

Solution robustness

Workshop on robust and stochastic optimization method
2021/11/19

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Sommaire

- 1 Solution robustness approach
- 2 Complexity results
- 3 Numerical results

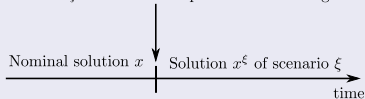
Nominal optimization problem (without uncertainty)

$$\bar{P} \begin{cases} \min & c(x) \\ \text{s.t.} & x \in X \end{cases}$$

Nominal cost

Adaptation to uncertainty

Scenario ξ occurs and the problem data change



Objective of most robust optimization approaches

Minimize the nominal cost $c(x)$ or $c(x^\xi)$

Quality robustness

What should also be optimized

Minimize a distance $d(x, x^\xi)$

Solution robustness

Solution robustness is important when...

... the nominal solution x is implemented on a regular basis

Risk of human errors

A traveler may miss a train which leaves earlier than usual
An operator may activate a railroad switch no longer required

... the uncertainty is revealed late

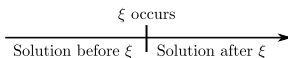
Not enough time to implement many changes

Transfers of trains between stations take time
Changes may require synchronization between different services

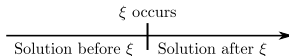
Definition - Solution cost

Quantify the cost of adapting x into x^z

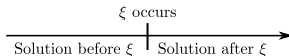
May disrupt the realization of x^z or even make it infeasible
→ can be more important than the nominal cost



Approach	Solution		Nominal cost		Solution cost
	Before ξ	After ξ	Before ξ	After ξ	
Classical robustness [Soyster, 1973, Bertsimas and Sim, 2004]	x	x ↑ No modification	Minimized	-	$= 0$
Recoverable robustness [Liebchen et al., 2009]	x, A ↑ Algorithm	$A(x, \xi)$	Minimized	-	A can limit $d(x, A(x, \xi))$



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k -distance [Büsing, 2012]	x	x^ξ	Minimized	-	$d(x, x^\xi) \leq k$
Anchored [Bendotti et al., 2019]	$(x_a, x_{\bar{a}})$ ↑ Anchored variables	$(x_a, x_{\bar{a}}^\xi)$	Constrained	-	Maximize anchored variables
Recovery to optimality [Goerigk and Schöbel, 2014]	x ↑ Not necessarily feasible	x^ξ	-	Minimized	Minimized (secondary objective)



Approach	Solution		Nominal cost		Solution cost
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Recovery to optimality [Goerigk and Schöbel, 2014]	x ↑ Not necessarily feasible	x^ξ	-	Minimized	Minimized (secondary objective)
Reactive [Ales and Elloumi, 2021]	x	x^ξ	-	-	Minimize $d(x, x^\xi)$ a posteriori
Proactive [Ales and Elloumi, 2021]	x	x^ξ	Constrained	-	Minimize $d(x, x^\xi)$ a priori

Our problems

Approach	Solution		Nominal cost		Solution cost
	Before ζ	After ζ	Before ζ	After ζ	
Reactive	x	x^ζ	-	-	Minimize $d(x, x^\zeta)$ a posteriori
Proactive	x	x^ζ	Constrained	-	Minimized $d(x, x^\zeta)$ a priori

Reactive problem

$$P^r(\zeta_i, x) \begin{cases} \min & d(x^i, x) \\ \text{s.t.} & x^i \in X_i \end{cases}$$

a scenario \downarrow ζ_i
 Feasible set of ζ_i \uparrow X_i

Returns

- one **reactive solution** x^i

Proactive problem

$$P^p(\mathcal{S}, c^*) \begin{cases} \min & \sum_{\zeta_i \in \mathcal{S}} w_i d(x, x^i) \\ \text{s.t.} & x \in X \\ & x^i \in X_i \\ & c(x) = c^* \end{cases}$$

Set of scenarios \downarrow \mathcal{S}
 Scenarios weight \downarrow w_i
 $\zeta_i \in \mathcal{S}$

Returns

- one **proactive solution** x and
- $|\mathcal{S}|$ scenario solutions $\{x^i\}_{i \in \mathcal{S}}$

