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Proceedings of the 2023 XCSP3 Competition

Gilles Audemard, Christophe Lecoutre, Emmanuel Lonca

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Proceedings of the XCSP³ Competition 2023

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(Revised* on December 10, 2023)

This document represents the proceedings of the XCSP³ Competition 2023. The website containing all **detailed results** of this international competition is available at:

<https://www.cril.univ-artois.fr/XCSP23>

The organization of this 2023 competition involved the following tasks:

- adjusting general details (dates, tracks, ...) by G. Audemard, C. Lecoutre and E. Lonca
- selecting instances (problems, models and data) by C. Lecoutre
- receiving, testing and executing solvers on CRIL cluster by E. Lonca
- validating solvers and rankings by C. Lecoutre and E. Lonca
- developing the 2023 website dedicated to results by G. Audemard

Important: for reproducing the experiments and results, it is important to use the set of XCSP³ instances used in the competition. These instances can be found in this [archive](#). Some (usually minor) differences may exist when compiling the models presented in this document and those that can be found in this [archive](#).

Revision (*) of December 2023: some models in this document have been simplified while using new possibilities offered by Version 2.2 of PyCSP³. As mentioned above, note that in order to reproduce results and/or to make fair new comparisons with respect to solvers engaged in the 2023 competition, you have to use the very [same set](#) of XCSP³ instances, as in the 2023 competition.

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Chapter 1

About the Selection of Problems in 2023

Remember that the complete description, **Version 3.1**, of the format (XCSP³) used to represent combinatorial constrained problems can be found in [6]. As usual for XCSP³ competitions, we have limited XCSP³ to its kernel, called XCSP³-core [7]. This means that the scope of the XCSP³ competition is restricted to:

- integer variables,
- CSP (Constraint Satisfaction Problem) and COP (Constraint Optimization Problem),
- a set of 24 popular (global) constraints for main tracks:
 - generic constraints: `intension` and `extension` (also called `table`)
 - language-based constraints: `regular` and `mdd`
 - comparison constraints: `allDifferent`, `allEqual`, `ordered`, `lex` and `precedence`
 - counting/summing constraints: `sum`, `count`, `nValues` and `cardinality`
 - connection constraints: `maximum`, `minimum`, `element` and `channel`
 - packing/scheduling constraints: `noOverlap`, `cumulative`, `binPacking` and `knapsack`
 - `circuit`, `instantiation` and `slide`

and a small set of constraints for mini tracks.

Note that XCSP³-core has been extended in Version 3.1 so as to accept `precedence`, `binPacking` and `knapsack`.

For the 2023 competition, 36 problems have been selected. They are succinctly presented in Table 1.1. For each problem, the type of optimization is indicated (if any), as well as the involved constraints. At this point, do note that making a good selection of problems/instances is a difficult task. In our opinion, important criteria for a good selection are:

- the novelty of problems, avoiding constraint solvers to overfit already published problems;
- the diversity of constraints, trying to represent all of the most popular constraints (those from XCSP³-core) while paying attention to not over-representing some of them;
- the scaling up of problems.

CSP Problems		Global Constraints
AnotherMagicSquare		allDifferent, sum
AntimagicSquare		allDifferent, maximum, minimum, sum
BinaryPuzzle		regular, sum, table (*)
CalvinPuzzle		allDifferent, count, table (*)
Coloring		
CoveringArray		allDifferent, channel, table
Dominoes		allDifferent, table
Fischer		
MagicSquare		allDifferent, mdd, sum
NonogramTernary		table
NonTransitiveDice		maximum, sum
PegSolitaire		
Primes		sum
PythagoreanTriples		nValues
Slant		count, sum
Soccer		allDifferent, sum, table
SquarePackingSuite		cumulative, noOverlap
WordDesignDNA		mdd, lex, sum, table
COP Problems	Optimization	Global Constraints
AircraftAssemblyLine	min SUM	cumulative, noOverlap
BeerJugs	max VAR	table
Benzenoide	min SUM	count, lex, precedence, sum, table (*)
CarpetCutting	min VAR	cumulative, element, noOverlap, table
GBAC	min SUM	binPacking, cardinality, maximum, table
GeneralizedMKP	max VAR	knapsack, sum
HCPizza	max VAR	sum, table
HSP	min VAR	allDifferent, maximum, noOverlap, table
KidneyExchange	max SUM	allDifferent, binPacking, element, precedence
KMedian	min SUM	allDifferent, element, minimum, sum
LargeScaleScheduling	min MAXIMUM	cumulative, maximum
ProgressiveParty	min SUM	allDifferent, channel, element, sum
PSP	min SUM	count, element, sum
RIP	min SUM	cumulative
RuleMining	max VAR	allDifferent, count, table (*)
Sonet	min SUM	lex, sum, table (*)
SRFLP	min SUM	allDifferent, sum, table
TSPTW	min SUM	allDifferent, circuit, element

