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Highlights

Iterative beam search algorithms for the permutation flowshop

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- First use of an iterative beam search for the permutation flowshop
- Simple yet efficient heuristic guidance strategies
- Bi-directional search strategy to minimize the makespan variant
- New best-so-far solutions on VRF instances (makespan, 105/160 open instances)
- New best-so-far solutions on Taillard instances (flowtime, 55/100 open instances)

Iterative beam search algorithms for the permutation flowshop

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ABSTRACT

We study an iterative beam search algorithm for the permutation flowshop (makespan and flowtime minimization). This algorithm combines branching strategies inspired by recent branch-and-bounds and a guidance strategy inspired by the LR heuristic. It obtains competitive results, reports many new-best-so-far solutions on the VFR benchmark (makespan minimization) and the Taillard benchmark (flowtime minimization) without using any NEH-based branching or iterative-greedy strategy.

The source code is available at: <https://gitlab.com/librallu/cats-pfsp>.

1. Introduction

In the flowshop problem, one has to schedule jobs, where each job has to follow the same route of machines. The goal is to find a job order that minimizes some criteria. The permutation flowshop, also called PFSP, is a common (and fundamental) variant that imposes the machines to process jobs in the same order (thus, a permutation of jobs is enough to describe a solution). The permutation flowshop has been one of the most studied problems in the literature [35, 30] and has been considered on various industrial applications [16, 42]. We may also note that the permutation flowshop is at the origin of multiple other variants, for instance, the blocking permutation flowshop [45], the multiobjective permutation flowshop [20], the distributed permutation flowshop [11], the no-idle permutation flowshop [31], the permutation flowshop with buffers [28] and many others. Regarding the criteria to minimize, we study in this paper, two of the most studied objectives: the makespan (minimizing the completion time of the last job on the last machine) and the flowtime (minimizing the sum of completion times of each job on the last machine). According to the scheduling notation introduced by Graham, Lawler, Lenstra, and Rinnooy Kan [13], the makespan criterion is denoted $F_m|prmu|Cmax$ and the flowtime criterion $F_m|prmu|\sum C_i$.

Consider the following example instance with $m = 3$ machines with $n = 4$ jobs (j_1, j_2, j_3, j_4) with the job processing time matrix P defined as follows where $P_{j,m}$ indicates the processing time of job j on machine m :

$$P = \begin{pmatrix} 3 & 2 & 1 & 3 \\ 3 & 4 & 3 & 1 \\ 2 & 1 & 3 & 2 \end{pmatrix}$$

One possible solution can be described in Figure 1. This solution has a makespan (completion time of the last job on the last machine) of 18 and a flowtime (sum of completion times on the last machine) of $8 + 11 + 16 + 18 = 53$.

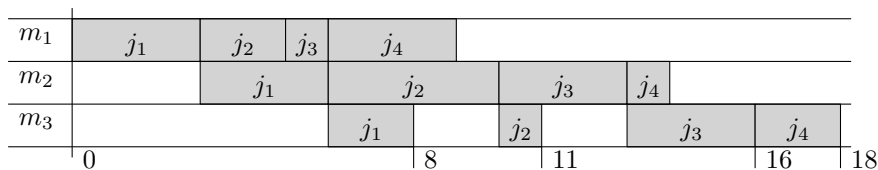


Figure 1: A solution for the example instance with a job order $\sigma = j_1, j_2, j_3, j_4$

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Regarding resolution methods, the makespan minimization permutation flowshop problem has been massively studied over the last 50 years and a large number of numerical methods have been applied.

In 1983, Nawaz, Ensore, Ham proposed an insertion based heuristic (later called NEH) [27]. This heuristic sorts jobs by some criterion (usually by a non-decreasing sum of processing times), then adds them one by one at the position that minimizes the objective function. The NEH, obtained, at the time, excellent results compared to other heuristics and can be used to perform greedy algorithms and perturbation-based algorithms as well. It has been largely considered as an essential component in order to solve large-scale permutation flowshop instances, and multiple methods have been built using it. One of the most famous ones is the Taillard's acceleration [39], that reduces the cost of inserting a job at all possible positions from $O(n^2.k)$ to $O(n.k)$. Considering these results, multiple works aim to improve the NEH heuristic [10, 26, 14, 4, 36, 44, 25] to cite a few.

The (meta-)heuristics state-of-the-art methods for the makespan minimization usually perform an iterated-greedy algorithm [38, 8]. Such algorithms start with a NEH heuristic to build an initial solution. Then, destroy a part of it and reconstruct it using again an NEH heuristic. To the best of our knowledge, the current state-of-the-art for the makespan minimization criterion is the variable block insertion heuristic [15]. The variable block insertion heuristic starts by finding an initial solution using the FRB5 heuristic [33]. It removes some block of jobs, applies a local search procedure, then reinserts the block in the best possible position. We may note that other algorithms exist to solve the makespan minimization. To cite a few, we can find some hybrid algorithms [46] (a combination of the NEH heuristic as a part of the initial population, a genetic algorithm, and simulated annealing to replace the mutation), memetic algorithms [17], an automatically designed local-search scheme [29].

The (meta-)heuristics methods for the flowtime minimization also involve the NEH heuristic, but also some other constructive methods as well. For instance, the Liu and Reeve's method (LR) [24]. This method performs a forward search (*i.e.* appending jobs at the end of the partial schedule). It was later improved to reduce its complexity from $O(n^3m)$ to $O(n^2m)$, later called the FF algorithm [6]. Later, this scheme was integrated into a beam search algorithm (more on that later) that obtained state-of-the-art performance [7]. Recently, this beam search was integrated within a biased random-key genetic algorithm as a warm-start procedure [1]. This is, to the best of our knowledge, the state-of-the-art method for the flowtime minimization.

Regarding exact-methods, a recent branch & bound [12] brought light on a bi-directional branching (*i.e.* constructing the candidate solution from the beginning and the end at the same time) combined with a simple yet efficient bounding scheme to solve the makespan minimization criterion. The resulting branch & bound obtained excellent performance and was even able to solve to optimality almost all large VFR instances with 20 machines.

Moreover, recently, an iterative beam search has been proposed and, successfully applied to various combinatorial optimization problems as guillotine 2D packing problems [22, 9], the sequential ordering problem [21] and the longest common subsequence problem [23]. This iterative beam search scheme, at the beginning of the search, behaves as a greedy algorithm and more and more as a branch & bound algorithm as time goes (it performs a series of beam search iterations with a geometric growth). It naturally combines search-space reductions from branch & bounds and guidance strategies from classical (meta-)heuristics. Considering the success of recent branch & bound branching schemes and the performance of greedy-like algorithms to solve the permutation flowshop, it would be a natural idea to combine them. However, to the best of our knowledge, it has not been studied before. This paper aims to fill this gap. For the makespan criterion, we implemented a bi-directional branching scheme and combined it with a variant of the LR [24] guidance strategy and use an iterative beam-search algorithm to perform the search. We report competitive results and find new best-known solutions on many large VFR instances (we improve the best-known solution for almost all instances with 500 jobs or more and 40 machines or more). Note that these results are interesting and new as almost all the efficient algorithms in the literature are based on the NEH heuristic or the iterated greedy algorithm. This is not the case for our algorithm as it is based on a variant of the LR heuristic and an exact-method branching scheme (bi-directional branching).

Regarding the flowtime criterion, the bi-directional branching cannot be directly applied (the bounding procedure is less efficient than for the makespan criterion). However, we show that an iterative beam search with a simple forward search (modified LR algorithm) is efficient, and, reports new best-solutions for the Taillard's benchmark (almost all solutions for instances with 100 jobs or more were improved).

This paper is structured as follows: Section 2 presents the branching schemes we implement (the forward and bi-directional search) for both criteria (makespan and flowtime). Section 3 present the guides we implement (the bound guide, the idle-time guide and mixes between these two first guides). Section 4 presents the iterative beam search

strategy and Section 5 presents the results obtained by running all variants described in this paper, showing that an iterative beam search combined with a simple variant of the LR heuristic can outperform the state-of-the-art.

2. Branching schemes

We present in this section the two branching schemes we use (*i.e.* the search tree structure): the forward search (*i.e.* constructing the solution from the beginning) and the bi-directional search (*i.e.* constructing the solution from the beginning and the end).

