

# Robust Network Planning Problems

Utz-Uwe Haus<sup>1</sup>   Carla Michini<sup>2</sup>   Marco Laumanns<sup>3</sup>

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<sup>1</sup>ETHZ   <sup>2</sup>U Wisconsin, Madison   <sup>3</sup>IBM Research (Switzerland)

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# Goal and motivation

- Robustifying Infrastructure
  - survivability, cost robustness
  - structural robustness
  - pre-disaster investment
- Different modeling and solution approaches
  - (worst-case-) robust optimization
  - fault-tolerant-feasibility models
  - multistage stochastic models

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# Networks with uncertain data: Robust Optimization

## Setting

A network problem with uncertain cost, supply/demand or capacity data: uncertainty set  $\Delta$

## Solution approaches

- Worst-case ( $\forall \delta \in \Delta$ ) or best-case ( $\exists \delta \in \Delta$ ) setting are interesting
- $\forall$ : Reformulate and solve robust counterpart
- $\exists$ : Reformulate as Generalized LP(/IP/...)
- ... or separate robust/generalized (split-)cuts directly
- Caveat 1: Reformulation often loses combinatorial structure
- Caveat 2: Shortest path with 2 cost scenarios is (weakly)  $\mathcal{NP}$ -hard

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# Structural Robustness – Fault-tolerant Feasibility

Deal with failure of resources, have certain cost structure

Requires: up-monotonicity of feasible sets

## Structural Robust Counterpart

Given nominal instance  $P = (A, S, w)$  ( $A$ : ground set,  $S$ : feasible solutions,  $w$ : cost function) and failure scenarios  $\Omega = \{F_1, \dots, F_k\}$  with  $F_i \subseteq A$  find  $X^*$  attaining

$$\min_{X \subseteq A: \forall i: X \setminus F_i \in S} w(X).$$

Idea: Accept (potentially more expensive) solutions that remain feasible in every scenario

# Structural Robustness: Survey

## Examples for $P = (A, S, w)$

Shortest Path (SP), Bipartite Matching (BM), Spanning Tree (ST),  
Matroid Linear Optimization (MLO), Sparsest  $k$ -Spanner ( $S_kS$ )

## Scenario encodings

- explicit  $\Omega = \{F_1, \dots, F_k\}$ : ERCC( $P, k$ )
- implicit:
  - uniform cardinality constrained  $\Omega = \{F \subseteq A : |F| \leq k\}$ : IRCC( $P, k$ )
  - uniform cardinality constrained in subset  $U \subseteq A$  ('unguarded' elements)  $\Omega = \{F \subseteq U : |F| \leq k\}$ : SIRCC( $P, U, k$ )

for details: see ADJIASHVILI ET AL, MathProg A 2014

# Structural Robustness: Some results

## ERCC(P,k) hardness

Assuming  $\mathcal{NP} \not\subseteq \text{DTIME}(n^{\log \log n})$  there is no polynomial  $c \log k$  approximation for ERCC(P) for any  $c < 1$ . ( $P = \text{SP, BM, ST, MLO, SkS}$ )

## ERCC(MLO,k) approximability

There is a polynomial  $\mathcal{O}(\log \text{rk}(M) + \log k)$  approximation algorithm for ERCC(MLO,k) ( $M$  a matroid).

## ERCC(SP,k, $|F_j| \leq 2$ ) approximability

There is a constant-factor approximation for ERCC(SP,k,  $|F_j| \leq 2$ ), and for  $|F_j| = 1$  the algorithm is exact.

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# Pre-Disaster Investment – Stochastic Models

## 2-stage stochastic problem

$$\min \mathbb{E}_{\xi|x} [f(\xi)]$$

$$Cx \leq d$$

$$x = (x_e)_{e \in E} \in \{0, 1\}^{|E|}, \quad \xi = (\xi_e)_{e \in E} \in \{0, 1\}^{|E|}$$

where computing  $f(\xi)$  means solving an optimization problem in scenario realization  $\xi$  after decisions  $x$  ( $\xi_e$  indep. rand. var.).

