Parallel Hybrid Best-First Search

Abdelkader Beldjilali
Université Fédérale de Toulouse, INRAE, UR 875, 31326 Toulouse, France

Pierre Montalbano
Université Fédérale de Toulouse, ANITI, INRAE, UR 875, 31326 Toulouse, France

David Allouche
Université Fédérale de Toulouse, ANITI, INRAE, UR 875, 31326 Toulouse, France

George Katsirelos
Université Fédérale de Toulouse, ANITI, INRAE, MIA Paris, AgroParisTech, 75231 Paris, France

Simon de Givry
Université Fédérale de Toulouse, ANITI, INRAE, UR 875, 31326 Toulouse, France

Abstract

While processor frequency has stagnated over the past two decades, the number of available cores in servers or clusters is still growing, offering the opportunity for significant speed-up in combinatorial optimization. Parallelization of exact methods remains a difficult challenge. We revisit the concept of parallel Branch-and-Bound in the framework of Cost Function Networks. We show how to adapt the anytime Hybrid Best-First Search algorithm in a Master-Worker protocol. The resulting parallel algorithm achieves good load-balancing without introducing new parameters to be tuned as is the case, for example, in Embarrassingly Parallel Search (EPS). It has also a small overhead due to its light communication messages. We performed an experimental evaluation on several benchmarks, comparing our parallel algorithm to its sequential version. We observed linear speed-up in some cases. Our approach compared favourably to the EPS approach and also to a state-of-the-art parallel exact integer programming solver.

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Supplementary Material *Software (Source Code)*: `https://github.com/toulbar2/toulbar2`
archived at `swh:1:dir:93fd0c2246746901b0391ac4c4c04ca57980b3bb`
Other (Results): `https://miat.inrae.fr/degivry/Beldjilali22Supp.pdf`

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Carbon footprint The experiments in this paper took approximately 17,000 hours and emitted 68kg of CO_2, with an estimate of $4g/h$ per core.

1 Introduction

Cost Function Networks (CFNs), also known as Weighted Constraint Satisfaction Problems (WCSPs) [17] is a mathematical framework which has been derived from Constraint Satisfaction Problems by replacing constraints with cost functions. In a CFN, we are given a set of variables with an associated finite domain and a set of local cost functions. Each cost function involves some variables and associates a non-negative integer cost to each of the possible combinations of values they may take. The usual WCSP problem considered is to assign all variables in a way that minimizes the sum of all costs. This minimization problem is NP-hard, and exact methods usually rely on Branch and Bound (B&B) algorithms exploring a binary search tree with *soft local consistency* maintained at each node in order to improve the problem lower bound (represented by $c_\emptyset$) and prune domain values with a forbidden cost (represented by a maximum cost k) [5].

Contraint Programming (CP) exact approaches usually rely on Depth-First Search (DFS) methods while Integer Linear Programming (ILP) approaches explore the tree in a best-first manner by exploiting strong bounds. We are interested in hybrid methods combining depth-first and best-first with possibly weaker bounds but faster to compute. This is the case of the Hybrid Best-First Search (HBFS) method [2]. HBFS is a B&B algorithm for solving WCSPs.

Dealing with parallel computers or grids to speed-up solving time of exact methods has been explored in many different ways. For grids, with slow network interconnection, MapReduce is a general approach exploiting problem decomposition into independent subproblems solved in parallel (*map* on the grid processors) and then sequentially *reduced* at the end of the resolution. In CP, this decomposition approach is called Embarrassingly Parallel Search (EPS) [15]. MapReduce has been applied also in the context of non serial dynamic programming in Graphical Models [19] and CFNs [3]. Message-passing approaches, on the other hand, take advantage of the low-latency communication of supercomputers, consisting of a large number of multiprocessor servers interconnected at high speed and low latency. This allows for finer granularity in B&B parallelization. According to a recent survey [9], parallelizing the search based on message-passing and parallel B&B in CP are difficult problems and still poorly explored. In CP, for example, COMET [18] uses *work-stealing* where workers which have run out of work take unexpanded nodes from other workers, leaving them less work to do and keeping all workers busy. In ILP, a recent review on parallel B&B was proposed in [21]. We selected the Master-Worker protocol as the basis for our approach. Other approaches rely on portfolios.