2.1. Forward branching

The forward branching assigns jobs at the first free position in the partial sequences (it constructs the solutions from the beginning). The root corresponds to a situation where the candidate solution contains no job (*i.e.* $c.STARTING = \emptyset$). Each of the search-tree node corresponds to the first jobs in the resulting solution. Children of a given node correspond to a possible insertion of each job that is not scheduled yet at the end of the schedule. Each node stores information about the partial candidate solution (jobs already added), the release time of each machine, and the partial makespan (resp. flowtime). A candidate solution (or node) c is considered as “goal” or “feasible” if all jobs are inserted (*i.e.* $c.STARTING = J$) and contains the following information:

- **STARTING**: vector of jobs inserted that lead to the candidate c (first jobs of the sequence we want to generate).
- **FRONTSTARTING**: vector of times where machines are first available after appending **STARTING** jobs.

Before presenting the forward children-generation, we present how to insert a job $j \in J$ in a candidate solution c (Algorithm 2.1). This insertion can be done in $O(m)$ where m is the number of machines.

Algorithm 2.1: Forward search: insertion of job j in candidate solution c (INSERTFORWARD(c, j))

Input: candidate solution (or node) c
Input: job to be inserted $j \in J$

```

1  c.FRONTSTARTING1 ← c.FRONTSTARTING1 + Pj,1
2  for i ∈ {2, ... m} do
3      if c.FRONTSTARTINGi-1 > c.FRONTSTARTINGi then
4          /* there is some idle time on machine i */
5          idle ← c.FRONTSTARTINGi-1 - c.FRONTSTARTINGi
6          c.FRONTSTARTINGi ← c.FRONTSTARTINGi-1 + Pj,i
7      else
8          /* no idle time on machine i */
9          c.FRONTSTARTINGi ← c.FRONTSTARTINGi + Pj,i
10     end
11 end
12 c.STARTING ← c.STARTING ∪ {j}
```

Algorithm 2.2 presents the forward branching pseudo-code (how to generate all children of a candidate solution c).

Algorithm 2.2: Forward search children generation from a candidate solution c (CHILDREN(c))

Input: candidate solution (or node) c

```

1  children ← ∅
2  for j ∈ unscheduled jobs do
3      children ← children ∪ INSERTFORWARD(Copy(c), j)
4  end
5  return children
```

2.2. Bi-directional branching

To the best of our knowledge, the bi-directional branching was first introduced in 1980 [32]. The bi-directional search appends jobs at the beginning and the end of the candidate solution. It aims to exploit the property of the inverse problem (job order inversed and machine order inversed). Since then, the efficiency of this scheme has been largely recognized to solve the makespan minimization optimally [2, 18, 19, 5, 3, 37]. Recently, a parallel branch & bound was successfully used to solve the makespan minimization criterion [12] using this bi-directional scheme. Multiple ways to decide if the algorithm performs a forward or backward insertion were studied (for instance alternating between a forward insertion and backward insertion). This study found out that the best way is selecting the insertion type that has the less remaining children after the bounding pruning step. Ties are broken by selecting the type of insertion that maximizes the sum of the lower bounds as large lower bounds are usually a more precise estimation.

A candidate solution (or node) c is considered as “goal” or “feasible” if all jobs are inserted (*i.e.* $c.\text{STARTING} \cup c.\text{FINISHING} = J$) and contains the following information:

- **STARTING**: vector of jobs inserted at the beginning of the partial permutation that lead to the candidate c (first jobs of the sequence we want to generate).
- **FRONTSTARTING**: vector of times where machines are first available after appending **STARTING** jobs.
- **FINISHING**: (inverted) vector of jobs inserted at the end of the partial permutation that lead to the candidate c (last jobs of the sequence we want to generate).
- **FRONTFINISHING**: vector of times where machines are no more available after appending **STARTING** jobs.

Algorithm 2.3 presents the bi-directional branching pseudo-code. We use **INSERTFORWARD** (Algorithm 2.1) to insert a job within the **STARTING** vector and **INSERTBACKWARD** that inserts a job within the **FINISHING** vector. This procedure is almost similar to **INSERTFORWARD** but iterates over machines in an inverted order ($m \rightarrow 2$ instead of $2 \rightarrow m$). It generates children of both the forward and backward search (lines 1-6), prunes nodes that are dominated by the best-known solution (or upper-bound, lines 7-8). Then, it chooses the scheme that has fewer children (thus, usually a smaller search-space) and breaks ties by selecting the scheme having the more precise lower bounds (sum of lower bounds).

Algorithm 2.3: Bi-directional search children generation from a candidate solution c (**CHILDREN**(c))

Input: candidate solution (or node) c

```

1 F ← ∅                                     /* F correspond to the children obtained by forward search */
2 B ← ∅                                     /* B correspond to the children obtained by backward search */
3 for j ∈ unscheduled jobs do
4   | F ← F ∪ INSERTFORWARD(Copy(c), j)
5   | B ← B ∪ INSERTBACKWARD(Copy(c), j)
6 end
7 F ← {c|c ∈ F if BOUND(c) < best known solution} /* removing forward nodes dominated by the UB */
8 B ← {c|c ∈ B if BOUND(c) < best known solution} /* removing backward nodes dominated by the UB */
9 if |F| < |B| ∨ (|F| = |B| ∧ ∑c∈F BOUND(c) > ∑c∈B BOUND(c)) then
10 | return F /* choosing the forward search */
11 else
12 | return B /* choosing the backward search */
13 end

```

3. Guides

In the previous section, we discussed the branching rules that define a search tree. As such trees are usually large, a way to tell which node is apriori more desirable is needed. In branch-and-bounds, this mechanism is called “bound” and also constitutes an optimistic estimate of the best solution that can be achieved in a given sub-tree. In constructive meta-heuristics, the guidance strategy is usually not an optimistic estimate which often allows finding better solutions

(for instance the LR [24] greedy guidance strategy). In this section, we present several guidance strategies for both the makespan and flowtime criteria.

3.1. Bound

We define the bound guidance strategy for the forward search and makespan minimization as follows. It measures the first time the last machine (machine m) is available and assumes that each remaining job can be scheduled without any idle time.

$$F g_1 = Cmax_{f,m} + R_m$$

The bound guidance strategy for the bi-directional search and makespan minimization is defined as follows. It generalizes the bound for the forward search by also taking into account the backward front. We may note that the bi-directional branching allows computing a better bound as all machines are relevant for this bound (compared to the forward branching bound in which only the last machine is used to compute a bound).

$$FB g_1 = \max_{i \in M} (Cmax_{f,i} + R_i + Cmax_{b,i})$$

The flowtime bound is defined as the sum of end times for each job scheduled in the forward search. Each time a job is added to the candidate solution, the flowtime value is modified.

3.2. idle time

The bound guide is an effective guidance strategy, but is known to be imprecise at the beginning of the search (*i.e.* the first levels of the search tree). Another guide that is usually considered as a part of effective greedy strategies (for instance the LR heuristic) is to use the idle time of the partial solution. Usually, a solution with a small idle time reaches good performance on both the makespan or flowtime criteria.

The idle time can be defined as follows:

$$FB g_2 = \sum_{i \in M} I_{f,i} + I_{b,i}$$

3.3. bound and idle time

As it is noted in many works [24, 7], another interesting guidance strategy is to combine both guidance strategies discussed earlier (*i.e.* the bound and idle time guides). Indeed, while the bound guide is usually ineffective to guide the search close to the root, it is very precise close to feasible solutions. Inversely, the idle time is an efficient guide close to the root but relatively inefficient close to feasible solutions. We study the *bound and idle time guide* that linearly reduces the contribution of the idle time to favor the bound depending on the completion level of the candidate solution.

The bound and idle time guide can be defined as follows, where C is a value used to make the idle time and bound comparable:

$$g_3 = \alpha \cdot g_1 + (1 - \alpha) \cdot C \cdot g_2$$

where α corresponds to the proportion of jobs added (*i.e.* 0 if no jobs are added, 1 if all jobs are added). It is defined as follows: $\alpha = \frac{|F|+|B|}{|J|}$ for the bi-directional branching or $\alpha = \frac{|F|}{|J|}$ for the forward branching.

3.4. bound and weighted idle time

Another useful remark found in greedy algorithms for the permutation flowshop problem [24] is to add additional weight to the idle time produced by the first machines at the beginning of the search (as it will have a greater impact on the objective function than the others). However, the LR heuristic cannot be directly applied in a general tree search context. Indeed, it is sometimes noted [7] that algorithms like the beam search usually compare nodes from different parents, thus, it is needed to adapt the LR heuristic guidance that only compares nodes with the same parent. We

propose two different simple yet efficient ways to implement similar ideas. The search is guided by a combination of a weighted idle time and by the bounding procedure.