Table 1.1: Selected Problems for the main tracks of the 2023 Competition. VAR/EXPR means that a variable/expression must be optimized. When extension is followed by (*), it means that starred tables are involved.

Novelty. Almost all problems are new in 2023, with models directly written in PyCSP³. Three problems have been submitted, in response to the call.

Scaling up. It is always interesting to see how constraint solvers behave when the instances of a problem become harder and harder. This is what we call the scaling behavior of solvers. For most of the problems in the 2023 competition, we have selected series of instances with regular increasing difficulty. It is important to note that assessing the difficulty of instances was mainly determined with ACE [19], which is the reason why ACE is declared to be off-competition (due to this strong bias).

Selection. This year, the selection of problems and instances has been performed by Christophe Lecoutre. As a consequence, the solver ACE was labeled off-competition.

Chapter 2

Problems and Models

In the next sections, you will find all models used for generating the XCSP³ instances of the 2023 competition (for main CSP and COP tracks). Almost all models are written in PyCSP³ [20], Version 2.1, officially released in November 2022; see <https://pycsp.org>.

2.1 CSP

2.1.1 Another Magic Square

Description. This puzzle is defined at the “Fun with num3ers” website; see benvitale-funwithnum3ers.blogspot.com. On a square grid of size $n \times n$, all numbers ranging from 1 to n^2 must be put so that the numbers surrounding each number add to a multiple of that number.

Data. Only one integer is required to specify a specific instance: the order n of the grid. The values of n used for generating the 2023 competition instances are:

2, 3, 4, 5, 6, 7, 8, 9, 10, 12

Model. The PyCSP³ model, in a file ‘AnotherMagicSquare.py’, used for the competition is:

```
 PyCSP3 Model 1  
  
from pycsp3 import *  
  
n = data  
  
# x[i][j] is the value at row i and column j  
x = VarArray(size=[n, n], dom=range(1, n * n + 1))  
  
satisfy(  
    AllDifferent(x),  
  
    # ensuring that the numbers surrounding a number v add to a multiple of v  
    [Sum(x.around(i, j)) % x[i][j] == 0 for i in range(n) for j in range(n)]  
)
```

The model involves a two-dimensional array of variable x , a constraint `AllDifferent` and a group of constraints `Sum`. A series of 10 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python AnotherMagicSquare.py -data=10
```

2.1.2 Antimagic Square

Description. An antimagic square of order n is an arrangement of the numbers 1 to n^2 in a square, such that the sums of the n rows, the n columns and the two diagonals form a sequence of $2n + 2$ consecutive integers; see [wikipedia](#).

Data. Only one integer is required to specify a specific instance: the order n of the square. The values of n used for generating the 2023 competition instances are:

3, 4, 5, 6, 7, 8, 9, 10, 11, 12

Model. The PyCSP³ model, in a file ‘AntimagicSquare.py’, used for the competition is:



PyCSP³ Model 2

```

from pycsp3 import *

n = data

lb, ub = (n * (n + 1)) // 2, ((n * n) * (n * n + 1)) // 2

# x[i][j] is the value put in the cell of the matrix at coordinates (i,j)
x = VarArray(size=[n, n], dom=range(1, n * n + 1))

# y[k] is the sum of values in the kth line (row, column or diagonal)
y = VarArray(size=2 * n + 2, dom=range(lb, ub + 1))

satisfy(
    # all values must be different
    AllDifferent(x),

    # computing sums
    [
        [y[i] == Sum(x[i]) for i in range(n)],
        [y[n + j] == Sum(x[:, j]) for j in range(n)],
        y[2 * n] == Sum(diagonal_down(x)),
        y[2 * n + 1] == Sum(diagonal_up(x))
    ],