In this work we describe a parallel version of HBFS. We give an empirical evaluation on combinatorial optimization academic problems from Operations Research and real-life Graphical Model problems occuring in genetics and biology. Our experimental study analyses solving time and speed-ups of the parallel version compared to the original sequential HBFS. We also compare our approach with a parallel ILP solver (IBM Ilog `cplex`). Moreover, we performed experiments on a high-performance cluster to study the scalability of our algorithm and compare with EPS.

2 Hybrid Best-First Search

The sequential version of HBFS [2] is a B&B method for CFNs that combines Best-First Search (BFS) and Depth-First Search (DFS). Like BFS, HBFS provides an anytime global lower bound on the optimum, while also providing anytime upper bounds, like DFS. Hence, it provides feedback on the progress of search and solution quality in the form of an optimality gap. Besides, it exhibits highly dynamic behavior that allows it to perform on par with methods like Limited Discrepancy Search [11] and frequent restarting [10, 7] in terms of quickly finding good solutions. As in BFS, HBFS maintains a frontier of open search nodes. It expands each open node using DFS with a limit on its number of backtracks. Each bounded DFS returns a new list of open nodes to be inserted in the BFS frontier.

The pseudo-code of HBFS is given in Algorithm 1. The main procedure is in charge of the BFS frontier of open nodes. Here a node ν corresponds to a sequence of decisions $\nu.\delta$. The root node has an empty decision sequence (line 1). When a node is explored by DFS (line 5), an unassigned variable is chosen and a branching decision to either assign the variable to a chosen value (left branch, positive decision) or remove the value from the domain (right branch, negative decision) is taken. The number of decisions taken to reach a given node ν is the depth of the node, $\nu.depth$. HBFS always chooses the next open node to explore with minimum lower bound $\nu.lb$ (best-first principle) and, in case of ties, maximum depth

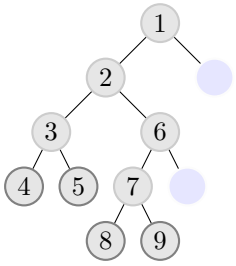

Figure 1 A tree that is partially explored by DFS with a backtrack limit $Z = 4$. Nodes with a bold border are leaves, nodes with no border are placed in the open list after the backtrack bound is exceeded. Nodes are numbered in the order they are visited.

$\nu.depth$ (depth-first principle) in the frontier. The minimum of all open node lower bounds, denoted $lb(open)$, is a valid global lower bound (kept in clb at line 6) for the problem. HBFS also maintains the current upper bound (cub) as the cost of the best solution found so far by DFS (line 5). The search ends when the open list is empty or contains nodes with a lower bound greater than or equal to cub (line 2).

Algorithm 1 Hybrid Best-First Search. Initial call: HBFS($c_\emptyset$,k) with $Z = 1$.

Function HBFS(clb,cub): integer ; /* Returns the optimum value */

1 $open := \{\nu(\delta = \varnothing, lb = clb)\}$; /* Initializes the open list with a root node */
2 **while** ($open \neq \varnothing$ **and** $clb < cub$) **do**
  $\nu :=$pop($open$) ; /* Chooses a node with minimum lower bound and maximum depth */
3 Restores state $\nu.\delta$, leading to assignment A_ν, maintaining soft local consistency ;
4 $NodesRecompute := NodesRecompute + \nu.depth$;
5 $cub :=$DFS(A_ν,cub,Z) ; /* Increase Nodes and put all right open branches in open */
6 $clb := \max(clb, lb(open))$;
  if ($NodesRecompute > 0$) **then**
7 **if** ($NodesRecompute/Nodes > \beta$ **and** $Z \leq N$) **then** $Z := 2 \times Z$;
8 **else if** ($NodesRecompute/Nodes < \alpha$ **and** $Z \geq 2$) **then** $Z := Z/2$;
return cub;