Two solution cost distances

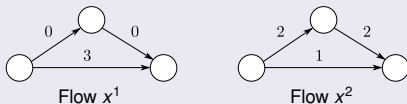
Distance in values (ℓ_1 norm)

$$d_{val}(x^1, x^2) \triangleq \sum_{j=1}^n |x_j^1 - x_j^2|$$

Distance in structure

$$d_{struct}(x^1, x^2) \triangleq \sum_{j=1}^n |\mathbb{1}_{x_j^1 > 0} - \mathbb{1}_{x_j^2 > 0}|$$

Example



- $d_{val}(x^1, x^2) = 6$
- $d_{struct}(x^1, x^2) = 2$

Sommaire

- 1 Solution robustness approach
- 2 Complexity results**
- 3 Numerical results

Polynomial problems considered

- Integer min-cost flow
Uncertain arc demands
- Integer max-flow
Uncertain capacities

Complexity results for both problems

Problem	Distance	
	d_{val}	d_{struct}
Proactive	?	?
Reactive	?	?

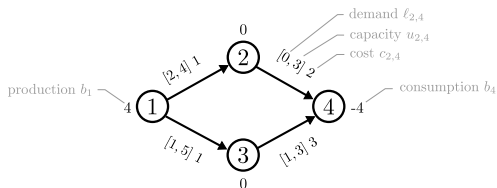
Integer min-cost flow

Data

- $G = (V, A)$
- b_v : production/consumption of $v \in V$ $\sum_v b_v = 0$
- c_a : unitary flow cost of $a \in A$
- ℓ_a / u_a : minimal demand / maximal capacity of $a \in A$

Definition (polynomial)

Find an integer flow of minimal cost which satisfies the productions, consumptions, demands and capacities



Uncertainty

Arc demands ℓ are uncertain

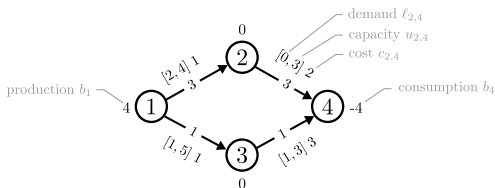
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Theorem

$MCF_{d_{val}}^r$ is polynomial

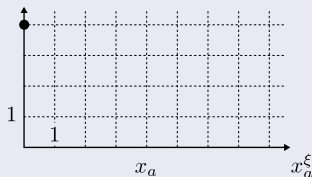
↑ Reactive problem with distance d_{val}

Problem	Distance	
	d_{val}	d_{struct}
Proactive	?	?
Reactive	Polynomial	?

Property

The cost of an arc is a piecewise linear convex function of its flow

↑ $|x_a - x_a^{\xi}|$



⇒ $MCF_{d_{val}}^r$ is a convex cost flow

Theorem [Ahuja et al., 1988]

A convex cost flow problem with piecewise linear convex cost functions can be transformed into a min-cost flow problem

Theorem

$MCF_{d_{val}}^r$ is polynomial

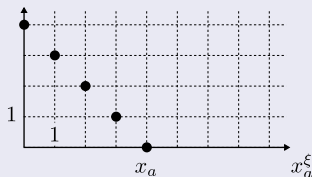
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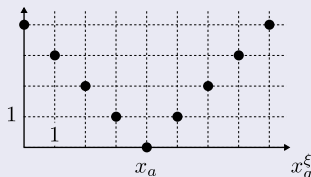
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Problem	Distance	
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Proactive	?	?
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Theorem

Proactive problem with distance d_{val}

$MCF_{d_{val}}^P$ is \mathcal{NP} -hard
Reduction from 3-SAT

Problem	Distance	
	d_{val}	d_{struct}
Proactive	\mathcal{NP} -hard	?
Reactive	Polynomial	?

3-SAT

• n boolean variables $X = \{x_1, \dots, x_n\}$

$\downarrow x_j$ or \bar{x}_j

• m clauses $\{C_1, \dots, C_m\}$ each containing a conjunction of three literals

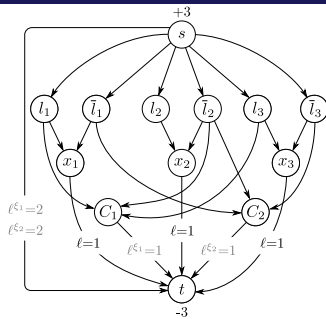
Is there an affectionation of X which satisfies all clauses?