The first guide, used for the forward search for the flowtime minimization is defined as follows, where I_w is the weighted idle time and $C = m \cdot \frac{\sum_{i \in M} I_i}{2}$:

$$F g_4 = \alpha \cdot g_1 + (1 - \alpha) \cdot (I_w + C)$$

At each time we add a job j to the end of the partial solution, we increase the weighted idle times as follows where v is the idle time added by the job j in machine i :

$$I_w = I_w + v \cdot (\alpha \cdot (m - i) + 1)$$

For the bi-directional branching, we present a new guidance strategy that considers the sum of idle time percentage for each front. Doing this, it allows making idle time on the first machines more important to the forward search and the idle time on the last machines more important to the backward search. The bound and weighted idle time guide for the bi-directional search is defined as follows:

$$FB g_4 = (1 - \alpha) \cdot g_1 \cdot \left(\sum_{i \in M} \frac{I_{f,i}}{Cmax_{f,i}} + \frac{I_{b,i}}{Cmax_{b,i}} \right) + \alpha \cdot g_1$$

4. The search strategy: Iterative beam search

Beam Search is a tree search algorithm that uses a parameter called the beam size (D). Beam Search behaves like a truncated *Breadth First Search (BrFS)*. It only considers the best D nodes on a given level. The other nodes are discarded. Usually, we use the bound of a node to choose the most promising nodes. It generalizes both a greedy algorithm (if $D = 1$) and a BrFS (if $D = \infty$). Figure 2 presents an example of beam search execution with a beam width $D = 3$.

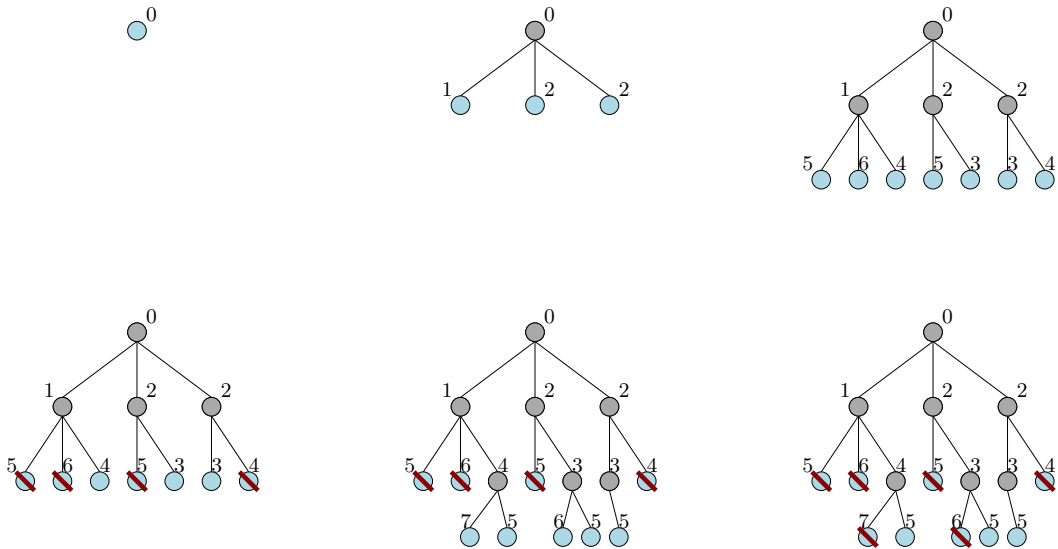


Figure 2: Beam Search Iterations with a beam width $D = 3$

Beam Search was originally proposed in [34] and used in speech recognition. It is an incomplete (*i.e.* performing a partial tree exploration and can miss optimal solutions) tree search parametrized by the beam width D . Thus, it is not an anytime algorithm. The parameter D allows controlling the quality of the solutions and the execution time. The larger D is, the longer it will take to reach feasible solutions, and the better these solutions will be.

Recently, a variant of beam search, called iterative beam search, was proposed and obtained state-of-the-art results on various combinatorial optimization problems [21, 22, 23, 9]. Iterative beam search performs a series of restarting beam search with geometrically increasing beam size until the time limit is reached. Algorithm 4.1 shows the pseudo-code of an iterative beam search. The algorithm runs multiple beam searches starting with $D = 1$ (line 1) and increases the beam size (line 8) geometrically. Each run explores the tree with the given parameter D . In the pseudo-code, we increase geometrically the beam size by 2. This parameter can be tuned, however, we did not notice a significant variation in the performance while adjusting this parameter. This parameter (that can be a real number) should be strictly larger than 1 (for the beam to expand) and should not be too large, say less than 3 or 5 (otherwise, the beam grows too fast and when the time limit is reached, most of the computational time was possibly wasted in the last incomplete beam, without providing any solution).

Algorithm 4.1: Iterative Beam Search algorithm

Input: root node

```

1  $D \leftarrow 1$ 
2 while stopping criterion not met do
3   Candidates  $\leftarrow$  {root}
4   while Candidates  $\neq \emptyset$  do
5     nextLevel  $\leftarrow \bigcup_{n \in \text{Candidates}} \text{children}(n)$ 
6     Candidates  $\leftarrow$  best  $D$  nodes among nextLevel
7   end
8    $D \leftarrow D \times 2$ 
9 end
    
```

5. Numerical results

In this section, we perform various experiments to evaluate the efficiency of the algorithms discussed in the previous sections. In Subsection 5.1, we present numerical results obtained in the makespan minimization version and Subsection 5.2, the results obtained in the flowtime minimization version. All algorithms have been implemented in C++ and executed on an Intel(R) Core(TM) i5-3470 CPU @3.20GHz with 8GB RAM. As the CPU has 4 physical cores, we ran 4 tests in parallel to obtain results faster. For both objectives, we study the ARPD (Average Relative Percentage Deviation), defined as follows:

$$ARPD_{Ia} = \sum_{i \in I} \frac{M_{ai} - M_i^*}{M_i^*} \cdot \frac{100}{|I|}$$

where I is a set of instances with similar characteristics, M_{ai} corresponds to the objective obtained by algorithm a on instance i . And M_i^* the best-so-far solution objective for instance i . The ARPD describes the performance of a given algorithm on a given instance type. A positive ARPD implies that the algorithm finds in average, solutions dominated by the best-known ones and a negative ARPD implies that the algorithm can improve on the best-known solutions.

5.1. Makespan minimization

We ran each algorithm for $m.n.45$ milliseconds where n is the number of jobs and m the number of machines as it is usually done in the literature for the makespan minimization. We evaluate our algorithms on the famous VFR set of instances [43]. That consists of sets of 10 instances with a job number $n \in \{100, 200 \dots 800\}$, a machine number $m \in \{20, 40, 60\}$. The benchmark is commonly used in the literature to evaluate the performance of optimization algorithms. Most instances with 20 machines are closed [12]. The best-so-far results are an aggregation of the results found in the literature [8, 15, 12]. Figure 3 presents the ARPD obtained on the VFR instances and makespan minimization.

	F g_1	F g_2	F g_3	F g_4	FB g_1	FB g_2	FB g_3	FB g_4
VFR100_20	18.70	3.45	3.79	3.43	2.29	11.05	9.84	0.58
VFR100_40	17.41	4.62	4.62	3.68	5.83	9.67	9.39	2.25
VFR100_60	16.54	5.18	5.07	4.79	6.35	9.50	9.52	3.68
VFR200_20	21.38	2.93	3.59	1.78	1.30	10.59	8.50	1.75
VFR200_40	21.93	4.69	4.82	2.56	5.73	14.68	14.50	0.24
VFR200_60	20.27	5.35	5.51	2.77	8.13	15.75	14.56	1.86
VFR300_20	22.44	2.02	2.72	1.72	0.83	7.40	5.53	1.43
VFR300_40	22.41	4.41	4.73	1.09	5.60	16.79	14.29	-0.80
VFR300_60	20.88	5.22	5.66	1.55	8.01	12.77	12.65	0.85
VFR400_20	22.68	1.98	2.52	1.86	0.76	4.32	3.20	1.40
VFR400_40	24.34	4.06	4.53	0.70	5.67	16.06	14.95	-0.97
VFR400_60	21.91	5.54	6.01	0.82	7.91	17.54	16.36	0.16
VFR500_20	24.42	1.57	2.43	1.63	0.50	3.51	3.01	1.30
VFR500_40	24.08	3.26	3.83	0.70	4.82	14.27	12.79	-0.86
VFR500_60	22.42	5.88	6.12	0.58	8.41	16.59	15.53	-0.59
VFR600_20	23.39	1.21	2.06	1.49	0.50	3.32	2.38	1.26
VFR600_40	24.47	3.46	3.83	0.63	5.50	16.12	14.46	-0.65
VFR600_60	22.94	5.46	5.89	0.40	7.94	13.22	12.39	-0.91
VFR700_20	24.51	1.38	2.05	1.63	0.30	2.49	1.98	1.20
VFR700_40	25.27	3.19	3.91	0.48	4.47	13.73	13.14	-0.27
VFR700_60	23.11	5.55	5.82	0.07	8.06	15.92	14.20	-1.19
VFR800_20	24.51	1.14	1.93	1.43	0.16	2.05	1.81	1.09
VFR800_40	25.12	3.30	4.08	0.32	4.18	13.95	13.42	0.09
VFR800_60	23.89	5.90	6.40	0.05	7.89	15.91	14.35	-1.25
nb new-best-known	0	0	0	20	0	0	0	104