    # all sums must be consecutive
    [
        AllDifferent(y),
        Maximum(y) - Minimum(y) == 2 * n + 1
    ],

    # tag(symmetry-breaking)
    # ensuring Frenicle standard form
    [
        x[0][0] < x[0][-1],
        x[0][0] < x[-1][0],
        x[0][0] < x[-1][-1],
        x[0][1] < x[1][0]
    ]
)

```

The model involves two arrays of variables x and y ; the second one allows us to compute/record the sums of the different lines. Consecutiveness is ensured by a constraint involving

Maximum and Minimum. A series of 10 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python AntimagicSquare.py -data=10
```

2.1.3 Binary Puzzle

Description. A binary puzzle (also known as a binary Sudoku) is a puzzle played on a $n \times n$ grid; initially some of the cells may contain 0 or 1 (but this is not the case for the 2023 competition). One has to fill the remaining empty cells with either 0 or 1 according to the following rules:

- no more than two similar numbers next to or below each other are allowed,
- each row and each column should contain an equal number of zeros and ones,
- each row is unique and each column is unique.

See [5].

Data. Only one integer is required to specify a specific instance: the order n of the grid. The values of n used for generating the 2023 competition instances are:

20, 40, 60, 80, 100, 120

Model. The PyCSP³ model, in a file ‘BinaryPuzzle.py’, used for the competition is:



PyCSP³ Model 3

```

from pycsp3 import *

n = data
assert n % 2 == 0
m = n // 2

# x[i][j] is the value in the cell of the grid at coordinates (i,j)
x = VarArray(size=[n, n], dom={0, 1})

if not variant():
    satisfy(
        # ensuring the same number of 0s and 1s in rows
        [Sum(x[i]) == m for i in range(n)],

        # ensuring the same number of 0s and 1s in columns
        [Sum(x[:, j]) == m for j in range(n)],

        # forbidding sequences of 3 consecutive 0s or 1s in rows
        [Sum(x[i, j:j + 3]) in {1,2} for i in range(n) for j in range(n - 2)],

        # forbidding sequences of 3 consecutive 0s or 1s in columns
        [Sum(x[i:i + 3, j]) in {1,2} for j in range(n) for i in range(n - 2)]
    )

elif variant("regular"):
    pairs = [(j, k) for j in range(3) for k in range(3) if (j==0 and k>0) or (j>0 and k==0)]

    q = Automaton.q
    t = [(q(0,0,0), 0, q(0,1,0)), (q(0,0,0), 1, (q(1,0,1)))]
        + [(q(i,j,k), 0, q(i,j+1,0)) for i in range(m + 1) for j, k in pairs if j < 2]

```

```

    + [(q(i,j,k), 1, q(i+1,0,k+1)) for i in range(m) for j, k in pairs if k < 2]
A = Automaton(start=q(0,0,0), final=[q(m,j,k) for j, k in pairs], transitions=t)

satisfy(
    # ensuring valid rows
    [x[i] in A for i in range(n)],

    # ensuring valid columns
    [x[:, j] in A for j in range(n)]
)

satisfy(
    # forbidding identical rows
    AllDifferentList(x[i] for i in range(n)),

    # forbidding identical columns
    AllDifferentList(x[:, j] for j in range(n))
)

```

This model involves 1 array of variables, and 3 types of constraints: `Sum`, `Regular`, and `AllDifferentList` (which are transformed into `Extension` constraints for the competition, as explained below). Actually, depending on the chosen variant, either `Sum` constraints are posted, or `Regular` constraints are posted. Note that valid rows and columns are guaranteed by the way automatas are constructed: we ensure that we have the same number of 0s and 1s, while forbidding sequences of 3 consecutive 0s or 1s. Because `AllDifferentList` is not within the perimeter of the 2023 competition (a mistake that will be fixed in 2024), such constraints have been translated into extensional forms (i.e., starred tables by calling the method `to_table()`) as in:

```
AllDifferentList(x[i] for i in range(n)).to_table()
```

A series of 2*6 instances has been selected for the competition (6 per variant). For generating an XCSP³ instance (file), you can execute for example:

```
python BinaryPuzzle.py -data=100
python BinaryPuzzle.py -data=100 -variant=regular
```

Note that when you omit to write ‘-variant=regular’, you get the main variant.

