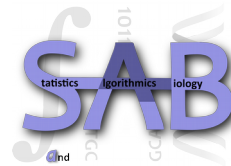


toulbar2

An exact cost function network solver

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ROADEF'23, Rennes, 02-23-2023

The logo for INRAE, featuring the letters 'INRAE' in a bold, teal, sans-serif font.The logo for MIA TOULOUSE, with 'MIA' in a large, blue, sans-serif font and 'TOULOUSE' in a smaller, blue, sans-serif font below it.The logo for SAB, with 'SAB' in a large, blue, sans-serif font. Above the letters are the words 'statistics', 'algorithmics', and 'ology' in a smaller font. To the right of the letters are the numbers '101', '100', and '100' stacked vertically.The logo for ANITI, with 'ANITI' in a large, blue, sans-serif font. Below it, the text 'ARTIFICIAL & NATURAL INTELLIGENCE' and 'TOULOUSE INSTITUTE' is written in a smaller, blue, sans-serif font.

Context

- Constraint Satisfaction Problems which are under/over constrained
 - Valued CSP (Schiex, Fargier, Verfaillie, IJCAI'1995) add preferences between solutions.
- Open-source branch-and-bound solver
 - *ToolBar (Toulouse & Barcelona)* (C code)
(Schiex, Larrosa IJCAI'2003)
 - **Toulbar2** (C++ code)
(Sanchez, Givry, Schiex, Constraints, 2008)

Collaborations

Research in optimization algorithms



Applied research in *protein design*



Optimization framework

X set of discrete variables,

Minimize $F(X)$

such that $C(X)$ is satisfied

Optimization framework

X set of discrete variables,

F set of cost functions, $f_s(X[S]) \in \mathbb{N}$

$$\text{Minimize } \sum_{f_s \in F} f_s(X[S])$$

such that $C(X)$ is satisfied

Optimization framework

X set of discrete variables,

F set of cost functions,

T infinite cost (forbidden assignment),

$$\text{Minimize } \sum_{f_s \in F} f_s(X[S])$$

Cost Function Network (CFN)

Optimization framework

X set of discrete variables,

F set of cost functions,

T infinite cost (forbidden assignment),

$$\text{Minimize } \sum_{f_s \in F} f_s(X[S])$$

NP-hard problem

X	f1(X)
a	0
c	1
g	1
t	1

+

X	Y	f2(X,Y)
a	a	∞
	c	1
	g	2
	t	0
c	a	1
	c	∞
	g	0
	t	2
g	a	2
	c	0
	g	∞
	t	1
t	a	0
	c	2
	g	1
	t	∞

+

Y	f3(Y)
a	0
c	1
g	1
t	1

Minimize $f1(X) + f2(X,Y) + f3(Y)$

Python3 interface

```
#pip install pytoulbar2
```

```
import pytoulbar2 as tb2
```

```
cfn = tb2.CFN()
```

```
cfn.AddVariable('X', ['a','c','g','t'])
```

```
cfn.AddVariable('Y', ['a','c','g','t'])
```

```
cfn.AddFunction(['X'], [0,1,1,1])
```

```
cfn.AddFunction(['Y'], [0,1,1,1])
```

```
cfn.AddFunction(['X', 'Y'], [cfn.Top,1,2,0,1,cfn.Top,0,2,2,0,cfn.Top,1,0,2,1,cfn.Top])
```

```
print(cfn.Solve(showSolutions=3))
```

```
#Output:
```

```
#New solution: 1 (0 backtracks, 0 nodes, depth 2, 0.003 seconds)
```

```
#X=a Y=t
```

```
#([0, 3], 1.0, 1)
```

Cost function in extension

X	Y	Z	f(X,Y,Z)
a	a	a	∞
	a	c	1
	a	g	2
	a	t	0
a	c	a	1
	c	c	1
	c	g	0
	c	t	2
a	g	a	2
	g	c	0
	g	g	2
	g	t	1
a	t	a	0
	t	c	2
	t	g	1
	t	t	0

... $4*4*4 = 64$ assignments!