Figure 3: Average Relative Percentage Deviation (ARPD) of all the presented algorithms on the VFR instances and the makespan minimization version. The Forward branching is denoted by F (FB for the Forward and Backward (bi-directional) branching). We remind that g_1 denotes the bound guide, g_2 the idle time, g_3 the alpha guide and g_4 the weighted alpha guide.

discussions: Regarding the forward branching procedures, we observe a significant improvement by including the idle time in the guide and obtain the best results by including a weighted idle time within the guide (similarly to the principles presented in the LR heuristic [24]). Indeed, ARPD ranges from 17% to 25% for the bound guide, and goes down between 1% to 5% for the idle time only and the guide combining the idle time and the bound. Finally, the best results for the forward search are obtained using a weighted idle time and bound guide. Sometimes with an ARPD close to 0% on large instances (meaning it competes with all the best results obtained in the literature), even finding 20 new-best-known solutions. We note that this result is interesting as this algorithm “only” combines ideas from the LR heuristic and an iterative beam search. Thus without using components present in recent meta-heuristic state-of-the-art algorithms like local-search moves, the iterated-greedy algorithm, or, NEH-based insertion schemes.

Regarding the bi-directional branching procedures, we observe that the bound guide performs well in most cases, from 0.16% to 8% ARPD. However, using the idle time in the guide (idle time only or idle time combined with the bound) decreases the performance of the algorithm (performances ranging from 2% to 17%). It seems to indicate that the idle time is a less efficient guide than the bound for this branching strategy. However, the weighted idle time proves to be a significant bonus and largely improves the quality of the solutions, from -1.25% to 3% ARPD, finding 100 new-best-known solutions on 160 open instances. Again “only” by combining simple ideas (in this case, the LR guidance strategy, the iterative beam search and the bi-directional branching).

5.2. Flowtime minimization

In the literature, algorithms are executed for exactly 1 hour per instance [1], which implies a lot of wasted time on the smallest instances. In this paper, we perform experiments using the following time limit: $m.n.360$ milliseconds where n is the number of jobs and m the number of machines. It allows spending less time on small instances where it is not needed and exactly 1 hour on the largest ones. We show that even using less time, our algorithm can compete with the state-of-the-art and even returns new best-known solutions on most open instances. We perform the comparison using

the well-known Taillard dataset [40] that contains instances ranging from 20 to 500 jobs and 5 to 20 machines. Each class of instance contains 10 instances. As the bi-directional branching is not suited for the flowtime minimization (due to the objective structure) and the impact of different variants of the LR heuristic guidance have been already performed in the literature [7], we only study the impact of the iterative beam search using LR-inspired guidance strategies (bound biased by the idle time and the bound biased by the weighted idle time). Figure 4 presents the results obtained for the flowtime minimization on the Taillard dataset.

	F g_3	F g_4
TAI_20_5	0.00	0.00
TAI_20_10	0.00	0.19
TAI_20_20	0.00	0.57
TAI_50_5	0.27	0.07
TAI_50_10	0.30	0.60
TAI_50_20	0.14	0.93
TAI_100_5	-0.10	-0.15
TAI_100_10	-0.02	-0.10
TAI_100_20	-0.18	0.62
TAI_200_10	-0.30	-0.50
TAI_200_20	-0.54	-0.22
TAI_500_20	-0.32	-0.45
nb new-best-known	51	44

Figure 4: Average Relative Percentage Deviation (ARPD) of all the presented algorithms on the Taillard instances and the flowtime minimization version. The “F g_3 ” algorithm is an iterative beam search guided by the bound guide biased using the idle time and the “F g_4 ” being the iterative beam search guided by the bound guide biased using the weighted idle time.

discussions: We observe that both algorithms perform well for many instances and find new-best-known solutions on approximately 50/100 open instances). By contrast with the makespan minimization, both guidance strategies are comparable in terms of performance (the weighted idle time did not have a significant impact): sometimes g_3 performs better than g_4 and vice-versa. We may note that the main difference between our results and the beam search algorithms found in the literature [7] is that we use an iterative beam search that allows performing beam search with larger if the remaining time allows it. This result seems to indicate that the iterative beam search can be of interest to the community as it reports good results compared to other search strategies.

6. Conclusions & perspectives

In this paper, we present some iterative beam search algorithms applied to the permutation flowshop problem (makespan and flowtime minimization). These algorithms use branching strategies inspired by the LR heuristic (forward branching) and recent branch-and-bound schemes [12] (bi-directional branching). We compare several guidance strategies (starting from the bound as commonly done in most branch-and-bounds) to more advanced ones (LR inspired guidance). We show that the combination of all of these components obtains state-of-the-art performance. We report 105/160 new-best-so-far solutions for the permutation flowshop (makespan minimization) on the open instances of the VFR benchmark and 55/100 new-best-so-far solutions for the permutation flowshop (flowtime minimization) on the open instances of the Taillard benchmark. These algorithms compare, and sometimes perform better, than the algorithms based on the NEH branching scheme (which is usually considered as “the most efficient constructive heuristic for the problem” [8]) and the iterated greedy algorithm (again considered as “the most efficient approximate algorithm for the problem” [8]). We believe that the performance of the bi-directional branching combined to the iterative beam search highlighted in this paper could draw the interest of the community for these techniques as they are rather unexplored, although simple and efficient. Studying these techniques leads to a few other questions: We considered the iterative beam search and showed that it is competitive with classical meta-heuristics for the permutation flowshop. However, many other exist. For instance Iterative Memory Bounded A* [9, 22], Beam Stack Search [47], Anytime Column Search [41]. To the best of our knowledge, they have not been tested yet for the permutation flowshop. In this paper, we studied the makespan and flowtime minimization criteria and achieved competitive results. Many more

flowshop variants have been studied. For instance, the blocking flowshop, the distributed permutation flowshop and many others. It could be interesting to assess the performance of the LR-based beam search on these variants.

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A. Notations

- J : all the jobs
- M : all the machines
- n : job number ($n = |J|$)
- m : machine number ($m = |M|$)
- F (resp. B): all the jobs scheduled in the prefix (resp. suffix)
- $Cmax_{f,i}$: first availability of machine i in the forward search
- $Cmax_{b,i}$: first availability of machine i in the backward search
- R_i : remaining processing time on machine i . $R_i = \sum_{j \in J \setminus \{F \cup B\}} p_{ij}$
- $I_{f,i}$: total idle time on machine i in the forward search
- $I_{b,i}$: total idle time on machine i in the backward search
- α : proportion of scheduled jobs. $\alpha = \frac{|F|+|B|}{|J|}$ on bi-directional branching or $\alpha = \frac{|F|}{|J|}$ on forward branching.
- g_1 : guidance function based on the bound (makespan or flowtime)
- g_2 : guidance function based only by the idle time
- g_3 : guidance function based on both the bound and idle time
- g_4 : guidance function based on both the bound and weighted idle time