DFS increases a counter $Nodes$ at each branching decision. It can backtrack (taking right branches) up to a limit of Z backtracks. When this limit is reached, all the unexplored right branches are placed in $open$. HBFS controls the balance between best-first search (partially exploring more open nodes) and depth-first search (complete exploration from a given starting node). Best-first search requires recomputing the state $\nu.\delta$ of a node (line 3) which can be costly in practice. HBFS uses a simple rule to limit this recomputation effort (measured by $NodesRecompute$ at line 4). It tries to keep the ratio $\frac{NodesRecompute}{Nodes}$ in the interval $[\alpha, \beta]$ by increasing (by a power of two) the backtrack limit Z if the ratio value is above β or decreasing Z if it is below $alpha$ (lines 7–8). Initially, Z is set to 1. In order to avoid exponential DFS behavior, HBFS limits the maximum value taken by Z to N. We kept the same value $\alpha = 5\%, \beta = 10\%, N = 2^{14}$ in our experiments as in the original paper [2].

3 Parallel HBFS

The parallel version of HBFS is based on the Master-Worker parallel paradigm [21] where the *Master* is in charge of the open node frontier and dispatches the current best (with minimum lower bound) open node plus the current best solution found so far to the next

available *Worker*. The Worker performs a bounded DFS starting from the received node and returns to the Master the resulting list of open nodes (see Fig. 1, with a DFS limit here of 4 backtracks). The Worker also returns the best solution found during its restricted search if any. Only the Master has a global view of the whole search and reports optimality gaps ($\frac{cub-clb}{cub}$) until the proof of optimality is reached: when the current best lower bound in the frontier of open nodes, including active worker starting nodes, is equal or greater than the cost of the best solution found so far or the frontier is empty and there are no active workers. When the problem is solved, the Master kills all the workers and returns the optimum value.

According to a round robin schema, the Master sends open nodes to every idle worker in a balanced way, ensuring a natural load balancing between the workers as soon as the number of open nodes in the frontier is larger than the number of workers. Moreover, an initial backtrack limit of $Z_i = 1$ associated to each Worker i favors the production of open nodes at the beginning of the search. Each Z_i is bounded by N as in sequential HBFS so that no worker takes too long.

The pseudo-code of the Master (resp. Worker) is given in Algorithm 2 (resp. Alg. 3). In the implementation, we avoid to send the same solution twice to a Worker. Moreover, workers send their solution only if it improves compared to the last solution sent by the Master. This strategy allows to shorten messages in the Master-Worker protocol.

Algorithm 2 Parallel HBFS-Master. Initial call for p workers: HBFS-Master($c_\emptyset$,k,$(1,\ldots,p)$).

Function HBFS-Master(*clb, cub, S*): integer ; /* *S queue of workers, return the optimum* */
  $open := \{\nu(\delta = \varnothing, lb = clb)\}$; /* *Initializes the open list with a root node* */
  $I := S$; /* *Queue of idle workers* */
  $A := \varnothing$; /* *Maps active workers to open nodes currently being processed* */
  while $((open \neq \varnothing$ **or** $A \neq \varnothing)$ **and** $clb < cub)$ **do**
    while $(open \neq \varnothing$ **and** $I \neq \varnothing)$ **do**
      ν :=pop($open$) ; /* *Chooses a node with minimum lower bound and maximum depth* */
      i :=popFront(I) ; /* *Unqueue the first idle worker* */
      $A := A \cup \{(i, \nu)\}$;
      Send ν and best solution cub to Worker i ;
9   Receive a list of open nodes $\mathcal{V}$ and solution cub' by worker j ; /* *Wait for message* */
    push($open$, $\mathcal{V}$) ; /* *Adds worker open nodes to the Master open list* */
    $cub := \min(cub, cub')$; /* *Checks if a better solution as been found* */
10 pushBack(I, j) ; /* *Pushes Worker j at the end of the idle worker queue I* */
11 $A := A \setminus \{(j, A[j])\}$; /* *Removes Worker j from active workers* */
    $clb := \max(clb, \min(lb(open), \min\{lb(\nu)$ **for** $(i, \nu) \in A\}))$; /* Global lower bound */
  return *cub*;

