



Toward a Global Constraint for Minimizing the Flowtime

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Context

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Relaxations of $1|r_j, d_j; prec| \sum C_j$

The FLOWTIME constraint

Experimental results

Conclusion and prospects



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1. Context



Scheduling problems

Definition (scheduling)

Allocating **resources** to **tasks** over **time** while respecting the tasks and resources **constraints**.

Often optimizing one or more objectives $(C_{\max}, \sum C_j...)$.

Context

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Scheduling problems

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Solving scheduling problems with CP

Context

- Disjunctive constraint [Carlier, 1982; Fahimi & Quimper, 2014]
- Cumulative constraint [Aggoun & Beldiceanu, 1993; Guy et al., 2015]
- Survey of CP techniques for scheduling [Baptiste et al., 2001]
- CP vs MIP for 12 scheduling problems [Naderi et al., 2023]...

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Consti	raint (Optimiza	ation Pro	blem (COP)
CP for scheduling	g: key po	oints			
 Declarative 		• (Components	f <mark>or schedu</mark> li	ng
• Global constra	aints	•	Exact method	l	
Example in OPL,	modelir	ng language	e of IBM		
dvar interval dvar int F; \\	tasks[j objecti [,]	in N] in ve variab]	r[j]d[j] .e	size p[j];
<pre>minimize F; subject to { noOverlap(ta F = sum(j in flowtime(tas }</pre>	usks); \ N) end Eks, F);	\resource Of(tasks[\\contri]	<pre>constraint j]); \\star oution of t</pre>	: (ct) dard sum his work	ct



Constraint Programming (CP)

Principle

CP = Filtering + Search

Context



Figure: Solving the 4-queens problem with CP. Picture from the "Guide to Constraint Programming" of Roman Barták, 1998



Constraint Programming (CP)

Principle

CP = Filtering + Search

Context

• Filtering = removing values from domains leading to non feasible solutions



Figure: Solving the 4-queens problem with CP. Picture from the "Guide to Constraint Programming" of Roman Barták, 1998



Constraint Programming (CP)

Principle

CP = Filtering + Search

Context

- Filtering = removing values from domains leading to non feasible solutions
- Search = systematic exploration of solution space



Figure: Solving the 4-queens problem with CP. Picture from the "Guide to Constraint Programming" of Roman Barták, 1998



Thesis main objective

Context

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 Improve CP integration of scheduling objectives that are not studied a lot in CP, in particular "∑" objectives



Thesis main objective

- Improve CP integration of scheduling objectives that are not studied a lot in CP, in particular "∑" objectives
- Focus on $\sum C_j$ (flowtime)

Context

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Chosen approach

• Cost-based domain filtering [Focacci et al., 99]: global constraints filter values not leading to a better-cost solution



Thesis main objective

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Context

Chosen approach

- Cost-based domain filtering [Focacci et al., 99]: global constraints filter values not leading to a better-cost solution
- Scheduling problems: a relaxation gives a lower bound



Main objective and chosen approach

Thesis main objective

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- Focus on $\sum C_j$ (flowtime)

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Chosen approach

- Cost-based domain filtering [Focacci et al., 99]: global constraints filter values not leading to a better-cost solution
- Scheduling problems: a relaxation gives a lower bound

Main objective of this work

Propose a **new global constraint** helping minimizing $\sum C_j$ using **new polynomial relaxations**





Context Relaxations FLOWTIME Res



2. Relaxations of $1|r_j, d_j; prec| \sum C_j$

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G SLUP		Pol	ynomia	l relaxat	ions
$1 d_j \sum C_j$	$\rightarrow 1 r_j; d_j \sum C_j \qquad \qquad$	$ d_j; pmtn \sum C_j $	$pomtn \sum w_iM_i$	\mathcal{P}	
$1 \sum C_j \longrightarrow 1 r_j \sum C_j$	$\frac{1 r_j; d_j; prec \sum C_j}{1 chai}$	$ns; r_j; pmtn \sum C_j$		$\mathcal{NP} ext{-hard}$	
$1 prec \sum C_j$	$1 sp-grapn \sum w_j C_j$ 1 pn	rec; $pmtn \sum C_j$			
problem	complexity	list algorithm	upda- ted	referen	се

		list	upda-	
problem	complexity	algorithm	ted	reference
$1 \sum C_j$	$O(n \log n)$	yes	no	[Horn, 1973]
$1 d_j \sum C_j$	$O(n \log n)$	yes	yes	[Chen & al, 1998]
$1 r_j$; pmtn $ \sum C_j$	$O(n \log n)$	yes	yes	[Baker, 1974]
$1 r_j; pmtn \sum w_j M_j$	$O(n \log n)$	yes	yes	[Kovàcs & Beck, 2011]
$1 sp$ -graph $ \sum w_j C_j$	$O(n \log n)$	no	yes	[Lawler, 1978]