2.1.4 Calvin Puzzle

Description. From ”An Exercise for the Mind: A 10 by 10 Math Puzzle: A Pattern Recognition Game: Meditation on an Open Maze” at <http://www.chycho.com>. The purpose of the game is to fill a grid of size $n \times n$ with all values ranging from 1 to n^2 such that:

- if the next number in the sequence is going to be placed vertically or horizontally, then it must be placed exactly three squares away from the previous number (there must be a two square gap between the numbers);
- if the next number in the sequence is going to be placed diagonally, then it must be placed exactly two squares away from the previous number (there must be a one square gap between the numbers).

Data. Only one integer is required to specify a specific instance: the order n of the grid. The values of n used for generating the 2023 competition instances are:

5, 6, 7, 8, 9, 10, 12

Model. The PyCSP³ model, in a file ‘CalvinPuzzle.py’, used for the competition is:

```

 PyCSP3 Model 4

from pycsp3 import *

n = data

# x[i][j] is the value in the grid at row i and column j
x = VarArray(size=[n, n], dom=range(1, n * n + 1))

# possible neighbours
offsets = [(-3,0), (3,0), (0,-3), (0,3), (-2,-2), (-2,2), (2,-2), (2,2)]
N = [[x[i + oi][j + oj] for (oi, oj) in offsets if 0 <= i + oi < n and 0 <= j + oj < n]
      for j in range(n)] for i in range(n)]

satisfy(
    # putting all values from 1 to n*n in the grid
    AllDifferent(x),

    # tag(symmetry-breaking)
    x[0][0] == 1
)

if not variant():
    satisfy(
        # each cell must be linked to its neighbors
        If(
            x[i][j] < n * n,
            Then=Exist(y == x[i][j] + 1 for y in N[i][j])
        ) for i in range(n) for j in range(n)
    )

elif variant("table"):

    def T(i, j):
        r = len(N[i][j]) + 1
        return [tuple(k if i == 0 else (k + 1) if i == j else ANY for i in range(r))
                for k in range(1, n * n) for j in range(1, r)]
        + [(n * n, *[ANY] * (r - 1))]

    satisfy(
        # each cell must be linked to its neighbors
        (x[i][j], N[i][j]) in T(i, j) for i in range(n) for j in range(n)
    )

```

This model only involves 1 array of variables x . The list of variables defined as neighbors of a variable $x[i][j]$ is (computed and) given by $N[i][j]$. Depending on the chosen variant, either Intension and Count (from Exist) constraints are posted, or Extension constraints are posted.

A series of 2*7 instances has been selected for the competition (7 per variant). For generating an XCSP³ instance (file), you can execute for example:

```
python CalvinPuzzle.py -data=10
python CalvinPuzzle.py -data=10 -variant=table
```

Note that when you omit to write ‘-variant=table’, you get the main variant.

2.1.5 Coloring

Description. This is the classical graph coloring problem: given an undirected graph, one has to color the nodes of this graph such that no two adjacent nodes have the same color.

Data. As an illustration of data specifying an instance of this problem, we have:

```
{
  "n": 450,
  "nColors": 5,
  "edges": [[0, 329], [0, 366], [0, 388], ...]
}
```

Model. The PyCSP³ model, in a file ‘Coloring.py’, used for the competition is:

 **PyCSP³ Model 5**

```
from pycsp3 import *

nNodes, nColors, edges = data

# x[i] is the color assigned to the ith node of the graph
x = VarArray(size=nNodes, dom=range(nColors))

satisfy(
  # two adjacent nodes must be colored differently
  [x[i] != x[j] for (i, j) in edges],

  # tag(symmetry-breaking)
  [x[i] <= i for i in range(min(nNodes, nColors))]
)
```