B. detailed numerical results

Iterative beam search algorithms for the permutation flowshop

	best-so-far	F g_1	F g_2	F g_3	F g_4	FB g_1	FB g_2	FB g_3	FB g_4
VFR100_20_1	6.173	7.307	6.317	6.324	6.359	6.252	7.112	7.035	6.172
VFR100_20_2	6.267	7.471	6.421	6.534	6.586	6.386	7.535	7.347	6.306
VFR100_20_3	6.221	7.384	6.384	6.394	6.398	6.319	6.787	6.650	6.231
VFR100_20_4	6.227	7.447	6.455	6.455	6.399	6.306	7.483	7.235	6.268
VFR100_20_5	6.264	7.410	6.362	6.386	6.609	6.468	7.254	7.098	6.330
VFR100_20_6	6.285	7.399	6.457	6.490	6.468	6.521	6.843	7.027	6.333
VFR100_20_7	6.401	7.594	6.669	6.683	6.558	6.593	6.656	6.650	6.409
VFR100_20_8	6.074	7.230	6.230	6.214	6.219	6.213	6.467	6.380	6.083
VFR100_20_9	6.328	7.470	6.719	6.747	6.464	6.472	6.542	6.500	6.426
VFR100_20_10	6.125	7.314	6.502	6.504	6.441	6.269	6.572	6.575	6.167
VFR100_40_1	7.846	9.303	8.233	8.214	8.230	8.300	8.558	8.640	8.010
VFR100_40_2	7.976	9.355	8.375	8.377	8.121	8.443	8.945	8.888	8.091
VFR100_40_3	7.894	9.366	8.258	8.255	8.142	8.331	8.846	8.867	8.018
VFR100_40_4	7.913	9.254	8.171	8.156	8.379	8.336	8.268	8.240	8.154
VFR100_40_5	7.997	9.275	8.472	8.475	8.353	8.481	8.522	8.476	8.108
VFR100_40_6	7.993	9.350	8.339	8.345	8.288	8.432	8.374	8.332	8.279
VFR100_40_7	7.980	9.356	8.317	8.335	8.206	8.523	8.298	8.284	8.344
VFR100_40_8	7.957	9.263	8.281	8.288	8.244	8.413	8.926	8.947	8.122
VFR100_40_9	7.888	9.332	8.208	8.208	8.174	8.361	9.142	9.052	7.987
VFR100_40_10	7.917	9.322	8.371	8.373	8.141	8.372	9.150	9.080	8.036
VFR100_60_1	9.353	10.808	9.946	9.935	9.868	10.050	10.285	10.287	9.757
VFR100_60_2	9.567	11.151	10.095	10.023	9.968	10.081	10.160	10.155	9.738
VFR100_60_3	9.349	11.033	9.823	9.817	9.743	9.902	10.681	10.690	9.656
VFR100_60_4	9.403	11.069	9.919	9.949	9.911	9.981	10.368	10.387	9.613
VFR100_60_5	9.431	10.917	9.916	9.929	9.740	10.039	9.976	9.912	9.966
VFR100_60_6	9.630	11.279	10.044	10.044	10.088	10.234	10.572	10.517	10.016
VFR100_60_7	9.346	10.933	9.852	9.874	9.861	10.008	10.344	10.414	9.654
VFR100_60_8	9.523	11.189	10.041	10.046	9.967	10.158	10.344	10.387	9.843
VFR100_60_9	9.488	10.866	10.008	9.954	10.050	10.082	10.326	10.391	10.070
VFR100_60_10	9.572	11.073	9.918	9.889	10.001	10.134	10.588	10.526	9.829
VFR200_20_1	11.272	13.546	11.436	11.553	11.513	11.473	11.605	11.549	12.213
VFR200_20_2	11.240	13.473	11.869	11.852	11.489	11.381	12.821	12.647	11.444
VFR200_20_3	11.294	13.716	11.514	11.556	11.433	11.445	12.422	12.306	11.328
VFR200_20_4	11.188	13.629	11.434	11.442	11.368	11.307	12.475	12.539	11.265
VFR200_20_5	11.143	13.504	11.442	11.573	11.494	11.340	11.903	11.733	11.242
VFR200_20_6	11.310	14.030	11.552	11.798	11.457	11.456	12.579	12.179	11.428
VFR200_20_7	11.365	13.840	11.532	11.590	11.584	11.523	12.631	12.260	11.437
VFR200_20_8	11.128	13.501	11.566	11.636	11.311	11.148	12.345	11.981	11.279
VFR200_20_9	11.091	13.449	11.636	11.720	11.240	11.365	12.830	12.592	11.285
VFR200_20_10	11.294	13.655	11.628	11.636	11.432	11.346	12.601	12.080	11.366
VFR200_40_1	13.124	15.833	13.856	13.786	13.442	13.731	15.301	14.977	13.139
VFR200_40_2	13.049	16.029	13.704	13.578	13.350	13.734	13.634	13.840	13.131
VFR200_40_3	13.222	16.167	13.750	13.758	13.523	13.835	15.590	15.677	13.228
VFR200_40_4	13.163	16.108	13.816	13.771	13.548	13.945	16.003	15.662	13.232
VFR200_40_5	12.974	16.077	13.569	13.741	13.273	13.744	14.560	15.661	12.997
VFR200_40_6	13.061	16.094	13.833	14.005	13.313	13.861	15.208	15.167	13.134
VFR200_40_7	13.220	15.921	13.719	13.733	13.507	14.070	15.188	14.883	13.296
VFR200_40_8	13.132	15.903	13.556	13.520	13.616	13.812	14.786	14.929	13.123
VFR200_40_9	13.033	15.939	13.706	13.754	13.429	13.921	15.665	15.172	13.051
VFR200_40_10	13.146	15.799	13.760	13.793	13.480	13.982	14.452	14.160	13.114
VFR200_60_1	14.906	18.193	15.741	15.744	15.258	16.128	18.063	17.883	15.029
VFR200_60_2	14.909	18.012	16.196	16.156	15.187	16.105	17.419	17.228	15.236
VFR200_60_3	15.134	17.970	15.898	15.906	15.645	16.544	17.430	17.156	15.598
VFR200_60_4	14.968	17.818	15.692	15.727	15.387	16.254	16.442	16.365	15.376
VFR200_60_5	15.042	18.084	15.767	15.756	15.695	16.207	17.747	17.464	15.414
VFR200_60_6	14.996	17.967	15.717	15.761	15.391	16.073	17.562	17.073	15.101
VFR200_60_7	15.006	17.917	15.814	15.827	15.334	16.322	17.957	17.801	15.180
VFR200_60_8	14.894	18.007	15.684	15.766	15.251	16.168	16.034	15.993	15.170
VFR200_60_9	14.925	18.102	15.725	15.764	15.372	16.042	17.563	17.328	15.167
VFR200_60_10	14.908	17.947	15.465	15.527	15.319	16.023	17.052	17.192	15.203