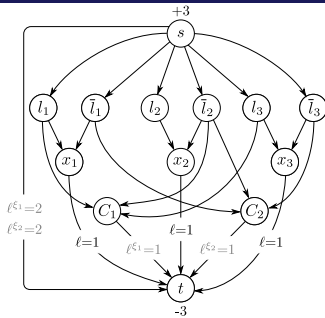
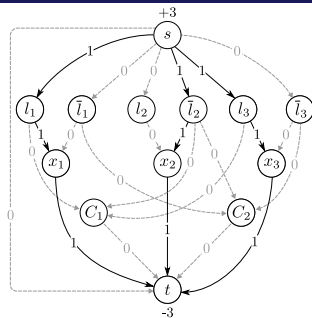
e.g.: $C_1 = (x_1 \vee \bar{x}_2 \vee x_3)$ and $C_2 = (\bar{x}_1 \vee \bar{x}_2 \vee \bar{x}_3)$

Sketch of the proof

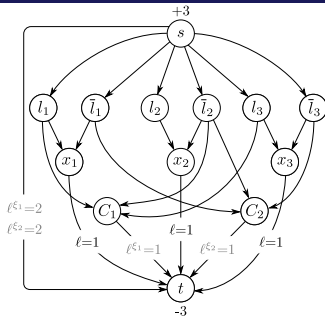
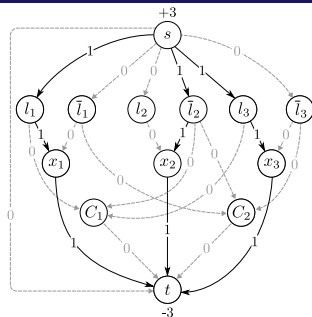
$\forall I_{SAT}$ $(\exists I_{MCF}$ of $d_{val} \leq 4mn$ iff I_{SAT} is true)

Instance of 3-SAT \uparrow \uparrow Instance of the proactive problem with d_{val}

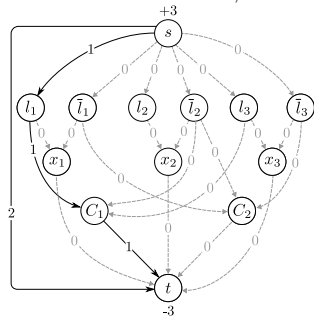


Arc demands which are $\neq 0$ 

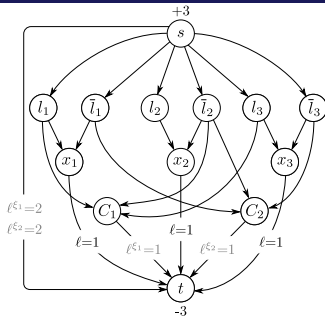
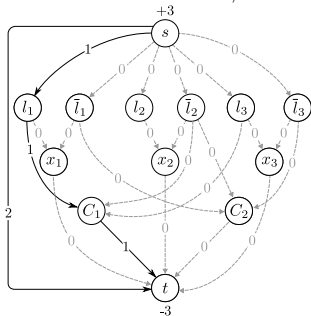
Nominal flow

Arc demands which are $\neq 0$ 

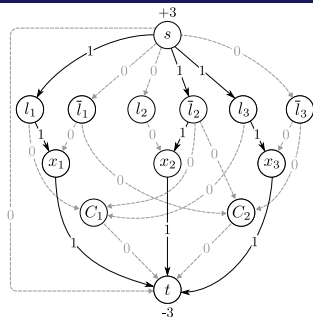
Nominal flow



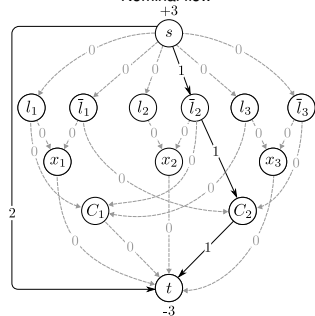
Flow of the first scenario

Arc demands which are $\neq 0$ 

Flow of the first scenario



Nominal flow



Flow of the second scenario


Complexity results summary for both flow problems

Problem	Distance	
	d_{val}	d_{struct}
Proactive	\mathcal{NP} -hard	\mathcal{NP} -hard even with 1 scenario
Reactive	Polynomial	\mathcal{NP} -hard

Sommaire

- 1 Solution robustness approach
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Approaches comparison