Cost function using a compact table

X1	X2	X3	X4	X5	X6	X7	f(X1,X2,X3,X4,X5,X6,X7)
g	a	t	t	a	c	a	1
Other tuples (i.e., default cost):							0

```
cfm.AddCompactFunction(['X1','X2','X3','X4','X5','X6','X7'], 0, [['g','a','t','t','a','c','a']], [1])
```

Here, it is a soft clause.

Cost functions in intention

```
cfm.AddAllDifferent(X), cfm.AddGlobalFunction(X, 'samong', params),  
cfm.AddGlobalFunction(X, 'sgcc', params), cfm.AddGlobalFunction(X, 'sregular',  
params), cfm.AddGlobalFunction(X, 'sgrammar', params), ...
```

Linear constraints

- Pseudo-Boolean linear constraint $X_i \in \{0,1\}$

$$2 * X_1 + 3 * X_2 + 4 * X_3 + 5 * X_4 \geq 10$$

```
cfn.AddLinearConstraint([2,3,4,5],['X1','X2','X3','X4'],'>=',10)
```

- Linear constraint $X_i \in \{0,1,2\}$

$$2 * X_1 + 3 * X_2 + 4 * X_3 + 5 * X_4 \leq 10$$

```
cfn.AddLinearConstraint([2,3,4,5],['X1','X2','X3','X4'],'<=',10)
```

Integer coefficients only!

Generalized linear constraint

- Hamming distance constraint

$$(X_1=2) + (X_2=3) + (X_3=4) + (X_4=5) \leq 2$$

```
cfn.AddGeneralizedLinearConstraint([(('X1',2,1),('X2',3,1),('X3',4,1),('X4',5,1)], '<=', 2)
```

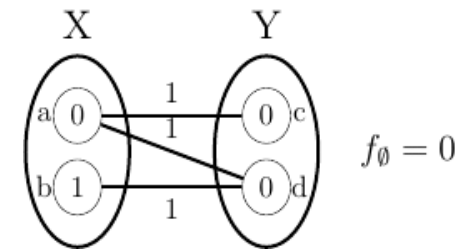
(propagation by a dedicated linear relaxation of Multiple-Choice Knapsack Problem)

- Used to translate many XCSP3 constraints

sum, count, nValues, cardinality, notAllEqual, cumulative

Toulbar2 XCSP3-core xml reader (20 constraints)

Exact solving methods



Branch-and-bound combined with
equivalence preserving transformations

strenght
↓

- FDAC (Schiex, Larrosa, IJCAI'2003)
- **EDAC** (Heras, Larrosa, Givry, Zytnicki, IJCAI'2005)
- VAC (Cooper, Givry, Sanchez, Schiex, Zytnicki, AAI'2008)
(Trösser, Givry, Katsirelos, CPAIOR'2020)
- VPWC (Montalbano, Givry, Katsirelos, Werner, CPAIOR'2023)
- OSAC (Cooper, Givry, Schiex, IJCAI'2007) \approx *Linear Programming*
- EDmaxRPC (Nguyen, Bessiere, Givry, Schiex, Constraints 2017)
- VSAC-SR (Dlask, Werner Givry, CP'2021, Constraints 2023)

X	f1(X)
a	0
c	1
g	1
t	1

+

X	Y	f2(X,Y)
a	a	∞
	c	1
	g	2
	t	0
c	a	1
	c	∞
	g	0
	t	2
g	a	2
	c	0
	g	∞
	t	1
t	a	0
	c	2
	g	1
	t	∞

+

Y	f3(Y)
a	0
c	1
g	1
t	1

X	f1(X)
a	0
c	1
g	1
t	1

+

X	Y	f2(X,Y)
a	a	∞
	c	1
	g	2
	t	1
c	a	1
	c	∞
	g	0
	t	3
g	a	2
	c	0
	g	∞
	t	2
t	a	0
	c	2
	g	1
	t	∞