This model involves 1 array of variables and 1 type of constraints: **Intension**. A series of 10 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python Coloring.py -data=graph1.json
```

where ‘graph1.json’ is a data file in JSON format.

2.1.6 Covering Array

This is Problem 045 on CSPLib, called the Covering Array problem.

Description (excerpt from CSPLib). A covering array $C(t, k, g, b)$ is a $k \times b$ array $A = (a_{ij})$ over $Z_g = 0, 1, 2, \dots, g - 1$ with the property that for any t distinct rows $1 \leq r_1 < r_2 < \dots < r_t \leq k$, and any member (x_1, x_2, \dots, x_t) of Z_g^t there exists at least one column c such that x_i equals the (r_i, c) -th element of A for all $1 \leq i \leq t$. Informally, any t distinct rows of the covering array must encode column-wise all numbers from 0 to $g^t - 1$ (repetitions being allowed).

Data. Four integers are required to specify a specific instance. Values of (t, k, g, b) used for the instances in the competition are:

```
(3,4,2,8), (3,5,2,10), (3,6,2,12), (3,7,2,12), (3,8,2,12), (3,9,2,12), (3,10,2,12), (3,11,2,12),
(4,6,2,21), (4,7,2,38), (4,8,2,42), (4,9,2,50)
```

Model. The PyCSP³ model, in a file ‘CoveringArray.py’, used for the competition is:

 **PyCSP³ Model 6**

```

from pycsp3 import *

t, k, g, b = data
n = factorial(k) // factorial(t) // factorial(k - t)
d = g ** t

T = {tuple(sum(pr[a] * g ** i for i, a in enumerate(reversed(co)))
           for co in combinations(range(k), t)) for pr in product(range(g), repeat=k)}

# p[i][j] is one of the position of the jth value of the ith 't'-combination
p = VarArray(size=[n, d], dom=range(b))

# v[i][j] is the jth value of the ith 't'-combination
v = VarArray(size=[n, b], dom=range(d))

satisfy(
    # all values must be present in each 't'-combination
    [AllDifferent(p[i]) for i in range(n)],

    [Channel(p[i], v[i]) for i in range(n)],

    # computing values
    [v[:, j] in T for j in range(b)]
)

```

This model involves 2 arrays of variables, and 3 types of constraints: `AllDifferent`, `Channel`, and `Extension`. Note that it is possible to get the covering array from the array of variables v . For example, $v[0][0]$ gives the t most significant bits of the first column (because the first t -combination is for the first t lines).

A series of 12 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python CoveringArray.py -data=[3,5,2,10]
```

2.1.7 Dominoes

Description. You are given a grid of size $n \times m$ containing numbers being parts of dominoes. For example, for $n = 7$ and $m = 8$, the grid contains all dominoes from 0-0 to 6-6. One has to find the position (and rotation) of each domino; see e.g., [28, 25].

Data. As an illustration of data specifying an instance of this problem, we have:

```

{
  "grid": [
    [0,5,2,2,5,4,6,5],
    [3,6,2,2,4,4,4,1],
    [3,6,1,2,3,4,6,1],
    [0,1,4,3,0,2,2,1],
    [3,5,3,0,3,1,5,6],
    [6,4,0,3,6,0,4,1],
    [1,6,0,0,2,5,5,5]
  ]
}

```

Model. The PyCSP³ model, in a file ‘Dominoes.py’, used for the competition is:



PyCSP³ Model 7

```

from pycsp3 import *

grid = data
nRows, nCols, nValues = len(grid), len(grid[0]), len(grid)
dominoes = [(i, j) for i in range(nValues) for j in range(i, nValues)]
indexes = range(nRows * nCols) # indexes of cells

P = [[i * nCols + j for i in range(nRows) for j in range(nCols) if grid[i][j] == v]
      for v in range(nValues)] # possible positions

# x[i][j] is the position in the grid of the value i of the domino i-j
x = VarArray(size=[nValues, nValues], dom=lambda i, j: indexes if i <= j else None)

# y[i][j] is the position in the grid of the value j of the domino i-j
y = VarArray(size=[nValues, nValues], dom=lambda i, j: indexes if i <= j else None)

satisfy(
    # each part of each domino in a different cell
    AllDifferent(x + y),

    # unary constraints
    [
        (
            x[i][j] in P[i],
            y[i][j] in P[j]
        ) for i, j in dominoes
    ],

    # adjacency constraints
    [
        If(
            dist != nCols, # if not same column
            Then=both(dist == 1, x[i][j] // nCols == y[i][j] // nCols) # then same line
        ) for i, j in dominoes if (dist := abs(x[i][j] - y[i][j]),)
    ]
)