3.1 Improving the ramp-up phase

We observed that at the beginning of the search the first active worker may take a long time to build its list of open nodes when it reaches the initial backtrack limit (equal to one). It can be explained by the fact that if it found a new solution then this improved upper bound will possibly imply more work in subsequent propagation made later when assessing the lower bound of each open node. This has the effect to slow-down the construction of the list of open nodes when HBFS stops backtracking. During this period, called the *ramp-up phase* (where some workers have not been assigned at least one task), no parallelism is exploited. We modified our communication protocol to send a message to the master as soon as an open-node has been collected or a new solution has been found by a worker inside its DFS

Algorithm 3 Parallel HBFS-Worker. Initial call for Worker i: HBFS-Worker(k,i) with $Z_i = 1$.

```
Procedure HBFS-Worker(cub,rank) ;                          /* rank: Worker ID */
    while (true) do
        open_i := ∅ ;                                      /* local open list of Worker i */
        Receive an open node ν and solution cub' by Master ;   /* Wait for message */
        cub := min(cub, cub') ;                            /* Updates cub and best solution if any */
        Restores state ν.δ, leading to assignment A_ν, maintaining soft local consistency ;
        NodesRecompute := NodesRecompute + ν.depth ;
12      cub :=DFS(A_ν,cub,Z_i) ;  /* Increase Nodes ; put all right open branches in open_i */
        if (NodesRecompute > 0) then
13          if (NodesRecompute/Nodes > β and Z_i ≤ N) then Z_i := 2 × Z_i;
14          else if (NodesRecompute/Nodes < α and Z_i ≥ 2) then Z_i := Z_i/2;
15      Send open_i and best solution cub to the Master ;   /* or closing-node mes. in burst
         mode */
```

subroutine (line 12). Such messages are received by the Master (line 9) which does not change the Worker state to idle (lines 10 and 11) until it receives a closing-node message by the Worker (sent at line 15). By doing so, it allows the Master to distribute open nodes to idle workers earlier before the first active worker has finished its initial DFS. We call this modified Master-Worker protocol the *burst mode*. However, the Worker can potentially send $O(nd)$ more messages and it disallows data compression of the open list messages.[1]

4 Experimental Results

We implemented in C++ our parallel HBFS in the CFN solver toulbar2.[2] We used the boost MPI library for the Master-Worker communication protocol. We kept default parameters of toulbar2 except no dichotomic branching in order to explore a binary search tree with DFS (option `-d:`). The variable ordering heuristic is *dom/wdeg* [4] combined with *last conflict* [14]. The value ordering heuristic exploits the last solution found if any [7] or else EDAC existential value [6]. EDAC is also used as soft local consistency during search. Instances were preprocessed by VAC [5] and the resulting CFNs saved to files before the experiments to reduce the setup sequential time of paralllel HBFS. We compared both the sequential and parallel version of HBFS and also with the integer programming solver cplex (version 20.1 with non-premature stop parameters `EPAGAP=EPGAP=EPINT=0`). We set the number of threads used by cplex to the desired number of cores.

Experiments were performed either on medium-scale computers (24-core Intel Xeon E5-2687W v4 at 3 GHz and 256 GB) with 1-hour timeout or on a large-scale cluster with more than 10,000 cores (36-core per node of Intel Skylake 6140 at 2.3 GHz and 192 GB) with a longer 10-hour timeout for the sequential version only. Solving times are reported in seconds and correspond to CPU (resp. wall-clock) time for the sequential (resp. parallel) methods. No initial upper bounds were provided.

We tested the methods on four benchmarks selected from [12] with a total of 134 instances: two academic benchmarks taken in Operations Research, uncapacitated warehouse location problem (Warehouses) with 15 instances [13] and DIMACS maximum clique problem with

[1] In non-burst mode, all right branches share a common prefix in their $\nu.\delta$ and only the deepest δ information need to be sent to the Master.

[2] `https://toulbar2.github.io/toulbar2` version 1.2.