### Example

Consider a graph  $G = (V, E)$ , edge lengths  $(l_e)_{e \in E}$ , and edge survivability probabilities  $(p_e)_{e \in E}$ . Scenarios correspond to sets of surviving edges after a disaster.  $f_{SP}(s, t, G_\xi)$  is the shortest path length between two designated nodes  $s, t \in V$ . Decisions are whether to strengthen edge  $e$ , i.e. improve resilience, to  $p_e + \delta_e$ .

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## Solution approaches

- sampling scenarios/simulation
- sample average/sample-path: may yield statistically testable bounds
- partition or **cover** scenario space and do exact reformulation

### Example (cont.): Computing expected path length

$$\min \sum_{\xi \in 2^E} \left( \prod_{e \in \xi} p_e \prod_{e \notin \xi} (1 - p_e) \right) f_{SP}(s, t, G_\xi = (V, \xi))$$

Instead of enumerating  $2^{|E|}$  scenarios the scenarios can be partitioned into sets with same  $f$ -value whose probabilities can be computed.  
(PRESTWICH ET AL., '13)

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A 2-stage stochastic optimization problem is called **aggregable** if

- $f$  is order-reversing (or order-preserving) wrt. taking subsets of scenarios,

$$\xi_1 \subseteq \xi_2 \Rightarrow f(\xi_1) \geq f(\xi_2) \quad (1)$$

for all  $\xi_1, \xi_2 \in 2^E$ ,

- the probabilities of events  $e \in E$  are independent.

We denote the range of  $f$  by  $\mathcal{C}(f) = \{\alpha : \alpha = f(\xi), \xi \in 2^E\}$ , and the minimal survivable scenarios for each critical value by

$\mathcal{M}(f) = \{\mathcal{M}_\alpha(f) : \alpha \in \mathcal{C}(f)\}$  with

$\mathcal{M}_\alpha(f) = \{\xi \in 2^E : f(\xi) = \alpha, \forall \xi' \subset \xi : f(\xi') > f(\xi)\}$ .



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## Examples

'friendly': where computing  $f(\xi)$  is polynomial time

- (multi-terminal-) shortest path
- number of edge-disjoint paths/ $k$ -connectivity
- longest path in acyclic networks
- maximal flow
- maximal/max weighted matching
- LP (with vanishing constraints)

but also

- clique number

Each  $\mathcal{M}_\alpha(f)$  induces a monotone Boolean function  $\Phi_\alpha^\leq$  on the scenarios whose minimal true points are the members of  $\mathcal{M}_\alpha(f)$  by

$$\Phi_\alpha^\leq(\xi) = 1 \text{ if and only if } f(\xi) \leq \alpha.$$

### Encoding $\Phi_\alpha^\leq$

- as DNF: using explicit list  $\mathcal{M}_\alpha(f)$
- as IP of covering type:  $p^\top x \geq 1 (\forall p \in \mathcal{M}_\alpha(f))$
- as binary decision diagram (BDD), built from explicit or implicit  $\mathcal{M}_\alpha(f)$
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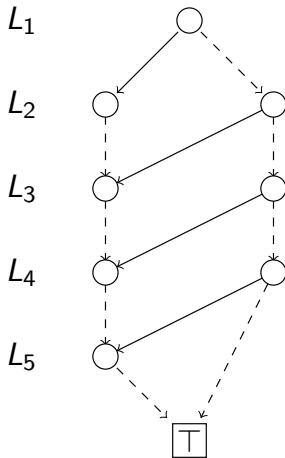
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# (Reduced Ordered) Binary Decision Diagrams (Bryant, 1986)

- Layered (rooted) digraph
- arcs only from  $L_i$  to  $L_j$  s.t.  $j > i$
- each node has at most two outgoing arcs
- **true**-arcs are plain, **false**-arcs are dotted
- each path from the root to  $\top$  defines a feasible solution (or a 'nice' family)
- each path from the root to some node defines a partial feasible solution
- each node is root of a unique sub-BDD encoding all completions
- Layer  $L_i$  has width  $\omega_i = |L_i|$
- BDD width  $\omega = \max_i \omega_i$