Approach	Solution		Nominal cost		Solution cost
	Before ζ	After ζ	Before ζ	After ζ	
Anchored [Bendotti et al., 2019]	$(x_a, x_{\bar{a}})$	$(x_a, x_{\bar{a}}^{\zeta})$	Constrained	-	Maximize anchored variables
	 Anchored variables				
k-distance [Büsing, 2012]	x	x^{ζ}	Minimized	-	$d(x, x^{\zeta}) \leq k$
Proactive [Ales and Elloumi, 2021]	x	x^{ζ}	Constrained	-	Minimize $d(x, x^{\zeta})$

Problem considered

A railway scheduling problem in which lines frequency must be fixed

Uncertainty

Number of passengers for each possible (origin, destination)

20% of the values are unchanged

80% of the values are in $\pm 10\%$ of their nominal value

Modelisation

MILP compact formulations solved with CPLEX

Approaches comparison

$ S $	Method	Nominal cost $c(x)$	Solution cost d_{val}	Number of anchored lines
2	Proactive	81742	50	196 (-2%)
	Anchored	81742	76 (+52%)	200
	0-distance	89028 (+9%)	0 (-100%)	210 (+5%)
	1-distance	86663 (+6%)	12 (-76%)	208 (+4%)
	2-distance	84740 (+4%)	19 (-62%)	206 (+3%)
	4-distance	82156 (+1%)	37 (-26%)	202 (+1%)
	10-distance	81742	81 (+62%)	196 (-2%)
6	Proactive	81742	120	186 (-7%)
	Anchored	81742	246 (+105%)	199
	0-distance	91998 (+13%)	0 (-100%)	210 (+6%)
	1-distance	87274 (+7%)	28 (-77%)	204 (+3%)
	2-distance	85178 (+4%)	53 (-56%)	200 (+1%)
	4-distance	82158 (+1%)	105 (-12%)	193 (-3%)
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Conclusion

- New robust approach
- Optimize the solution robustness
- Complexity results for two network problems and two distances
- Numerical results which highlight advantages over other approaches



Ales, A., and Elloumi, S. (2021).

A solution robustness approach applied to network optimization problems.

Available on arXiv: <https://arxiv.org/abs/2110.11647>

Perspectives

- Identification of polynomial proactive integer problems
- Uncertainty sets rather than set of scenarios
Box, budgeted, polytope, ...
- Bi-objective resolution
Solution cost and nominal cost

Références I



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Bendotti, P., Chrétienne, P., Fouilhoux, P., and Pass-Lanneau, A. (2019).

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Bertsimas, D. and Sim, M. (2004).

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Büsing, C. (2012).

Recoverable robust shortest path problems.

Networks, 59(1):181–189.



Goerigk, M. and Schöbel, A. (2014).

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Computers & Operations Research, 52:1–15.



Liebchen, C., Lübbecke, M., Möhring, R., and Stiller, S. (2009).

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Soyster, A. L. (1973).

Convex programming with set-inclusive constraints and applications to inexact linear programming.

Operations research, 21(5):1154–1157.

Theorem

Proactive problem with distance d_{struct}

$MCF_{d_{struct}}^P$ is \mathcal{NP} -hard
Reduction from 3-Partition

Problem	Distance	
	d_{val}	d_{struct}
Proactive	\mathcal{NP} -hard	\mathcal{NP} -hard even with 1 scenario
Reactive	Polynomial	?

3-Partition

- $E = \{1, 2, \dots, 3m\}$: elements
- $s(i)$: size of $i \in E$ in $]\frac{B}{4}, \frac{B}{2}[$
 $B \in \mathbb{N}$

Is there a partition $\{E_1, \dots, E_m\}$ of E such that $\sum_{i \in E_j} s(i) = B$?

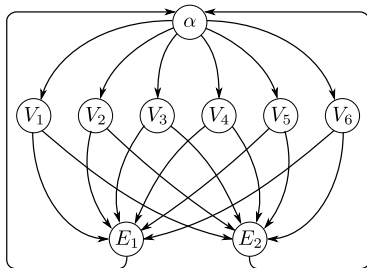
e.g.: $B = 100$, $m = 2$, elements size $\{30, 30, 30, 35, 35, 40\}$

Sketch of the proof

$\forall I_P$ (Instance of 3-partition) \uparrow $(\exists I_{MCF}$ of $d_{struct} \leq 3m^2 + 4m$ iff I_P is true) \uparrow Instance of the proactive problem with d_{struct}

Example of instance I_P

- $B = 100$
- Partition with 2 subsets
- Elements size: $\{30, 30, 30, 35, 35, 40\}$