62 instances (MaxClique)[3] and two real-life Graphical Model benchmarks, linkage analysis problem occuring in genetics (Linkage) with 22 instances coming from UAI Evaluation 2008 [4] and computational protein design problem in biology (CPD) with 35 instances [1]. We applied the *tuple encoding* to convert Linkage and CPD to integer linear programs [12]. For a comparison on MaxClique with another parallel branch and bound implementation, see [16].

4.1 Comparison of parallel HBFS with its sequential version

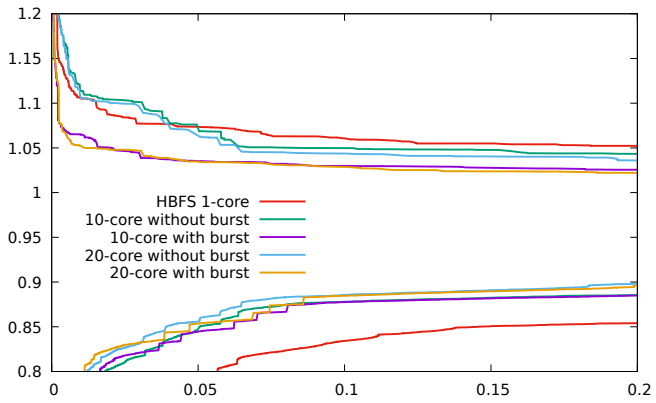

Figure 2 Comparison on a medium-scale computer between sequential versus parallel HBFS with or without burst mode. The x-axis represents normalized time (with 0.2 corresponding to 720 seconds). The y-axis corresponds to normalized lower and upper bounds on 134 instances (with 1 corresponding to the optimum or best known cost, see the text description).

We compared the anytime behavior of sequential (HBFS-1) and parallel HBFS (with 10 or 20 cores) with or without burst mode (see Sec. 3.1) on a medium-scale computer. We summarize the evolution of lower (*clb* in Alg. 1 and 2) and upper bounds (*cub*) for each method over all instances in Fig. 2. Specifically, for each instance we normalize all costs as follows: the initial lower bound $c_\emptyset$ produced by EDAC is 0; the best but potentially suboptimal solution found by any method is 1; the worst solution is 2. This normalization is invariant to translation and scaling. Additionally, we simply normalize time from 0 to 1, corresponding to 1 hour. A point x, y on the lower bound line for method M in Fig. 2 means that after normalized runtime x, method M has proved on average over all instances a normalized lower bound of y and similarly for the upper bound.

First, we observed that all parallel versions significantly outperformed the sequential HBFS lower bound curve. Concerning upper bound curves, the burst mode gave a clear advantage to parallel HBFS especially at the beginning of the search. In the sequel of the paper, we always report results of parallel HBFS with burst mode. As shown in the figure, increasing the number of cores from 10 to 20 slightly improved the bounds.

In Table 1 we report the number of instances solved by sequential and parallel HBFS for each benchmark. Parallel HBFS solved 1 more instance than the single core version in Linkage and 1 (resp. 3) in MaxClique using 10 (resp. 20) cores. We made local comparisons of solving times (shown in parentheses) by averaging on the subset of instances solved by the

[3] We removed the largest instances keller6 and p_hat1500-1,2,3 from the original 66 DIMACS instances.
[4] Linkage instances were further preprocessed by variable elimination limited to at most 8 neighbors [8].

three methods (HBFS-1, HBFS-10, HBFS-20). It allows us to display overall speed-up of parallel approaches by giving the ratio of total sequential over parallel time. Parallel HBFS obtained near linear speed-up on MaxClique. Recall that 1 core is used by the master and the rest by the workers in the Master-Worker approach preventing us from full linear speed-up. On CPD and Linkage the speed-up was halved. For Warehouses, only 50% of reduction in overall time was observed. This can be explained partly by the limited number of search nodes (Table 4 in Supplementary Material).We also observed that the evaluation of right branches made by the first active worker starting from the root node took most of the time. This is due to the fact that a first solution has been found by the worker resulting in more propagation on the right branches especially near the root. This pathological phenomenon did not appear on the other benchmarks.