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3. The FLOWTIME constraint

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The FLOWTIME constraint

• FLOWTIME($[S_1, \ldots, S_n]$, $[p_1, \ldots, p_n]$, F) $\stackrel{\text{def}}{\longleftrightarrow} ((\underbrace{S_i + p_i \leq S_j \lor S_j + p_j \leq S_i}_{\text{no tasks overlap}}) \land \underbrace{\sum (S_i + p_i) = F}_{\text{no precemption}})$



The FLOWTIME constraint

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• FLOWTIME($[S_1, \ldots, S_n], [p_1, \ldots, p_n], F$) $\stackrel{\text{def}}{\longleftrightarrow} ((S_i + p_i \leq S_j \lor S_j + p_j \leq S_i) \land \sum (S_i + p_i) = \textbf{\textit{F}})$ no tasks overlap

• Relaxation used: many relaxations possible

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Global schema

Global schema of the filtering algorithm

• Choose a relaxation



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- Choose a relaxation
- Two rules:



Global schema

Global schema of the filtering algorithm

- Choose a relaxation
- Two rules:
 - Update the lower bound of the objective variable (<u>F</u>)

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Global schema

Global schema of the filtering algorithm

- Choose a relaxation
- Two rules:

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- Update the lower bound of the objective variable (<u>F</u>)
- Filter the bounds of the domains of the S_j variables

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Global schema

Global schema of the filtering algorithm

- Choose a relaxation
- Two rules:
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Remarks

G-SCOP

• The relaxation can be changed

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Global schema

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- Choose a relaxation
- Two rules:
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G-SCOP

- The relaxation can be changed
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Conclusion

Global schema

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- Choose a relaxation
- Two rules:
 - Update the lower bound of the objective variable (<u>F</u>)
 - Filter the bounds of the domains of the S_j variables

Remarks

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- The relaxation can be changed
- The relaxation is considered a "black box"
- Allows to compare the performances of different relaxations



Objective bound update: example

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Tj	1	2	3	4	5	6
pj	14	5	2	3	6	3
rj	0	0	1	12	16	17
d_j	24	∞	10	∞	26	∞



Objective bound update: example

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Relaxation used: $1|r_j; pmtn| \sum C_j$



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Relaxation used: $1|r_j; pmtn| \sum C_j$ $F \in [100, 130]$

j	1	2	3	4	5	6
Sj	[0, 10]	[0, 46]	[1, 8]	[12, 49]	[16, 20]	[17, 17]
r'_i	0	0	1	12	16	17
d'_j	24	51	10	51	26	20



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FLOWTIME

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 $\begin{array}{ll} \mbox{Relaxation used: } 1|r_j; \mbox{ pmtn}| \sum C_j \\ F \in [100, 130] & \sum C_j = {\bf 104} > \underline{F} \end{array}$







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FLOWTIME

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Relaxation used: $1|r_j; pmtn| \sum C_j$ $F \in [104, 130] \qquad \sum C_j = 104 > \underline{F}$







Filter bounds of S_j: example

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Filter $\underline{S_1}$ (symmetrical for $\overline{S_1}$) $F \in [104, 130]$ Relaxation used: $1|r_j$; $pmtn| \sum C_j$

j	1	2	3	4	5	6
Sj	[2, 10]	[0, 46]	[1, 8]	[12, 49]	[16, 20]	[17, 17]
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Step 2 : t = 3, $relax_{1,3} = 123 \le 130(=F)$ STOP

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4. Experimental results



Experimental environment

Results

Environment and parameters

• C++ and IBM ILOG CPLEX Optimization Studio 22.1

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Experimental environment

- C++ and IBM ILOG CPLEX Optimization Studio 22.1
- The code of **COMPLETION** has been **adapted** to the solver version (IlcActivity \longrightarrow IloIntervalVar)

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Experimental environment

- C++ and IBM ILOG CPLEX Optimization Studio 22.1
- The code of **COMPLETION** has been **adapted** to the solver version (IlcActivity \longrightarrow IloIntervalVar)
- Dell computer with 256 GB of RAM and 4 Intel E7-4870
 2.40 GHz processors running on CentOS Linux release 7.9 (each processor has 10 cores)

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- Dell computer with **256 GB** of **RAM** and **4** Intel E7-4870 2.40 GHz processors running on **CentOS Linux** release 7.9 (each processor has 10 cores)
- Parallelism is disabled
- Time limit is 1000 seconds for each run