## Boolean function in CNF: A covering problem

Let  $A \in \{0, 1\}^{m \times n}$ .

$$\begin{aligned} Ax &\geq 1 \\ x &\in \{0, 1\}^n \end{aligned} \quad (\text{SC})$$

TOP-DOWN BDD COMPILATION:

Let  $u, v \in L_4$  with paths  $(1, 0, 0)$  and  $(0, 0, 1)$

Example:

$$\begin{array}{rcccccc} x_1 + & & x_3 + & & x_6 & \geq 1 \\ & & & & x_4 + & x_6 & \geq 1 \\ & & x_2 + & & x_4 + & x_5 & \geq 1 \\ x_1 + & x_2 + & x_3 + & & & & \geq 1 \\ & & x_3 + & x_4 + & x_5 & & \geq 1 \\ x \in & \{0, 1\}^n & & & & & \end{array}$$

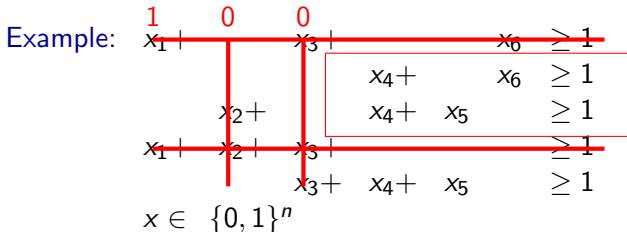
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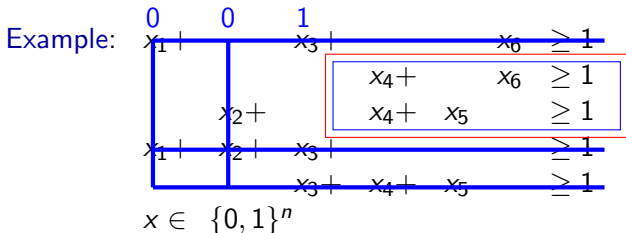
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Completions at  $u$  and  $v$  determined by same matrix minor

$\Rightarrow u$  and  $v$  can be merged!

Example:

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(having DNF of  $\Phi_\alpha^{\leq}$  gives us CNF of its dual for free; resulting BDD only needs arc label flipping)

# BDDs encoding the members of an Independence System/Circuit System

Top-down compilation rule for BDDs encoding the members of  $\mathcal{I}$ .

Key ingredient: an oracle to decide if two minors of the circuit system of  $\mathcal{I}$  are equivalent.

Examples: stable sets, packing, matching, covering, knapsack.

If an efficient oracle is available, the procedure yields an output-linear time algorithm for BDD compilation (e.g.: stable sets, packing, covering, or graphic matroid, but not 0/1-knapsack)

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# Graphic matroid

## Enumerating all spanning forests of a graph

- Independence system: spanning forests of  $G$
- Circuit system: simple cycles of  $G$

## Circuit system minor equivalence check

Needs to check whether two minors of  $G$  have the same simple cycles

- Need to check graph 2-isomorphism, but only for two minors of  $G$  under edge deletion/contraction of a common initial segment of the edge order: linear time!
  - Choose basis for minors (necessarily same for both minors)
  - compute basis representation
  - compare coefficients (feature of binary matroids)

## Bandwidth and BDD width

Let  $\mathcal{C}$  be a clutter and let  $A$  be the matrix whose rows are the incidence vectors of the members of  $\mathcal{C}$ .

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$$A = \begin{pmatrix} 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \end{pmatrix}$$

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For the BDD  $B$  associated to  $\mathcal{C}$  (in the variable ordering given by the constraint matrix), it holds that  $\omega(B) \leq 2^{b(A)-1}$ .