+

Y	f3(Y)
a	0
c	1
g	1
t	0

X	f1(X)
a	1
c	1
g	1
t	1

+

X	Y	f2(X,Y)
a	a	∞
	c	0
	g	1
	t	0
c	a	1
	c	∞
	g	0
	t	3
g	a	2
	c	0
	g	∞
	t	2
t	a	0
	c	2
	g	1
	t	∞

+

Y	f3(Y)
a	0
c	1
g	1
t	0

X	f1(X)
a	1
c	1
g	1
t	1

+

X	Y	f2(X,Y)
a	a	∞
	c	0
	g	2
	t	0
c	a	1
	c	∞
	g	1
	t	3
g	a	2
	c	0
	g	∞
	t	2
t	a	0
	c	2
	g	2
	t	∞

+

Y	f3(Y)
a	0
c	1
g	0
t	0

X	f1(X)
a	1
c	2
g	1
t	1

+

X	Y	f2(X,Y)
a	a	∞
	c	0
	g	2
	t	0
c	a	0
	c	∞
	g	0
	t	2
g	a	2
	c	0
	g	∞
	t	2
t	a	0
	c	2
	g	2
	t	∞

+

Y	f3(Y)
a	0
c	1
g	0
t	0

X	f1(X)
a	1
c	2
g	1
t	1

+

X	Y	f2(X,Y)
a	a	∞
	c	1
	g	2
	t	0
c	a	0
	c	∞
	g	0
	t	2
g	a	2
	c	1
	g	∞
	t	2
t	a	0
	c	3
	g	2
	t	∞

+

Y	f3(Y)
a	0
c	0
g	0
t	0

X	f1(X)
a	1
c	2
g	2
t	1

+

X	Y	f2(X,Y)
a	a	∞
	c	1
	g	2
	t	0
c	a	0
	c	∞
	g	0
	t	2
g	a	1
	c	0
	g	∞
	t	1
t	a	0
	c	3
	g	2
	t	∞

+

Y	f3(Y)
a	0
c	0
g	0
t	0

X	f1(X)
a	0
c	1
g	1
t	0

+

X	Y	f2(X,Y)
a	a	∞
	c	1
	g	2
	t	0
c	a	0
	c	∞
	g	0
	t	2
g	a	1
	c	0
	g	∞
	t	1
t	a	0
	c	3
	g	2
	t	∞

+

Y	f3(Y)
a	0
c	0
g	0
t	0

$$f_{\emptyset} = 1$$

f_{\emptyset} is the current problem lower bound !
 f_{X_i} used by value and variable heuristics

$T=2$

X	f(X)
a	0
c	∞
g	∞
t	0

+

X	Y	g(X,Y)
a	a	∞
	c	∞
	g	∞
	t	0
c	a	0
	c	∞
	g	0
	t	∞
g	a	∞
	c	0
	g	∞
	t	∞
t	a	0
	c	∞
	g	∞
	t	∞

+

Y	f(Y)
a	0
c	0
g	0
t	0

$f_{\emptyset}=1$

T is decreasing at each new solution found!

More value pruning!!

$T=2$

X	f(X)
a	0
c	∞
g	∞
t	0

+

X	Y	g(X,Y)
a	a	∞
	c	∞
	g	∞
	t	0
c	a	0
	c	∞
	g	∞
	t	∞
g	a	∞
	c	∞
	g	∞
	t	∞
t	a	0
	c	∞
	g	∞
	t	∞