```

This model involves 2 arrays of variables and 3 types of constraints: **AllDifferent**, **Extension** and **Intension**. A series of 12 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python Dominoes.py -data=grid.json
```

where ‘grid.json’ is a data file in JSON format.

2.1.8 Fischer

This problem has already been selected in previous XCSP competitions. The instances selected for the 2023 competition come from a series of Fischer SMT Instances from MathSat converted to CSP by Lucas Bordeaux. The translation is a straightforward encoding of the SMT syntax in which Boolean combinations of arithmetic constraints are decomposed into primitive constraints, using reification where appropriate. Note that the domains have been artificially bounded, whereas in SMT theorem proving should be done over the unbounded integers.

A series of 8 instances has been selected for the competition.

2.1.9 Magic Square

This problem has already been selected in previous XCSP competitions. A series of 14 instances has been selected for the competition (half of the instances involving the constraint MDD).

2.1.10 Nonogram

This problem has already been selected in previous XCSP competitions. This series of instances is from Trieu Hung Tran (when studying, in 2019, with Berthe Y. Choueiry at the University of Nebraska-Lincoln). He has generated these instances (involving ternary tables) from those available at xcsp.org, by using the reformulation proposed in [4]. It may be the case that these instances take less space and can be solved more quickly than the original instances.

A series of 8 instances has been selected for the competition.

2.1.11 Non Transitive Dice

Description. A set of dice is intransitive if the binary relation “X rolls a higher number than Y more than half the time” on its elements is not transitive. This situation is similar to that in the game Rock, Paper, Scissors, in which each element has an advantage over one choice and a disadvantage to the other. The problem is to exhibit such a set of dice. See wikipedia.

Data. Three integers are required to specify a specific instance: the number n of dices, the number m of sides on each die, and the number d of possible values (from 0 to $d - 1$) to be print on die sides. Values of (n, m, d) used for generating the 2023 competition instances are:

(06,06,0), (08,08,0), (08,08,3), (10,10,0), (10,10,3), (15,15,3),
(15,15,4), (20,20,3), (20,20,4), (30,30,3), (30,30,4), (40,40,0)

Model. The PyCSP³ model, in a file ‘NonTransitiveDice.py’, following the model described by [Hakan Kjellerstrand](#), and used for the competition is:

```

 PyCSP3 Model 8

from pycsp3 import *

n, m, d = data # number of dice, number of sides of each die, and number of possible values
d = 2 * m if d == 0 else d # computing the number of possible values when 0
P = [(r1, r2) for r1 in range(m) for r2 in range(m)]

# x[i][j] is the value of the jth face of the ith die
x = VarArray(size=[n, m], dom=range(d))

# y[i] is the number of winnings of the ith die against the i+1th die (two directions)
y = VarArray(size=[n, 2], dom=range(m * m + 1))

# gap[i] is the dominance gap of the ith die
gap = VarArray(size=n, dom=range(1, m * m + 1))

# z is the maximal value on die sides
z = Var(dom=range(d))

satisfy(
    # tag(symmetry-breaking) ordering numbers on each die
    [Increasing(x[i]) for i in range(n)],

    # computing dominance

```

```

[
  [y[i][0] == Sum(x[i][r1] > x[(i + 1) % n][r2] for r1, r2 in P) for i in range(n)],
  [y[i][1] == Sum(x[(i + 1) % n][r1] > x[i][r2] for r1, r2 in P) for i in range(n)]
],

# computing dominance gap
[gap[i] == y[i][0] - y[i][1] for i in range(n)],

# computing z
z == Maximum(x)
)

```

This model involves 3 arrays of variables, a stand-alone variable, and 4 types of constraints: **Increasing**, **Sum**, **Intension** and **Maximum**. A series of 12 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python NonTransitiveDice.py -data=[8,8,3]
```

2.1.12 Peg Solitaire

This is Problem [037](#) on CSPLib.

Description. From [17]: “Peg Solitaire is played on a board with a number of holes. In the English version of the game considered here, the board is in the shape of a cross with 33 holes. Pegs are arranged on the board so that at least one hole remains. By making horizontal or vertical draughts-like moves, the pegs are gradually removed until a goal configuration is obtained. In the classic ‘central’ Solitaire, the goal is to reverse the starting position, leaving just a single peg in the central hole.”

