the averages shown in Tables 1 and 2. We carry out a multi-factor ANOVA where all the instance factors, as well as ρ and the type of algorithm are controlled. In the experiment for the small instances the methods ACO and ACO_K had to be removed as their deviations were so large that they were creating normality problems. Similarly, for the large instances, ACO, ACO_K and AIS were removed as well. The results of the experiment are sound. For the small instances, the differences observed in the four proposed methods IG, IGT, ILS and ILST are not statistically significant and all have a statistically equivalent performance. However, all of them are statistically better than the closest competitors HSA and ILS_N.

The average RDI values are statistically different for all the algorithms in the large instances. . Figure 9 shows the interaction between the four proposed algorithms and ρ on the left and a zoom for the four proposed methods on the right for the large instances. The statistical test confirms

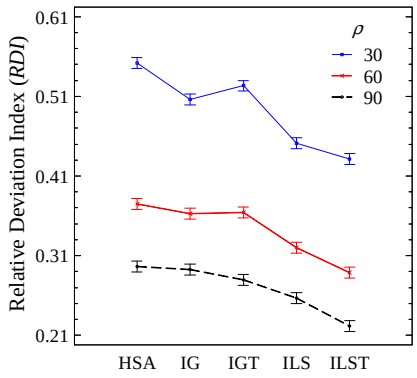


Figure 9: Interaction between the proposed methods, HSA and stopping criterion (ρ). All means with Tukey's Honest Significant Difference (HSD) 95% confidence intervals. Large instances.

that the closest competitor gives results that are statistically worse than the presented methods. As a matter of fact, it should be stressed that any of our proposed methods with the shortest processing time of $\rho = 30$ give better solutions than HSA with the largest time of $\rho = 90$. We can also observe in the zoom that the effect of the θ-tournament becomes statistically significant for the largest CPU times of $\rho = 90$. As a conclusion, ILS is slightly better than IG and in turn the θ-tournament also provides an advantage for large CPU times. Therefore, ILST is the best proposed method.

6. Conclusions and future research

In this paper we have studied hybrid flowshop problems with due windows with the minimization of the total weighted earliness and tardiness from the due window. The literature review has shown that this problem has scarcely been studied. After presenting and formalizing the problem we have proposed an Iterated Local Search and Iterated Greedy procedures. These methods are simple and have few parameters. Specific to earliness tardiness objectives is the insertion of idle time before tasks. We have also devised an optimal procedure that delays the completion of tasks by the exact amount necessary. We have also presented a key procedure, which is a two stage local search. In the first stage, a VND works with an indirect representation of a solution. In the second stage, we identify the most promising movements and work over the exact representation. This proposal, together with improvements in the acceptance criterion and perturbation constitute the core of our algorithmic contribution. In our opinion, experimentation should be complete and thorough. In order to compare our proposed methods we have reimplemented and adapted 9 high performing competing methods. Then, all procedures have been calibrated using the DOE approach. A comprehensive benchmark of more than 3000 instances has been used in a complete computational and statistical evaluation to analyze the effect of the proposed contributions and to compare with existing algorithms. Results have shown that the proposed methods, particularly those with the new θ-tournament acceptance criterion, produce the best results. There are several future research avenues. Introducing more realistic elements into the problem, like setup times, release dates, or unrelated parallel machines at each stage is a possibility. Further exploration of the effect of the different possible representations on other objectives seems also promising. Finally, we would like to call the attention of the scheduling community as to how earliness penalties are usually calculated. Delaying the last manufacturing stage (and therefore the completion time) of a job that was started at a given point in time does not reduce earliness costs in most real cases. What usually counts in when the job was started in the first stage as at that moment resources are mobilized, raw materials used, etc. Therefore, more sensible earliness costs penalties must be considered in order to make the objective function more realistic.

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