+

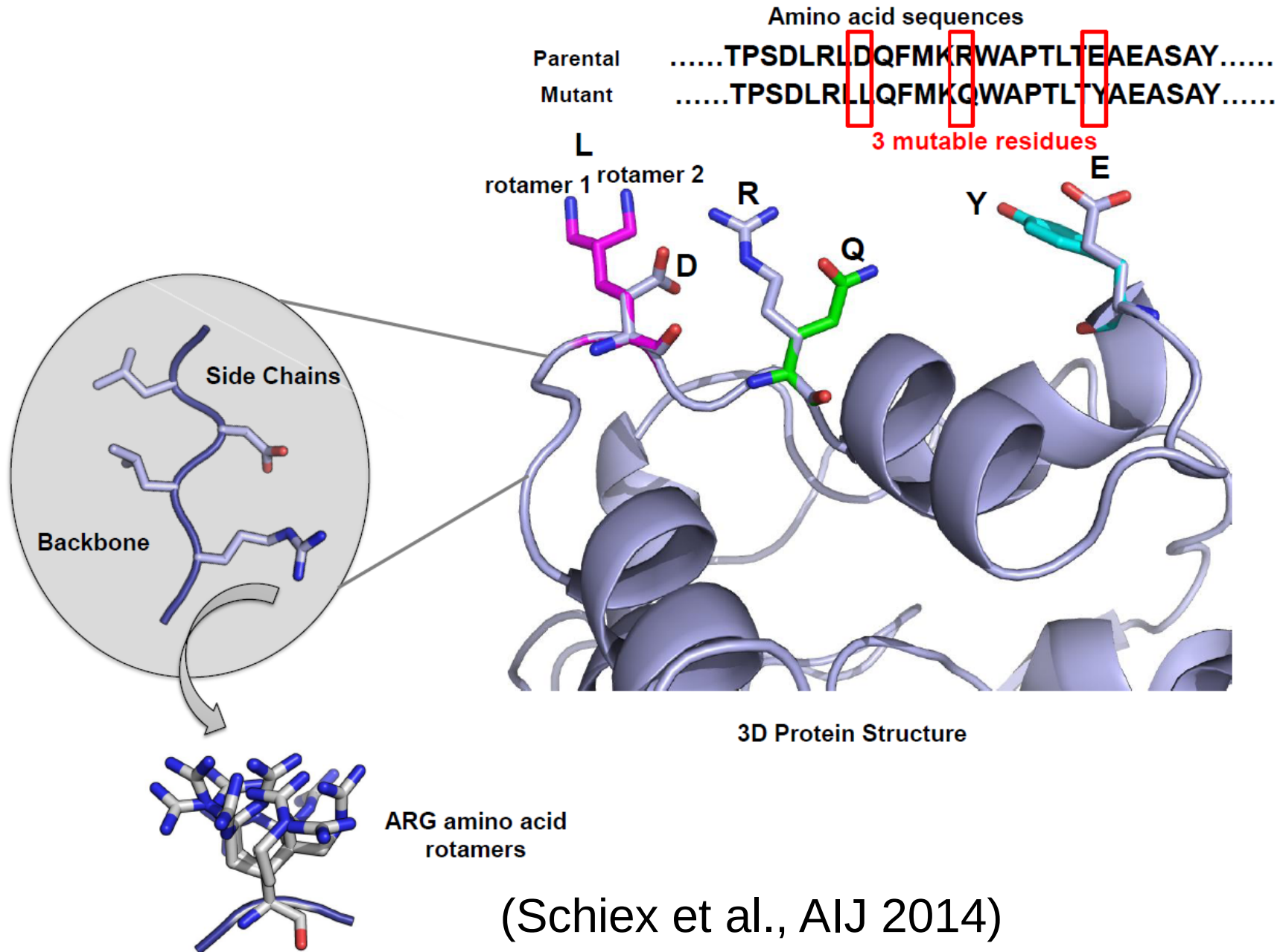
Y	f(Y)
a	0
c	0
g	0
t	0

$f_{\emptyset}=1$

T is decreasing at each new solution found!

More value pruning!!