Data. English boards will be used (this will be acted by using the model variant ‘english’). We then have to decide what is the position of the initial hole, as well as the the number of moves (0 for removing all pegs but one). Three integers are then required to specify a specific instance: the coordinates (o_x, o_y) of the missing peg in the initial board, and the number d of moves. The values of (o_x, o_y, d) used for generating the 2023 competition instances are:

```
(0,2,0), (0,3,0), (0,4,0), (1,2,0), (1,3,0), (1,4,0), (2,0,0), (2,2,0), (2,3,0), (2,4,0),
(2,6,0), (3,3,0)
```

Model. The PyCSP³ model, in a file ‘PegSolitaire.py’, used for the competition is:

PyCSP³ Model 9

```

from pycsp3 import *

from PegSolitaire_Generator import generate_boards, build_transitions

assert variant() in {"english", "french"}

origin_x, origin_y, nMoves = data

init_board, final_board = generate_boards(variant(), origin_x, origin_y)
n, m = len(init_board), len(init_board[0])
transitions = build_transitions(init_board)
nTransitions = len(transitions)

```

```

v1 = sum(sum(v for v in row if v) for row in init_board)
v2 = sum(sum(v for v in row if v) for row in final_board)
horizon = v1 - v2
nMoves = horizon if nMoves == 0 or horizon < nMoves else nMoves
assert 0 < nMoves <= horizon

pairs = [(i, j) for i in range(n) for j in range(m) if init_board[i][j] is not None]

# x[i][j][t] is the value at row i and column j at time t
x = VarArray(size=[nMoves + 1, n, m], dom=lambda t,i,j: {0,1} if init_board[i][j] else None)

# y[t] is the move (transition) performed at time t
y = VarArray(size=nMoves, dom=range(nTransitions))

def unchanged(i, j, t):
    valid = [k for k, tr in enumerate(transitions) if (i, j) in (tr[0:2], tr[2:4], tr[4:6])]
    if len(valid) == 0:
        return None
    return conjunction(y[t] != k for k in valid) == (x[t][i][j] == x[t + 1][i][j])

def to0(i, j, t):
    valid = [k for k, tr in enumerate(transitions) if (i, j) in (tr[0:2], tr[2:4])]
    if len(valid) == 0:
        return None
    return disjunction(y[t] == k for k in valid) == both(x[t][i][j] == 1, x[t + 1][i][j] == 0)

def to1(i, j, t):
    valid = [k for k, tr in enumerate(transitions) if (i, j) == tr[4:6]]
    if len(valid) == 0:
        return None
    return disjunction(y[t] == k for k in valid) == both(x[t][i][j] == 0, x[t + 1][i][j] == 1)

satisfy(
    # setting the initial board
    x[0] == init_board,

    # setting the final board
    x[-1] == final_board,

    # setting transitions
    [
        [unchanged(i, j, t) for (i, j) in pairs for t in range(nMoves)],
        [to0(i, j, t) for (i, j) in pairs for t in range(nMoves)],
        [to1(i, j, t) for (i, j) in pairs for t in range(nMoves)]
    ]
)

```

This model involves 2 array of variables and 2 types of constraints: **Instantiation**, and **Intension**. The generator used to build boards is available on XCSP³ website. Note how the expressions forming intensional constraints are rather complex.