Table 1 Number of solved instances within 1 hour (except for sequential HBFS-1 run on the cluster with a larger timeout of 10 hours) and average time in seconds in parentheses. To compute the mean we only consider for a given method (toulbar2 HBFS or cplex) the instances solved with any number of cores on the same computer (server with 3 GHz cores or cluster with 2.3 GHz cores).

Method	CPD (35)		Warehouses (15)		Linkage (22)		MaxClique (62)	
		Speed-up		*Speed-up*		*Speed-up*		*Speed-up*
HBFS-1	30 (43.44s)		15 (128.96s)		20 (23.24s)		37 (364.25s)	
HBFS-10	30 (8s)	*5.43*	15 (80.174s)	*1.61*	21 (3.5s)	*6.64*	38 (40.24s)	*9.05*
HBFS-20	30 (4.43s)	*9.81*	15 (85.39s)	*1.51*	21 (2s)	*11.62*	40 (19.9s)	*18.3*
cplex-1	24 (331.2s)		15 (123.83s)		22 (8.04s)		42 (282.16s)	
cplex-10	24 (226.51s)	*1.46*	**15 (68.82s)**	*1.8*	22 (2.56s)	*3.14*	45 (**55.48s**)	*5.08*
cplex-20	24 (198.49s)	*1.67*	15 (72.06s)	*1.72*	**22 (2.29s)**	*3.51*	**46** (71.47s)	*3.95*
HBFS-1 (cluster)	30 (66.46s)		15 (392.30s)		21 (427.21s)		37 (504s)	
HBFS-180 (cluster)	**30 (3.7s)**	***17.96***	15 (126s)	***3.11***	22 (4.15s)	***102.94***	45 (6.44s)	***78.26***

4.2 Comparison of parallel HBFS with integer programming

In Table 1 we also report the number of instances solved and their average solving time (as explained above) by cplex using multithreading. It clearly dominates HBFS on Linkage (Supp. Fig. 5).For Warehouses, the differences are less important still in favor of cplex. For MaxClique, although the global picture shows that it solved six more instances than HBFS with 20 cores, both methods performed well on different subsets of instances (e.g., HBFS-20 solved two instances – brock400_4 and sanr400_0.7 – unsolved by cplex-20 whereas cplex-20 solved eight instances unsolved by HBFS-20). For CPD, the CFN approach largely dominates the integer programming approach for all the instances. Concerning anytime curves shown in Fig. 3 (see also Supp. Fig. 4 and 5), the CFN approach is also significantly superior to cplex on average in producing good upper bounds faster, HBFS-20 being the best method. Concerning overall speed-up, cplex had difficulties to benefit from parallelism on CPD, Linkage, and Warehouses where it usually develops a small amount of search nodes (less than $7,059$ nodes except on Linkage/pedigree19 and pedigree40), resulting in poor speed-up except in a few cases. The speed-up is better on MaxClique but seems to stagnate when going from 10 to 20 cores (it was even slower on four instances).

4.3 Comparison of parallel HBFS with EPS on a cluster

The EPS approach is a two-phase procedure. First, the problem to be solved is decomposed into a list of l independent subproblems. Next, all the subproblems are solved in parallel (with at most p workers running at the same time) based on a particular scheduling strategy

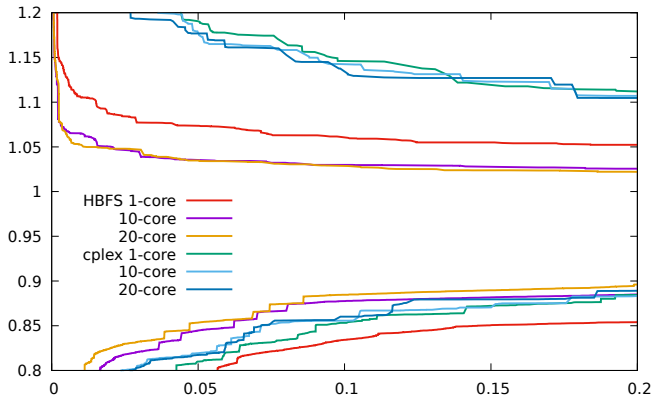

Figure 3 Comparison on a medium-scale computer between toulbar2 using parallel HBFS (with burst mode) and cplex using multiple threads. The x-axis represents normalized time (with 0.2 corresponding to 720 seconds). The y-axis corresponds to normalized lower and upper bounds on 134 instances (with 1 corresponding to the optimum or best known cost, see the text description).