Protein design



Protein design

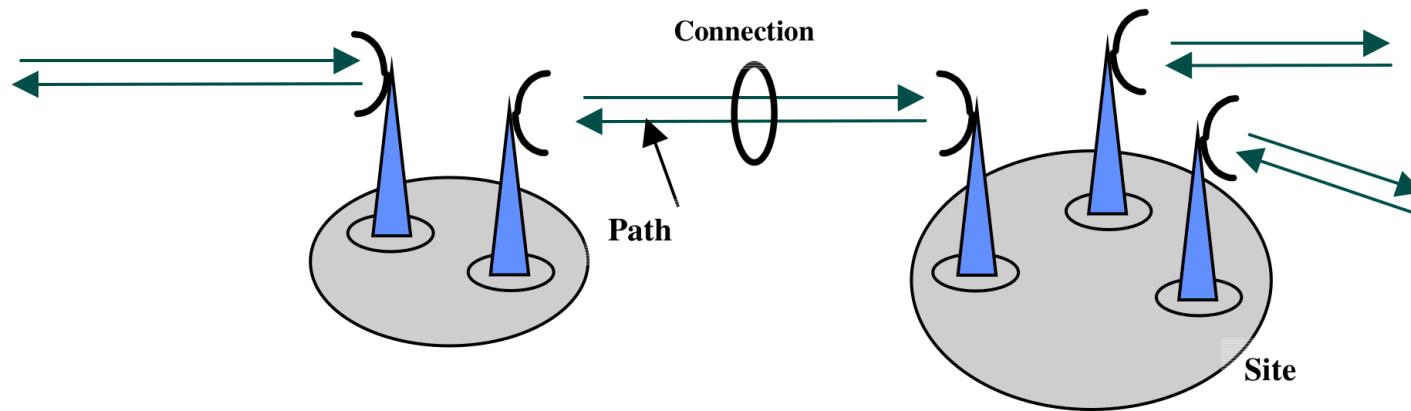
$$E = E_{\emptyset} + \sum_i E(i_r) + \sum_i \sum_{j>i} E(i_r, j_s)$$

	CPLEX 20.1	toulbar2 1.1.1
1BK2.matrix.24p.17aa	42.84 sec (0 node)	0.37 sec (38 nodes)
	Reduced MIP has 16,090 rows 284,424 columns 584,143 nonzeros 805 binaries	X =24 max(D)=182 F =300

(Intel Xeon 2.5GHz with 256GB RAM)

Frequency Assignment Problem with Polarization

Challenge ROADEF 2001



The problem is to assign a pair (frequency f , polarization p) to every path.

$$1 \leq f \leq \sim 151 \quad p \in \{-1, 1\}$$

Constraints are:

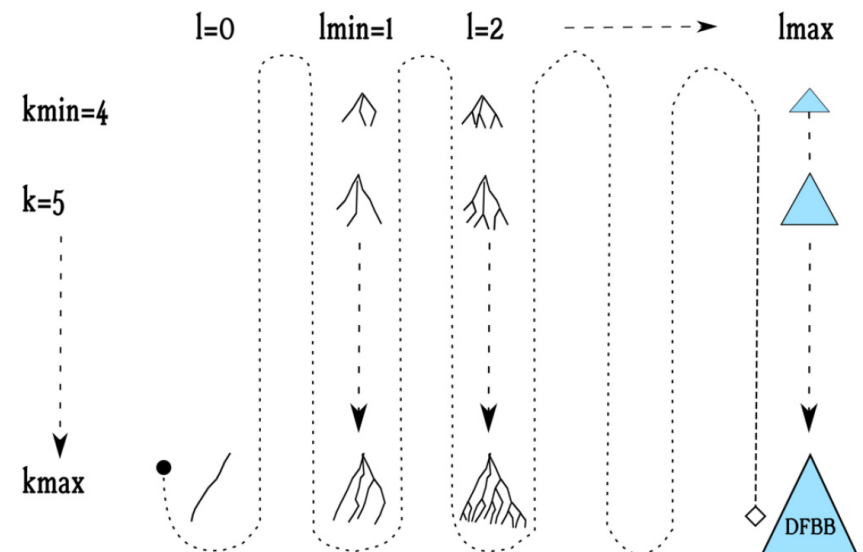
- (I) two paths must use equal or different frequencies
- (II) the absolute difference between two frequencies should exactly be equal or different to a given number
- (III) two paths must use equal or different polarizations
- (IV) the absolute difference between two frequencies should be greater at a relaxation level l (0 to 10) than a given number g_l (resp. d_l) if polarization are equal (resp. different, usually $g_l > d_l$)