Figure 5: Makespan minimization full results: 100 and 200 jobs

Iterative beam search algorithms for the permutation flowshop

	best-so-far	F g_1	F g_2	F g_3	F g_4	FB g_1	FB g_2	FB g_3	FB g_4
VFR300_20_1	16.089	19.716	16.249	16.356	16.336	16.207	17.343	16.970	16.278
VFR300_20_2	16.483	20.454	16.888	16.928	16.793	16.638	17.818	17.770	16.735
VFR300_20_3	16.129	19.805	16.365	16.561	16.414	16.166	17.637	16.907	16.340
VFR300_20_4	16.168	19.634	16.377	16.575	16.356	16.308	17.829	17.346	16.368
VFR300_20_5	16.283	19.889	16.701	16.738	16.508	16.369	17.755	17.477	16.524
VFR300_20_6	16.021	20.082	16.264	16.333	16.464	16.237	17.306	16.900	16.292
VFR300_20_7	16.244	19.974	16.689	16.741	16.507	16.373	16.643	16.643	16.705
VFR300_20_8	16.369	19.789	16.688	16.919	16.558	16.524	17.844	17.408	16.487
VFR300_20_9	16.324	19.827	16.725	16.839	16.767	16.441	17.167	16.958	16.473
VFR300_20_10	16.780	20.256	17.252	17.341	16.977	16.983	17.582	17.510	17.010
VFR300_40_1	18.199	22.319	19.114	19.025	18.255	19.130	21.391	20.768	18.059
VFR300_40_2	18.373	22.648	19.382	19.212	18.657	19.191	21.625	21.656	18.218
VFR300_40_3	18.348	22.609	19.088	19.322	18.536	19.562	21.062	21.465	18.242
VFR300_40_4	18.227	22.412	18.759	18.864	18.539	19.407	21.573	20.973	18.095
VFR300_40_5	18.343	22.435	19.175	19.285	18.536	19.327	22.067	21.332	18.195
VFR300_40_6	18.340	22.392	19.225	19.300	18.428	19.553	21.679	20.951	18.177
VFR300_40_7	18.396	22.311	19.166	19.188	18.733	19.461	21.678	21.004	18.202
VFR300_40_8	18.290	22.166	19.120	19.316	18.393	19.184	21.599	20.101	18.187
VFR300_40_9	18.261	22.488	18.991	18.964	18.530	19.171	19.291	18.902	18.093
VFR300_40_10	18.286	22.307	19.123	19.255	18.452	19.331	21.832	22.076	18.132
VFR300_60_1	20.483	24.419	21.397	21.554	20.648	22.086	21.573	21.744	20.662
VFR300_60_2	20.249	24.526	21.252	21.234	20.457	21.783	23.896	23.536	20.444
VFR300_60_3	20.328	24.647	21.556	21.740	20.621	22.050	24.072	24.053	20.468
VFR300_60_4	20.293	24.520	21.321	21.391	20.467	22.027	23.651	23.176	20.564
VFR300_60_5	20.200	24.549	21.436	21.549	20.801	21.738	23.405	23.159	20.235
VFR300_60_6	20.280	24.383	21.367	21.415	20.621	21.713	21.890	21.998	20.400
VFR300_60_7	20.358	24.822	21.779	21.737	20.922	22.099	21.531	21.726	20.638
VFR300_60_8	20.319	24.576	21.236	21.378	20.566	22.085	23.574	23.972	20.647
VFR300_60_9	20.405	24.744	21.159	21.431	20.645	21.905	24.039	23.736	20.503
VFR300_60_10	20.385	24.561	21.411	21.370	20.698	22.101	21.616	21.898	20.458
VFR400_20_1	21.042	25.934	21.577	21.639	21.215	21.116	22.145	21.766	21.383
VFR400_20_2	21.346	26.270	21.693	21.784	21.795	21.553	22.493	22.112	21.611
VFR400_20_3	21.380	26.822	21.910	22.012	21.742	21.523	21.726	21.749	21.979
VFR400_20_4	21.200	25.776	21.567	21.689	21.628	21.307	21.523	21.516	21.432
VFR400_20_5	21.399	25.910	21.953	22.269	21.829	21.613	22.744	22.152	21.666
VFR400_20_6	21.134	25.799	21.402	21.670	21.399	21.345	22.269	21.823	21.311
VFR400_20_7	21.507	26.199	21.998	22.040	22.084	21.664	23.064	22.548	21.825
VFR400_20_8	21.198	26.071	21.432	21.527	21.710	21.320	21.728	21.620	21.478
VFR400_20_9	21.236	25.898	21.714	21.743	21.668	21.508	22.472	22.441	21.480
VFR400_20_10	21.456	26.513	21.869	21.895	21.796	21.564	21.942	21.990	21.705
VFR400_40_1	23.393	29.121	24.225	24.328	23.602	24.563	27.809	27.111	23.159
VFR400_40_2	23.380	29.227	24.260	24.347	23.467	24.886	24.384	25.004	23.055
VFR400_40_3	23.467	28.986	24.182	24.452	23.783	24.590	26.893	26.908	23.258
VFR400_40_4	23.269	29.285	24.277	24.365	23.226	25.029	28.186	27.259	22.896
VFR400_40_5	23.213	28.818	24.188	24.199	23.330	24.818	27.737	27.594	22.984
VFR400_40_6	23.298	28.837	24.212	24.376	23.400	24.300	27.429	27.585	23.103
VFR400_40_7	23.415	29.280	24.236	24.321	23.529	24.782	28.610	27.597	23.197
VFR400_40_8	23.290	28.982	24.561	24.700	23.438	24.667	24.853	24.991	23.149
VFR400_40_9	23.424	29.172	24.537	24.608	23.764	24.507	28.395	27.655	23.322
VFR400_40_10	23.606	28.946	24.563	24.636	23.848	24.867	26.990	26.992	23.362
VFR400_60_1	25.395	30.869	27.068	27.209	25.563	27.677	29.938	29.502	25.359
VFR400_60_2	25.549	31.091	27.035	27.034	25.737	27.770	30.060	29.120	25.636
VFR400_60_3	25.707	31.170	27.079	27.467	25.793	27.647	30.053	29.892	25.658
VFR400_60_4	25.638	30.985	27.317	27.339	25.983	27.314	29.051	29.451	25.797
VFR400_60_5	25.669	31.179	26.822	26.942	26.025	27.394	30.367	29.596	25.788
VFR400_60_6	25.407	30.940	26.444	26.615	25.689	27.306	30.083	29.858	25.473
VFR400_60_7	25.415	31.320	26.987	26.990	25.525	27.335	30.479	30.247	25.434
VFR400_60_8	25.603	31.200	27.006	27.187	25.702	27.794	30.167	30.038	25.509
VFR400_60_9	25.673	31.645	26.830	27.050	25.825	28.023	30.021	29.551	25.731
VFR400_60_10	25.658	31.353	27.284	27.262	25.957	27.691	30.348	30.292	25.747

Figure 6: Makespan minimization full results: 300 and 400 jobs

Iterative beam search algorithms for the permutation flowshop

	best-so-far	F g_1	F g_2	F g_3	F g_4	FB g_1	FB g_2	FB g_3	FB g_4
VFR500_20_1	26.253	32.562	26.600	26.812	26.703	26.318	27.582	27.139	26.656
VFR500_20_2	26.555	32.773	26.875	27.161	27.035	26.786	27.433	27.202	26.862
VFR500_20_3	26.268	32.757	26.647	26.835	26.685	26.444	26.907	27.006	26.593
VFR500_20_4	25.994	32.623	26.551	26.949	26.488	26.102	26.744	26.715	26.295
VFR500_20_5	26.703	33.177	26.915	27.198	27.048	26.843	27.271	27.187	27.169
VFR500_20_6	26.325	32.944	27.027	27.247	26.854	26.374	27.506	27.314	26.544
VFR500_20_7	26.313	32.861	26.693	26.863	26.749	26.474	27.105	27.208	26.723
VFR500_20_8	26.217	32.349	26.570	26.703	26.555	26.420	26.803	26.803	26.559
VFR500_20_9	26.345	33.100	26.810	26.873	26.777	26.466	27.473	26.759	26.719
VFR500_20_10	26.034	32.078	26.435	26.748	26.410	26.101	27.414	27.588	26.302
VFR500_40_1	28.402	35.162	29.766	29.764	28.331	30.083	29.277	29.905	28.183
VFR500_40_2	28.613	35.761	29.421	29.714	29.011	29.631	33.786	32.957	28.310
VFR500_40_3	28.526	36.006	29.575	29.713	28.653	29.672	33.521	32.471	28.401
VFR500_40_4	28.615	34.798	29.289	29.361	28.803	30.232	33.067	32.001	28.378
VFR500_40_5	28.579	35.521	29.516	29.735	28.844	29.753	33.390	33.081	28.289
VFR500_40_6	28.432	34.683	29.435	29.633	28.643	29.568	33.687	33.024	28.138
VFR500_40_7	28.553	35.589	29.683	29.853	28.704	30.068	30.463	30.460	28.307
VFR500_40_8	28.488	35.555	29.337	29.643	28.844	30.000	32.417	32.260	28.299
VFR500_40_9	28.640	35.728	29.467	29.448	28.839	30.413	32.792	32.856	28.407
VFR500_40_10	28.644	35.448	29.294	29.562	28.813	29.820	33.841	33.006	28.318
VFR500_60_1	30.682	38.110	32.619	32.681	30.848	33.467	36.212	35.569	30.491
VFR500_60_2	30.664	37.489	32.537	32.344	30.924	33.207	35.416	34.622	30.532
VFR500_60_3	30.852	37.768	33.114	33.011	30.979	33.486	36.670	35.404	30.671
VFR500_60_4	30.793	37.687	32.518	32.819	31.145	33.130	35.390	35.383	30.672
VFR500_60_5	30.763	37.624	32.553	32.475	31.051	33.527	36.672	36.371	30.540
VFR500_60_6	30.788	37.843	32.524	32.614	31.069	33.482	35.603	35.779	30.597
VFR500_60_7	30.826	37.800	32.687	32.932	30.893	33.532	35.810	36.018	30.528
VFR500_60_8	30.837	37.261	32.696	32.807	30.808	33.202	36.844	36.117	30.584
VFR500_60_9	30.805	37.763	32.424	32.589	30.836	33.702	35.728	35.279	30.645
VFR500_60_10	30.866	37.553	32.316	32.452	31.119	33.030	34.603	35.138	30.787
VFR600_20_1	31.303	38.430	31.801	32.271	31.774	31.402	32.495	32.088	31.600
VFR600_20_2	31.281	38.305	31.675	31.953	31.887	31.731	32.781	32.394	31.753
VFR600_20_3	31.374	38.812	31.817	32.104	31.694	31.501	32.521	32.066	31.670
VFR600_20_4	31.417	38.879	31.648	31.718	31.702	31.669	32.000	31.857	31.759
VFR600_20_5	31.354	38.842	31.590	31.831	31.799	31.450	32.287	31.983	31.769
VFR600_20_6	31.613	38.684	31.974	32.243	32.112	31.792	32.094	32.058	32.035
VFR600_20_7	31.461	38.728	31.995	32.188	31.962	31.530	32.957	32.432	31.951
VFR600_20_8	31.414	38.590	31.825	32.097	31.991	31.528	32.468	32.292	31.701
VFR600_20_9	31.473	39.149	31.638	31.881	31.960	31.511	32.611	32.168	32.052
VFR600_20_10	31.021	38.671	31.528	31.890	31.508	31.156	31.910	31.828	31.361
VFR600_40_1	33.683	41.668	34.398	34.702	33.991	35.621	38.040	37.455	33.385
VFR600_40_2	33.405	41.752	34.639	34.843	33.654	35.047	39.863	39.017	33.237
VFR600_40_3	33.713	41.633	35.217	35.230	33.957	35.529	37.783	38.386	33.587
VFR600_40_4	33.584	41.596	34.554	34.510	33.544	35.394	37.975	37.514	33.254
VFR600_40_5	33.401	41.423	34.637	34.815	33.615	34.932	39.009	38.767	33.220
VFR600_40_6	33.626	42.297	34.312	34.520	33.869	35.259	38.919	38.553	33.420
VFR600_40_7	33.545	42.007	35.204	35.289	33.725	35.658	40.408	38.749	33.413
VFR600_40_8	33.298	41.441	34.812	34.814	33.397	35.294	38.126	38.396	33.078
VFR600_40_9	33.567	41.588	34.623	34.849	33.839	35.529	39.483	38.086	33.250
VFR600_40_10	33.473	41.931	34.483	34.571	33.816	35.458	39.720	38.830	33.284
VFR600_60_1	35.976	43.980	37.649	37.956	36.009	38.931	37.908	38.353	35.920
VFR600_60_2	35.923	44.098	37.462	37.834	35.836	38.626	42.296	40.873	35.561
VFR600_60_3	35.917	44.400	37.718	37.742	36.350	38.643	41.393	41.845	35.670
VFR600_60_4	36.000	44.670	38.001	37.889	36.227	38.731	42.377	42.419	35.640
VFR600_60_5	36.004	44.049	38.112	38.201	35.902	38.630	41.973	40.904	35.606
VFR600_60_6	35.943	44.676	38.074	38.258	36.042	38.814	42.807	40.751	35.529
VFR600_60_7	35.965	43.729	37.971	38.011	36.265	38.802	38.278	39.218	35.717
VFR600_60_8	35.894	43.914	38.344	38.570	36.052	38.827	38.491	38.780	35.499
VFR600_60_9	35.987	44.365	38.297	38.627	36.328	39.316	39.006	39.172	35.588
VFR600_60_10	35.943	44.166	37.551	37.658	35.974	38.765	42.554	41.788	35.563