Example:

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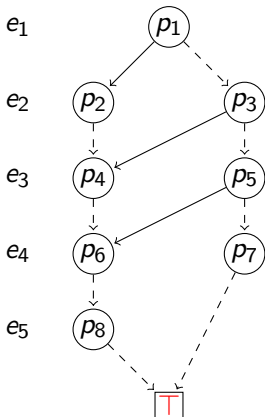
$$\omega(B) \leq 2^3$$

## Proof:

- Consider a node  $u \in L_j$  in layer  $j$  of the BDD encoding the transversals of the clutter. Since the clutter is nonempty every row of  $A$  has at least one nonzero.
- If the  $i$ -th row of  $A$  has all nonzeros before  $j$  it is deleted in  $M(u)$  (otherwise the empty row in the minor would make it infeasible, so  $u$  would not be a node in the BDD.)
- By the bandwidth limit, if  $A_{ih} \neq 0$  for  $h \geq j$ , among the entries preceding  $h$  only those in  $\{A_{i,h-(k-1)}, \dots, A_{i,h-1}\}$  can be nonzero.
- Since there are at most  $2^{k-1}$  ways of differently assigning values to the  $k-1$  variables directly preceding  $x_j$ , we can construct at most  $2^{k-1}$  different deletion/contraction minors at layer  $L_j$ , limiting the BDD-width to  $2^{k-1}$ .

## Computing $\text{Prob}[\Phi_{\alpha}^{\leq} = 1]$ : BDD to LP

Recursive definition of intermediate probabilities for 'scenarios sharing suffix' at node in layer  $e^*$ . Survival probabilities  $p_e$  for each event.

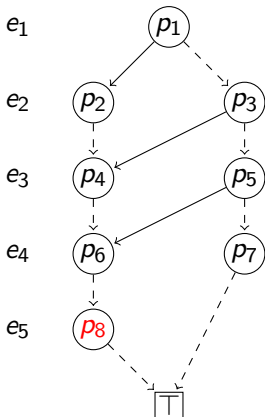


leaf  $\top$ :

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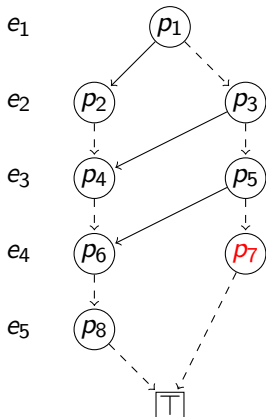


1-child node  $p_8$ :

$$\text{Prob}[\Phi(\xi) = 1] = (1 - p_{e_5})p_{\text{child}}$$

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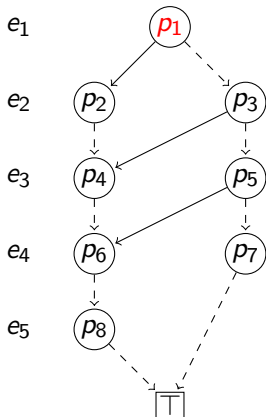


layer  $e_5$  skipped below  $p_7$ :

$$\begin{aligned}
 & \text{Prob}[\Phi(\xi) = 1] \\
 &= (1 - p_{e_4}) \\
 & \cdot \left( \prod_{i=5}^5 (p_{e_i} + (1 - p_{e_i})) \right) \cdot \\
 & \cdot p_{\text{child}} \\
 &= p_{e_4} p_{\text{child}}
 \end{aligned}$$

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otherwise, e.g.,  $p_1$ :

$$\begin{aligned} & \text{Prob}[\Phi(\xi) = 1] \\ &= p_{e^*} p_{\text{TRUE-child}} + (1 - p_{e^*}) p_{\text{FALSE-child}} \end{aligned}$$



## Computing $\text{Prob}[\Phi_{\alpha}^{\leq} = 1]$ : BDD to LP

Recursive definition of intermediate probabilities for 'scenarios sharing suffix' at node in layer  $e^*$ . Survival probabilities  $p_e$  for each event.