Find a feasible assignment with the smallest relaxation level l and which minimizes the number of violations of (IV) at lower levels

Frequency Assignment Problem with Polarization

- Combine frequency with polarization into a single variable
 - Better propagation (only binary cost functions)
- Use **Parallel Variable Neighborhood Search** (Ouali et al., AIJ 2020)

- See our CP'2020 [tutorial](#)



Frequency Assignment Problem with Polarization

Small instances	k	ROADEF'2001 Best Results	toulbar2	(time to best solution)
fapp01_0200	4	35,758,830	35,758,826	(1.333s)
fapp02_0250	2	40,370,567	40,370,566	(16.689s)
fapp03_0300	7	294,380,136	294,380,135	(26.155s)
fapp04_0300 X =300 max(D)=270 F =2100	1	24,648,190	24,616,970	(3.282s) <i>(optimality proof in 27 seconds!)</i>
fapp05_0350 X =350 max(D)=270 F =2839	11	521,348,004	521,348,429	(53.496s) <i>(521,348,004 in 89.788 seconds)</i>
test01_0150	4	18,292,591	18,292,585	(1.691s)

ROADEF competitors: 1 hour on Intel Pentium III 500MHz 128MB
Toulbar2: 1 minute on 21 cores of Intel Xeon 2.5GHz 256GB

Grid operation-based outage maintenance planning

Challenge ROADEF 2020

Find an optimal planning regarding a risk-based objective

$$18 \leq |I| \leq 706$$

Planning horizon within a year (day or week discretization)