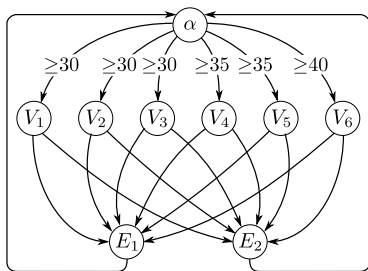


I_{MCF} graph ($b = \ell = 0, c = 1, c^* = 0, u = 100$)

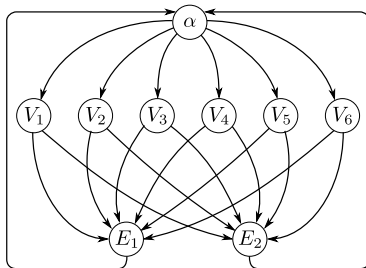
Nominal flow is empty \uparrow
 $\Rightarrow d_{struct} = \#$ or arcs in the scenario flow

Example of instance I_P

- $B = 100$
- Partition with 2 subsets
- Elements size: $\{30, 30, 30, 35, 35, 40\}$



Scenario demands $\ell^s \neq 0$

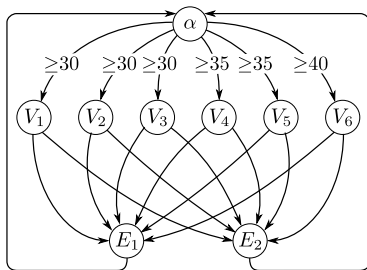
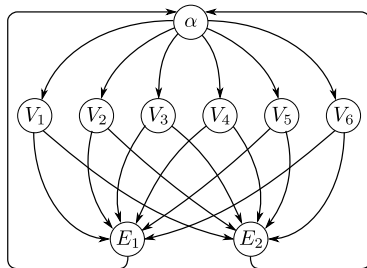


I_{MCF} graph ($b = \ell = 0$, $c = 1$, $c^* = 0$, $u = 100$)

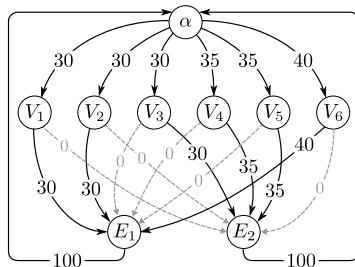
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Proactive flow

Theorem

$MCF_{d_{struct}}^r$ is \mathcal{NP} -hard.

↑
Reactive problem with distance d_{struct}

Problem	Distance	
	d_{val}	d_{struct}
Proactive	\mathcal{NP} -hard	\mathcal{NP} -hard even with 1 scenario
Reactive	Polynomial	\mathcal{NP} -hard

Proof

Same reduction but with the unique optimal flow as an input rather than an output

Integer max-flow problem with uncertain capacities

Same 4 complexity results

Proactive / Reactive comparison

$ \mathcal{S} $	Solution	Solution cost
		d_{val}
2	Proactive	50
	Reactive (x^A, f^A)	50
	Reactive (x^B, f^B)	57 (+14%)
	Reactive (x^C, f^C)	62 (+24%)
	Reactive (x^D, f^D)	56 (+12%)
6	Proactive	120
	Reactive (x^A, f^A)	120
	Reactive (x^B, f^B)	123 (+2%)
	Reactive (x^C, f^C)	133 (+11%)
	Reactive (x^D, f^D)	121 (+1%)
10	Proactive	196
	Reactive (x^A, f^A)	197 (+1%)
	Reactive (x^B, f^B)	211 (+8%)
	Reactive (x^C, f^C)	220 (+12%)
	Reactive (x^D, f^D)	204 (+4%)

$ \mathcal{S} $	Solution	Solution costs
		d_{struct}
2	Proactive	10
	Reactive (x^A, f^A)	10
	Reactive (x^B, f^B)	12 (+20%)
	Reactive (x^C, f^C)	11 (+10%)
	Reactive (x^D, f^D)	11 (+10%)
6	Proactive	23
	Reactive (x^A, f^A)	26 (+13%)
	Reactive (x^B, f^B)	28 (+22%)
	Reactive (x^C, f^C)	24 (+4%)
	Reactive (x^D, f^D)	23
10	Proactive	37
	Reactive (x^A, f^A)	38 (+3%)
	Reactive (x^B, f^B)	43 (+16%)
	Reactive (x^C, f^C)	39 (+5%)
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