Figure 7: Makespan minimization full results: 500 and 600 jobs

Iterative beam search algorithms for the permutation flowshop

	best-so-far	F g_1	F g_2	F g_3	F g_4	FB g_1	FB g_2	FB g_3	FB g_4
VFR700_20_1	36.285	45.173	36.881	37.169	36.812	36.496	37.447	37.104	36.916
VFR700_20_2	36.220	44.898	36.563	36.884	36.820	36.355	36.684	37.310	36.676
VFR700_20_3	36.419	44.634	37.156	37.263	37.107	36.594	37.326	37.121	36.971
VFR700_20_4	36.361	45.075	36.800	36.907	36.777	36.361	37.556	37.084	36.619
VFR700_20_5	36.496	46.158	37.076	37.518	37.128	36.647	37.452	37.169	36.956
VFR700_20_6	36.556	45.744	37.030	37.433	37.219	36.558	37.376	37.073	36.927
VFR700_20_7	36.540	45.561	36.945	37.235	37.055	36.586	37.506	37.293	36.912
VFR700_20_8	36.418	44.983	36.938	37.205	37.209	36.527	37.199	37.128	36.790
VFR700_20_9	36.212	45.545	36.880	37.025	36.923	36.329	37.482	37.059	36.634
VFR700_20_10	36.362	45.284	36.636	36.687	36.762	36.505	36.898	36.737	36.839
VFR700_40_1	38.767	48.140	39.786	39.882	39.053	40.619	43.966	43.673	38.573
VFR700_40_2	38.560	48.750	39.855	40.379	38.548	39.797	40.433	45.233	38.316
VFR700_40_3	38.460	48.388	39.710	39.852	38.692	40.847	45.858	44.636	38.261
VFR700_40_4	38.597	48.549	39.597	40.064	38.799	40.163	45.958	44.192	38.460
VFR700_40_5	38.490	47.881	39.485	39.771	38.846	40.108	39.145	40.199	38.339
VFR700_40_6	38.440	48.035	40.004	40.418	38.452	39.979	46.046	44.169	38.352
VFR700_40_7	38.355	48.340	39.312	39.589	38.531	40.452	45.127	43.757	38.189
VFR700_40_8	38.817	48.138	40.213	40.298	39.106	40.580	45.685	44.259	38.778
VFR700_40_9	38.569	48.418	39.637	39.722	38.854	40.270	40.997	41.780	38.825
VFR700_40_10	38.712	48.596	40.482	40.860	38.752	40.190	45.522	44.575	38.635
VFR700_60_1	41.192	50.359	43.381	43.904	41.430	44.966	48.093	47.887	40.772
VFR700_60_2	41.002	50.651	43.732	43.890	41.350	44.532	48.688	46.729	40.664
VFR700_60_3	41.173	50.511	43.257	43.176	40.981	44.841	48.492	47.555	40.581
VFR700_60_4	41.120	50.625	43.033	42.841	41.008	43.658	48.858	47.026	40.491
VFR700_60_5	41.167	50.535	43.605	43.772	41.071	44.793	48.514	46.562	40.641
VFR700_60_6	41.159	50.536	43.816	43.722	41.082	44.476	47.269	47.437	40.714
VFR700_60_7	40.734	50.379	43.191	43.170	40.737	44.130	47.259	47.224	40.331
VFR700_60_8	41.305	50.534	43.482	43.868	41.443	44.338	47.951	46.697	40.830
VFR700_60_9	41.111	50.864	43.404	43.546	41.163	44.446	47.823	47.859	40.501
VFR700_60_10	41.186	51.162	43.049	43.207	41.182	44.099	43.649	44.563	40.730
VFR800_20_1	41.413	52.067	41.877	42.181	41.976	41.521	42.044	42.158	41.843
VFR800_20_2	41.282	51.449	41.657	42.107	41.957	41.323	41.886	42.119	41.623
VFR800_20_3	41.319	52.365	41.683	42.024	41.818	41.367	42.245	42.006	41.693
VFR800_20_4	41.375	52.005	41.878	42.106	41.923	41.452	42.226	41.942	42.056
VFR800_20_5	41.626	51.981	42.209	42.666	42.250	41.704	42.496	42.479	41.959
VFR800_20_6	41.919	52.373	42.644	42.918	42.556	41.919	42.640	42.549	42.416
VFR800_20_7	41.395	51.177	41.645	41.747	41.742	41.541	42.014	41.725	41.812
VFR800_20_8	41.390	50.761	42.006	42.605	42.093	41.505	42.518	42.443	42.022
VFR800_20_9	41.697	51.467	42.197	42.316	42.435	41.697	42.916	42.706	42.113
VFR800_20_10	41.489	50.943	41.847	42.245	42.073	41.557	42.408	42.272	41.908
VFR800_40_1	43.466	53.765	45.065	45.367	43.691	45.513	50.262	50.510	43.261
VFR800_40_2	43.575	54.404	44.440	44.650	43.818	45.174	48.957	48.298	43.289
VFR800_40_3	43.596	54.709	44.876	45.287	43.668	44.863	52.525	49.450	43.313
VFR800_40_4	43.743	55.055	45.069	45.659	43.828	45.522	51.327	51.034	43.491
VFR800_40_5	43.794	54.471	45.621	45.977	43.750	45.993	47.330	47.583	46.117
VFR800_40_6	43.638	54.697	44.938	44.997	43.659	45.709	48.982	50.102	43.370
VFR800_40_7	43.484	54.649	44.562	44.641	43.787	45.310	48.764	48.729	43.384
VFR800_40_8	43.666	54.693	45.720	46.263	43.834	45.532	50.455	49.794	43.469
VFR800_40_9	43.643	54.597	44.772	44.927	44.008	45.540	47.844	49.387	43.477
VFR800_40_10	43.630	54.773	45.571	46.286	43.595	45.294	50.638	49.907	43.446
VFR800_60_1	46.279	57.427	48.747	48.952	46.498	49.897	54.669	54.027	45.680
VFR800_60_2	46.232	58.017	48.663	49.075	46.159	50.324	53.338	52.429	45.728
VFR800_60_3	46.258	57.295	49.104	49.153	46.243	49.567	54.299	53.912	45.698
VFR800_60_4	46.261	57.072	48.430	48.699	46.218	49.707	53.221	52.813	45.696
VFR800_60_5	46.164	56.947	48.705	49.005	46.526	49.924	52.729	52.635	45.490
VFR800_60_6	46.288	56.301	49.747	50.097	46.350	49.451	53.784	53.185	45.504
VFR800_60_7	46.061	57.252	49.565	49.885	46.186	49.896	53.804	52.550	45.600
VFR800_60_8	46.257	57.812	49.104	49.183	46.029	49.979	52.997	52.442	45.964
VFR800_60_9	46.279	57.744	49.071	49.162	46.171	50.146	53.303	52.208	45.766
VFR800_60_10	46.211	56.850	48.420	48.665	46.162	49.850	53.702	52.451	45.383