$$53 \leq H \leq 365$$



Grid operation-based outage maintenance planning

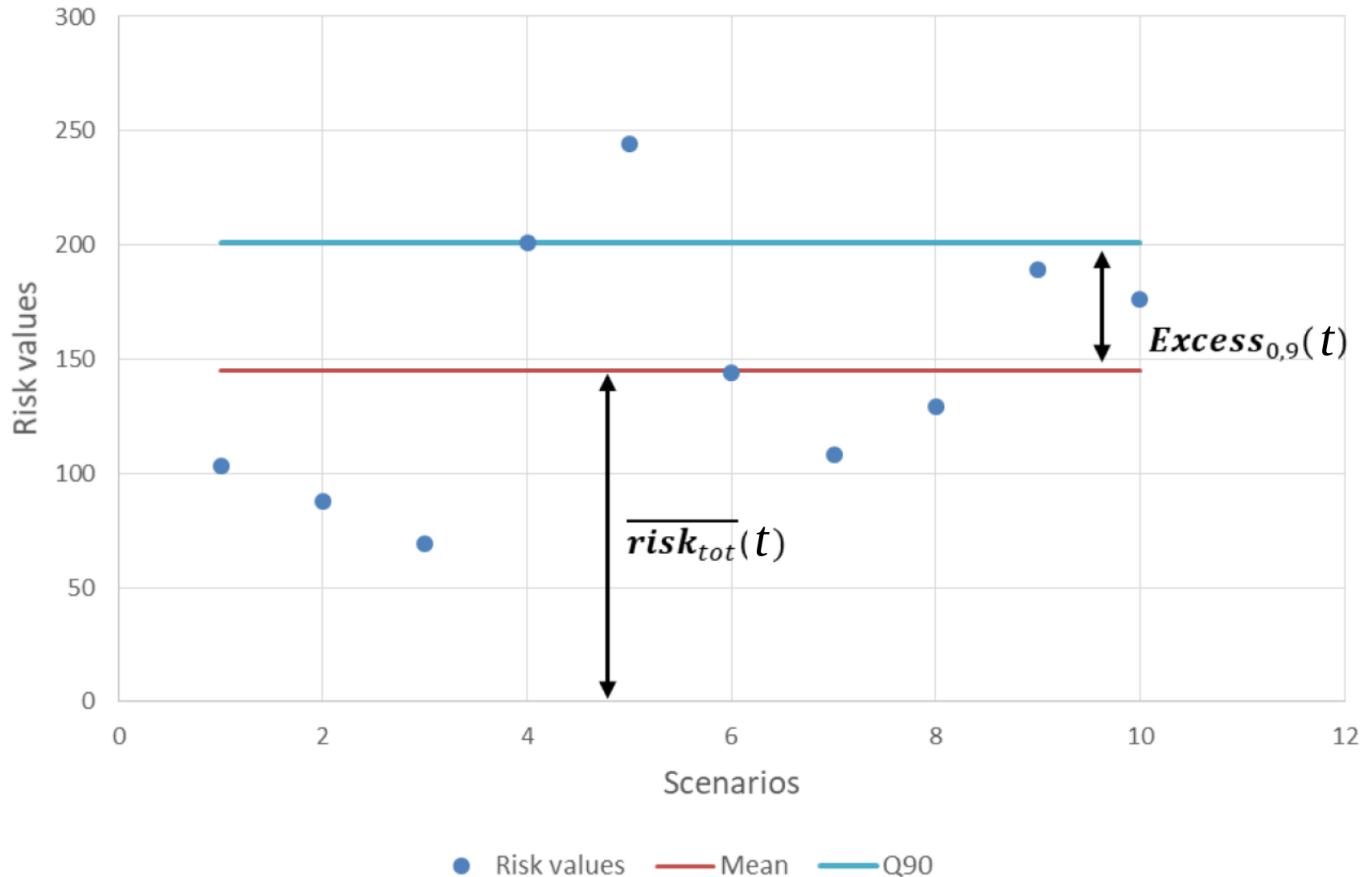
CFN model

- $|I|$ variables (start time of each intervention)
with domain size H
- **Two approximations (without solution quality guarantee)**
 - Resource constraint (using generalized linear constraints)
 - Integer approximation of continuous weights (r multiplier)
 - Risk-based objective decomposed into $|I|$ cost functions for every intervention

Grid operation-based outage maintenance planning

each

Sum of risk values over all interventions planned at time t



Grid operation-based outage maintenance planning

Instance	Best Results 15 min	toulbar2 15min <i>r=10</i>	Best Results 90 min	toulbar2 1hour <i>r=100</i>
A_01(I =181,H=90)	1,767.82	1,770.15	1,767.82	1,769.50
A_02(I =89,H=90)	4,671.38	4,732.05 (9.870s)	4,671.38	4,732.02 (9.132s)
A_03(I =91,H=90)	848.18	848.18 (5.060s)	848.18	848.18 (4.325s)
A_04(I =706,H=365)	2,085.88	-	2,085.88	-
A_05(I =180,H=182)	635.22	651.49 (50.63s)	635.22	651.24 (49.59s)
A_06(I =180,H=182)	590.62	-	590.62	640.69
A_07(I =36,H=17)	2,272.78	2,280.16 (0.103s)	2,272.78	-
A_08(I =18,H=17)	744.29	750.03 (0.269s)	744.29	750.03 (0.252s)
A_09(I =18,H=17)	1,507.28	1,507.32 (0.063s)	1,507.28	1,507.32 (0.061s)
A_10(I =108,H=53)	2,994.85	3,022.76 (1.452s)	2,994.85	3,022.76 (1.623s)
A_11(I =54,H=53)	495.26	504.95 (2.544s)	495.26	504.95 (2.452s)
A_12(I =54,H=53)	789.63	828.88 (0.668s)	789.63	793.04 (1.289s)
A_13(I =179,H=90)	1,998.66	2,009.79	1,998.66	2,009.66
A_14(I =108,H=53)	2,264.12	2,302.56 (90.13s)	2,264.12	2,295.65 (1,215s)
A_15(I =108,H=53)	2,268.57	2,310.25 (113.4s)	2,268.57	2,305.29 (1,036s)
<i>Distance to best results (except A04,A06,A07):</i>		<i>1.39%</i>		<i>0.96%</i>

XCSP 2022 Competition Results

solver	score	optimum	best bound
Mistral	93.00	34	99
toulbar2	86.00	51	87
miniRBO	74.50	41	78
Sat4j-both	58.50	39	60
Sat4j-rs	43.00	33	46
Glasgow	31.50	21	34

Mini COP Track (158 instances)

(subset of constraints: allDifferent, Extension, Intension, sum, element)

Score computation:

1 pt. (optimum found or single best solution), 0.5pt. (best sol. Exaquo), else 0 pt.