Linear equations with  $\mathcal{O}(\omega(BDD) \cdot |E|)$  auxiliary variables:

- leaf:

$$\text{Prob}[\Phi(\xi) = 1] = 1$$

- 1-child node (wlog: True-edge):

$$\text{Prob}[\Phi(\xi) = 1] = p_{e^*} p_{\text{child}}$$

- layers 2..( $l - 1$ ) skipped (wlog: True-edge):

$$\text{Prob}[\Phi(\xi) = 1] = p_{e^*} p_{\text{child}}$$

- otherwise:

$$\text{Prob}[\Phi(\xi) = 1] = p_{e^*} p_{\text{TRUE-child}} + (1 - p_{e^*}) p_{\text{FALSE-child}}$$

Consider binary decisions  $x_e$  such that

$$p_e(x) = \begin{cases} p_e & \text{if } x_e = 0, \\ p_e + \Delta_e & \text{if } x_e = 1 \end{cases}$$

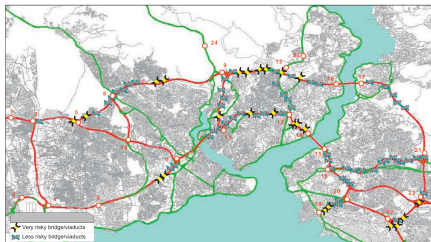
(where  $\Delta_e \in [-p_e, 1 - p_e]$ ).

Then we can define for each arc  $(u, v) \in A$  with label  $\epsilon(u) = e$  of the BDD

$$p_{(u,v)}(x) = \begin{cases} p_e(x) & \text{if } (u, v) \in A, \epsilon(u) = e, l((u, v)) = 1 \\ (1 - p_e(x)) & \text{if } (u, v) \in A, \epsilon(u) = e, l((u, v)) = 0, \end{cases}$$

and write the computations as linear constraints coupled to the binaries  $x_e$  by big- $M$  ( $M = 1$ ).

Yields a MIP of size  $4(\# \text{ BDD nodes}) \times ((\# \text{ BDD nodes}) + |E|)$ .



Pre-disaster investment decisions  
for Istanbul road network from  
PEETA ET AL. '10 (30 decision  
variables)  
(total construction time < 1s)

O-D-pair	cutoff dist	#bundles (in PRESTWICH '13)	MIP size	# BDDs	MIP size (using BDD bundles)
14-20	31	39		4	$237 \times 89$
14-7	31	29		6	$333 \times 113$
12-18	28	56		4	$237 \times 89$
9-7	19	26		4	$164 \times 71$
4-8	35	73		6	$421 \times 135$
$\Sigma$		223	$14174 \times 6221$	24	$1466 \times 454$

No cutoff: BDD construction  $< 1s$

O-D-pair	#bundles (in PRESTWICH '13)	MIP size	# BDDs	MIP size (using BDD bundles)
14-20	378		14	$2609 \times 682$
14-7	712		30	$13097 \times 3304$
12-18	233		8	$997 \times 1026$
9-7	266		8	$1137 \times 314$
4-8	305		12	$2301 \times 605$
$\sum$	1894	$123682 \times 56851$	72	$20137 \times 5064$
MIP solve				36s

# Generic application framework

... for 2-stage stochastic problems with scenario-monotone objective

Construct BDDs  $B_{\alpha}^{\leq}$  for all  $\alpha \in [L, U]$

Can be achieved by

- enumerating  $\alpha$ -solutions, or
- enumerating  $\alpha$ -cutsets, or
- circuit system oracle and equivalence check

BDD size may be bounded due to structural properties, e.g.,  
bandwidth, treewidth, ...

## Build MIP

- linear in BDD size
- has network-flow flavor
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## Expected shortest path with failing edges

... was the running example (interdiction problems also fit)

## Expected assignment value with failing edges

crew/task assignments, assignment costs, probabilities of assignment failing (e.g., to complete task before deadline), decisions to invest in training crew members

## Expected network flow with edge failures

network flow problem, edge capacities, probabilities of discrete edge capacity changes, decisions to influence edge capacities

## Expected maximum clique size with edge failures

maximum clique problem, probabilities of edges failing, decisions to suppress or strengthen edges



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