Figure 8: Makespan minimization full results: 700 and 800 jobs

	best-so-far	F_{g_3}	F_{g_4}
TA1 / tai20_5_0	14.033	14.033	14.033
TA2 / tai20_5_1	15.151	15.151	15.151
TA3 / tai20_5_2	13.301	13.301	13.301
TA4 / tai20_5_3	15.447	15.447	15.447
TA5 / tai20_5_4	13.529	13.529	13.529
TA6 / tai20_5_5	13.123	13.123	13.123
TA7 / tai20_5_6	13.548	13.548	13.548
TA8 / tai20_5_7	13.948	13.948	13.948
TA9 / tai20_5_8	14.295	14.295	14.295
TA10 / tai20_5_9	12.943	12.943	12.943
TA11 / tai20_10_0	20.911	20.911	20.911
TA12 / tai20_10_1	22.440	22.440	22.440
TA13 / tai20_10_2	19.833	19.833	19.872
TA14 / tai20_10_3	18.710	18.710	18.769
TA15 / tai20_10_4	18.641	18.641	18.641
TA16 / tai20_10_5	19.245	19.245	19.350
TA17 / tai20_10_6	18.363	18.363	18.376
TA18 / tai20_10_7	20.241	20.241	20.268
TA19 / tai20_10_8	20.330	20.330	20.455
TA20 / tai20_10_9	21.320	21.320	21.325
TA21 / tai20_20_0	33.623	33.623	33.623
TA22 / tai20_20_1	31.587	31.587	31.726
TA23 / tai20_20_2	33.920	33.920	34.318
TA24 / tai20_20_3	31.661	31.661	31.661
TA25 / tai20_20_4	34.557	34.557	34.726
TA26 / tai20_20_5	32.564	32.564	32.988
TA27 / tai20_20_6	32.922	32.922	33.160
TA28 / tai20_20_7	32.412	32.412	32.412
TA29 / tai20_20_8	33.600	33.600	33.902
TA30 / tai20_20_9	32.262	32.262	32.474
TA31 / tai50_5_0	64.802	65.020	64.817
TA32 / tai50_5_1	68.051	68.149	68.074
TA33 / tai50_5_2	63.162	63.247	63.162
TA34 / tai50_5_3	68.226	68.241	68.226
TA35 / tai50_5_4	69.351	69.738	69.360
TA36 / tai50_5_5	66.841	66.852	66.841
TA37 / tai50_5_6	66.253	66.427	66.277
TA38 / tai50_5_7	64.332	64.447	64.401
TA39 / tai50_5_8	62.981	63.566	63.203
TA40 / tai50_5_9	68.770	68.845	68.834

Figure 9: Flowtime minimization full results: TAI1 to TAI40

	best-so-far	F_{g_3}	F_{g_4}
TA41 / tai50_10_0	87.114	87.140	87.353
TA42 / tai50_10_1	82.820	82.967	83.241
TA43 / tai50_10_2	79.931	80.094	80.106
TA44 / tai50_10_3	86.446	86.475	86.637
TA45 / tai50_10_4	86.377	86.567	86.628
TA46 / tai50_10_5	86.587	86.729	87.010
TA47 / tai50_10_6	88.750	89.720	89.759
TA48 / tai50_10_7	86.727	86.730	87.719
TA49 / tai50_10_8	85.441	85.952	86.197
TA50 / tai50_10_9	87.998	88.392	88.722
TA51 / tai50_20_0	125.831	125.831	126.245
TA52 / tai50_20_1	119.247	119.397	120.594
TA53 / tai50_20_2	116.459	116.536	117.727
TA54 / tai50_20_3	120.261	120.811	121.359
TA55 / tai50_20_4	118.184	118.379	119.434
TA56 / tai50_20_5	120.586	120.637	121.526
TA57 / tai50_20_6	122.880	123.120	124.274
TA58 / tai50_20_7	122.489	122.583	123.447
TA59 / tai50_20_8	121.872	121.872	123.022
TA60 / tai50_20_9	123.954	124.275	125.425
TA61 / tai100_5_0	253.232	252.821	252.624
TA62 / tai100_5_1	242.093	241.593	241.737
TA63 / tai100_5_2	237.832	237.240	237.345
TA64 / tai100_5_3	227.738	227.420	227.329
TA65 / tai100_5_4	240.301	240.114	240.024
TA66 / tai100_5_5	232.342	232.131	232.008
TA67 / tai100_5_6	240.366	240.745	239.843
TA68 / tai100_5_7	230.945	230.304	230.371
TA69 / tai100_5_8	247.677	247.472	247.437
TA70 / tai100_5_9	242.933	243.254	243.062
TA71 / tai100_10_0	298.385	298.002	297.749
TA72 / tai100_10_1	273.826	273.852	273.765
TA73 / tai100_10_2	288.114	288.275	287.614
TA74 / tai100_10_3	301.044	300.545	300.601
TA75 / tai100_10_4	284.279	283.961	283.637
TA76 / tai100_10_5	269.686	269.436	269.453
TA77 / tai100_10_6	279.463	280.681	280.467
TA78 / tai100_10_7	290.908	290.219	289.947
TA79 / tai100_10_8	301.970	301.843	302.110
TA80 / tai100_10_9	291.283	291.439	290.735

Figure 10: Flowtime minimization full results: TAI41 to TAI80

	best-so-far	F g_3	F g_4
TA81 / tai100_20_0	365.463	366.544	368.283
TA82 / tai100_20_1	372.449	371.544	374.585
TA83 / tai100_20_2	370.027	369.571	373.153
TA84 / tai100_20_3	372.393	370.754	374.532
TA85 / tai100_20_4	368.915	366.924	370.549
TA86 / tai100_20_5	370.908	370.950	374.142
TA87 / tai100_20_6	373.408	372.225	374.978
TA88 / tai100_20_7	384.525	383.271	386.348
TA89 / tai100_20_8	374.423	374.413	376.850
TA90 / tai100_20_9	379.296	378.948	381.513
TA91 / tai200_10_0	1.042.494	1.040.290	1.035.022
TA92 / tai200_10_1	1.028.957	1.025.209	1.024.879
TA93 / tai200_10_2	1.043.467	1.041.260	1.037.699
TA94 / tai200_10_3	1.029.244	1.021.739	1.018.655
TA95 / tai200_10_4	1.029.384	1.027.978	1.024.342
TA96 / tai200_10_5	999.241	995.394	994.499
TA97 / tai200_10_6	1.042.663	1.040.074	1.038.736
TA98 / tai200_10_7	1.035.981	1.034.159	1.034.056
TA99 / tai200_10_8	1.015.389	1.013.444	1.012.533
TA100 / tai200_10_9	1.022.277	1.018.518	1.017.258
TA101 / tai200_20_0	1.223.860	1.210.533	1.219.147
TA102 / tai200_20_1	1.234.081	1.230.809	1.233.361
TA103 / tai200_20_2	1.259.866	1.250.456	1.253.413
TA104 / tai200_20_3	1.228.060	1.221.033	1.222.571
TA105 / tai200_20_4	1.219.886	1.209.411	1.215.093
TA106 / tai200_20_5	1.219.432	1.213.883	1.217.223
TA107 / tai200_20_6	1.234.366	1.232.351	1.237.431
TA108 / tai200_20_7	1.240.627	1.229.895	1.231.867
TA109 / tai200_20_8	1.220.873	1.216.338	1.221.412
TA110 / tai200_20_9	1.235.462	1.235.641	1.238.120
TA111 / tai500_20_0	6.558.547	6.542.681	6.529.190
TA112 / tai500_20_1	6.679.507	6.659.112	6.656.697
TA113 / tai500_20_2	6.624.893	6.608.608	6.596.258
TA114 / tai500_20_3	6.649.855	6.623.800	6.612.598
TA115 / tai500_20_4	6.590.021	6.578.189	6.576.523
TA116 / tai500_20_5	6.603.691	6.581.804	6.571.552
TA117 / tai500_20_6	6.576.201	6.551.244	6.546.293
TA118 / tai500_20_7	6.629.393	6.612.945	6.605.891
TA119 / tai500_20_8	6.589.205	6.552.881	6.543.443
TA120 / tai500_20_9	6.626.342	6.606.392	6.590.453

Figure 11: Flowtime minimization full results: TAI81 to TAI120