Time limit: 40 min. on single core 3.5GHz ; space limit: 64 GB.

XCSP 2022 Competition Results

solver	score	optimum	best bound
Picat	137.00	121	139
CoSoCo	122.00	66	144
Mistral	95.50	51	118
toulbar2	91.00	73	100
RBO	89.50	55	104
Choco	83.00	59	97
Sat4j-both	56.00	47	62
Sat4j-rs	48.00	38	57

Full COP Track (250 instances)

solver	score	optimum	best bound
Choco	184.50	71	191
toulbar2	118.50	80	119

Parallel COP Track (250 instances, using 4 cores)

Toulbar2 platform

<https://forgemia.inra.fr/thomas.schiex/cost-function-library> (+18.281 instances)

<http://genoweb.toulouse.inra.fr/~degivry/evalgm> (3.026 instances)

<https://miat.inrae.fr/toulbar2/> (main site)

<https://toulbar2.github.io/toulbar2> (documentation, tutorials, examples)

Debian and ubuntu packages v1.1.1

Github latest source and release v1.2.0 (linux, macos, win exe)

Q&A User discussions

Python interface v1.2.0 (pip install [pytoulbar2](#))

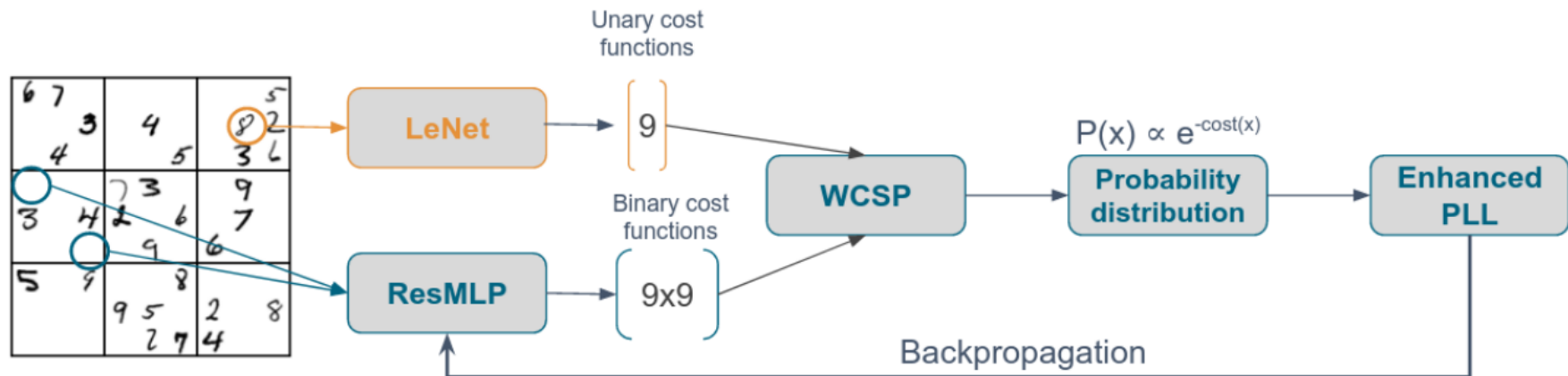
toulbar2 read many input formats: cfn, wcsp, wcnf, uai, qpbo, opb, xml (xcsp3)

Current work on **bilevel discrete optimization** (see another ROADEF'23 talk), **multicriteria**, and CFN **learning** from data [Defresne et al, AAAI-23 workshop]

Application on natural-input problems

Visual sudoku

> Learn to play Sudoku & to recognize digit



► Solver able to correct digit mis-classification

SATNet	Theoretical (no corrections)	Ours
63.2 %	74.2%	94.1 ± 0.8%