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Instances used

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• Single-machine problems: $1|r_j| \sum C_j$

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Instances used

G-SCOP

- Single-machine problems: $1|r_j| \sum C_j$
- 900 instances from [Pan & Shi, 08]

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Instances used

G-SCOP

- Single-machine problems: $1|r_j| \sum C_j$
- 900 instances from [Pan & Shi, 08]
- Less than 100 tasks

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Instances used

G-SCOP

- Single-machine problems: $1|r_j| \sum C_j$
- 900 instances from [Pan & Shi, 08]
- Less than 100 tasks
- Different relative ranges of the release time

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Alternatives tested

Main alternatives tested

• Most efficient alternatives for the FLOWTIME constraint:

name	filter Sj	; relaxation		
pmtnFlow	no	$1 r_j; pmtn \sum C_j$		
pmtnBusy	no	$ 1 r_j; pmtn \sum M_j$		
filtFlow	yes	$1 r_j; pmtn \sum C_j$		
filtBusy	yes	$1 r_j; pmtn \sum M_j$		

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filtFlow	yes	$1 r_j; pmtn \sum C_j$
filtBusy	yes	$1 r_j; pmtn \sum M_j$

• sum: standard sum constraint

• complBusy: adapts COMPLETION $(1|r_j; pmtn| \sum M_j)$

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Detailed results

alternative	OPT	SAT	mean t*	median t*	mean #b*	median #b*
pmtnFlow	824	76	50.5	2.62	484613	51618
pmtnBusy	777	123	55.4	2.87	666864	60633
filtFlow	565	335	169	58.8	10776	8704
filtBusy	578	322	158	47.3	18942	10832
sum	246	654	76.9	5.21	1629165	150508
complBusy	610	290	114	17.8	63835	25356

[*]only on OPT solved instances

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Conclusion of experimental results

Results

Summary of the results

• Less time taken to solve single-machine problems with FLOWTIME



Conclusion of experimental results

Results

- Less time taken to solve single-machine problems with FLOWTIME
- +500 more instances solved to optimality with pmtnFlow than with sum



Conclusion of experimental results

Results

- Less time taken to solve single-machine problems with FLOWTIME
- +500 more instances solved to optimality with pmtnFlow than with sum
- pmtnFlow quicker than pmtnBusy, and visits less branches



Conclusion of experimental results

Results

- Less time taken to solve single-machine problems with FLOWTIME
- +500 more instances solved to optimality with pmtnFlow than with sum
- pmtnFlow quicker than pmtnBusy, and visits less branches
- complBusy visits more branches than filtFlow



Conclusion of experimental results

Results

- Less time taken to solve single-machine problems with FLOWTIME
- +500 more instances solved to optimality with pmtnFlow than with sum
- pmtnFlow quicker than pmtnBusy, and visits less branches
- complBusy visits more branches than filtFlow
- Currently, filtering S_j: uses less branches than just updating <u>F</u>, but takes more time

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5. Conclusion and prospects



Conclusion

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Conclusion

• Global constraint minimizing $\sum C_j$



Conclusion

- Global constraint minimizing $\sum C_j$
- FLOWTIME can be used to model any problem with $\sum C_j$



Conclusion

- Global constraint minimizing $\sum C_j$
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- Filtering algorithm allows using different relaxations



Conclusion

- Global constraint minimizing $\sum C_j$
- FLOWTIME can be used to model any problem with $\sum C_j$
- Filtering algorithm allows using different relaxations
- Effective for single-machine problems



Conclusion

- Global constraint minimizing $\sum C_j$
- FLOWTIME can be used to model any problem with $\sum C_j$
- Filtering algorithm allows using different relaxations
- Effective for single-machine problems
- Less effective for flowshop problems



Conclusion

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- Global constraint minimizing $\sum C_j$
- FLOWTIME can be used to model any problem with $\sum C_j$
- Filtering algorithm allows using different relaxations
- Effective for single-machine problems
- Less effective for flowshop problems

Prospects

• Improve the incrementality of the filtering algorithm (t = t + 1)



Conclusion

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Prospects

- Improve the incrementality of the filtering algorithm (t = t + 1)
- Add conditions to use the filtering algorithm



Conclusion

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- Global constraint minimizing $\sum C_j$
- FLOWTIME can be used to model any problem with $\sum C_j$
- Filtering algorithm allows using different relaxations
- Effective for single-machine problems
- Less effective for flowshop problems

Prospects

- Improve the incrementality of the filtering algorithm (t = t + 1)
- Add conditions to use the filtering algorithm
- Add $1|sp-graph| \sum w_j C_j$ relaxation