with no communication between the workers. For optimization problems, we need to provide a good initial upper bound. Otherwise the search tree can be much larger than needed. In the first phase, we used the original HBFS method to collect l subproblems. As soon as HBFS has more than l open nodes in its frontier it stops and returns the current upper bound (cub) and the list of open nodes (without those having a lower bound $lb(\nu) \geq cub$). Each open node ν defines an independent subproblem with partial assignment $\nu.\delta$. In order to collect open nodes more rapidly we fix the (maximum) backtrack limit $Z = N = 1$. Ideally l should be $30 \times p$ with p the number of available cores [15]. In the second phase, we schedule on the cluster the subproblems that are solved by the original HBFS method using a simple scheduling heuristic based on increasing $|\nu.\delta|$.

In Table 2 we report for nine difficult instances their optimum value, the upper bound found at the end of EPS Phase-1, the actual number of generated subproblems, the average solving time of all subproblems, the maximum solving time, the number of failed subproblems (timeout of 1 hour) and the overall solving time of EPS Phase-2 using 180 cores on the cluster. We compare with HBFS using the same number of cores. Our EPS strategy failed on 4/9 instances. In parentheses, we indicate the maximum depth $\nu.depth$ of failed subproblems. Clearly, finding the right number l of not-too-difficult subproblems corresponding to partial assigments greater than a given depth is a challenging task. In our experiments, we tried with different values for $l \in [50, 6000]$, selecting the largest threshold value with a Phase-1 duration being less than 1 second for Linkage ($l = 6000$), 6 seconds for MaxClique ($l = 6000$) and 44 seconds for CPD ($l = 1000$). On the opposite, we did not tune any specific parameter for our parallel HBFS method.

In Table 1 we also report the overall speed-up of HBFS-180 compared to HBFS-1 on the cluster. HBFS-180 got a two-order-of-magnitude speed-up on Linkage.

5 Conclusion

Although the speed-up offered by the parallel version of HBFS was very instance dependent, we observed significant gain on several instances, outperforming in some cases state-of-the-art solvers like `cplex`. Even if the scalability of our approach must be subject of deeper investigation, due to the minimal size of the information shared between the Master and the Workers, our approach is very likely compliant with a larger number of cores.

Table 2 EPS and HBFS-180 results on hard instances (with n variables and maximum domain size d). A '-' indicates that some (see #failed) subproblems could not be solved in less than 3,600sec.

instance	n	d	opt.	*cub*	l	av. time	max. t.	#fail(depth)	EPS-180	HBFS-180
linkage/pedigree19	259	5	4625	5684	5114	20.57	-	1 (4)	-	**69.1**
linkage/pedigree40	274	6	7300	8838	5641	101.99	-	49 (21)	-	**1680**
linkage/pedigree51	295	5	6406	6802	5798	0.61	497.38	0	499	**5.7**
cpd/1BRS	38	178	4007610	4007679	956	2.94	38.90	0	44	**37.5**
cpd/1CDL	38	170	3590514	3590825	1001	6.66	79.04	0	79	**18.3**
cpd/1GVP	52	170	5196719	5196841	979	14.59	170.66	0	171	**17.0**
maxcl./brock400_1	400	2	373	379	6010	63.95	-	12 (149)	-	**1812**
maxcl./brock400_2	400	2	371	379	5975	65.27	-	18 (149)	-	**880**
maxcl./san400_0.5_1	400	2	387	392	6073	5.07	414.96	0	3652	**1220**

A more challenging task which remains as future work is to exploit the structure of CFNs by parallelizing Backtrack with Tree Decomposition (BTD-HBFS) [2]. Shared memory protocols may be more suitable for this task to make learnt nogoods available to all Workers.

On the practical side, our parallel HBFS could ran in conjunction with a parallel large neighborhood search strategy [20] offering even better anytime lower and upper bounds.

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