A series of 12 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python PegSolitaire.py -data=[3,3,0] -variant=english
```

2.1.13 Primes

This problem has already been selected in previous XCSP competitions. The instances selected for the 2023 competition come from a series created by Marc van Dongen: “All instances are satisfiable. The domains of the variables consist of prime numbers and all constraints are linear equations. The coefficients and constants in the equations are also prime numbers.

These instances are interesting because solving them using Gaussian elimination is polynomial, assuming that the basic arithmetic operations have a time complexity of $O(1)$. In reality this assumption does not hold and the choice of prime numbers in the equations gives rise to large intermediate coefficients in the equations, making the basic operations more time consuming. It was hoped this would allow to compare the trade-off between using a GAC approach on the original equations and the Gaussian elimination approach. The translation is a straightforward encoding of the SMT syntax in which Boolean combinations of arithmetic constraints are decomposed into primitive constraints, using reification where appropriate. Note that the domains have been artificially bounded, whereas in SMT theorem proving should be done over the unbounded integers.”

A series of 8 instances has been selected for the competition.

2.1.14 Pythagorean Triples

Description (excerpt from Wikipedia). The Boolean Pythagorean triples problem is a problem from Ramsey theory about whether the positive integers can be colored red and blue so that no Pythagorean triples consist of all red or all blue members. The Boolean Pythagorean triples problem was solved by Marijn Heule, Oliver Kullmann and Victor W. Marek in May 2016 through a computer-assisted proof. More specifically, the problem asks if it is possible to color each of the positive integers either red or blue, so that no triple of integers a , b , c , satisfying $a^2 + b^2 = c^2$ are all the same color. For example, in the Pythagorean triple 3, 4 and 5 ($3^2 + 4^2 = 5^2$), if 3 and 4 are colored red, then 5 must be colored blue. See [wikipedia](#).

Data. Only one integer is required to specify a specific instance: the limit n of integers for checking the property. The values of n used for generating the 2023 competition instances are:

2000, 4000, 5000, 6000, 7000, 7500, 7824, 7825

Model. The PyCSP³ model, in a file ‘PythagoreanTriples.py’, used for the competition is:



PyCSP³ Model 10

```

from pycsp3 import *
from math import sqrt

n = data

def conflicts():
    t = []
    for i in range(1, n + 1):
        i2 = i * i
        for j in range(i + 1, n + 1):
            j2 = j * j
            s = i2 + j2
            if s > n * n:
                break
            sr = int(sqrt(s))
            if sr * sr == s:
                t.append((i, j, sr))
    return t

conflicts = conflicts()

# x[i] is 0 (resp., 1) if integer i is in part/subset 0 (resp., 1)
x = VarArray(size=n + 1, dom={0, 1})

```

```
satisfy(
    # setting an arbitrary value to integer 0
    x[0] == 0,

    # ensuring that no Pythagorean triple is present in the same part
    [NValues(x[i], x[j], x[k]) > 1 for i, j, k in conflicts]
)
```

This model involves 1 array of variables and 2 types of constraints: `Intension`, and `NValues`. A series of 8 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python PythagoreanTriples.py -data=4000
```

2.1.15 Slant

Description (from LP/CP Programming Contest 2022). From [LPCP'22](#): “The problem is the [Slant](#) puzzle and instances are taken/adapted from the game. The problem is about a mission regarding islands and bridges. The objective is to cover a map with bridges, all of them diagonals, and not necessarily connecting islands. The only requirements regard the number of bridges reaching islands, and the avoiding of cycles.”

Data. As an illustration of data specifying an instance of this problem, we have:

```
7
-1 1 -1 -1 -1 -1 1 -1
-1 3 1 1 -1 2 -1 -1
-1 2 -1 1 -1 3 1 1
-1 -1 1 -1 -1 2 1 -1
-1 -1 -1 2 -1 -1 -1 -1
1 -1 1 1 -1 2 1 -1
1 -1 2 2 2 3 -1 -1
-1 1 -1 -1 -1 1 1 -1
```

Model. The PyCSP³ model, in a file ‘Slant.py’, used for the competition is:

PyCSP³ Model 11

```
from pycsp3 import *

grid = data
n = len(grid)

DOWN_DIAG, UP_DIAG = 0, 1

# e[k][l] is 1 if the edge in the intermediate cell at coordinates (k,l) is an upward
# downward, 0 if a downward diagonal
e = VarArray(size=[n - 1, n - 1], dom={DOWN_DIAG, UP_DIAG})

# x[i][j] is the number of connected nodes (effective neighbors, or bridges) to node (i,j)
x = VarArray(size=[n, n], dom=lambda i, j: {grid[i][j]} if grid[i][j] != -1 else range(5))

# d[i][j] is the distance of node (i,j) from the root to the chain/tree it belongs
d = VarArray(size=[n, n], dom=range(n * n + 1))
```

```

def connections_of(i, j):
    # returns a list of tuples (k,l,a,ii,jj) where (ii,jj) is a possible node that
    # can be reached from (i,j) by using a diagonal a on the edge (k,l)
    t = []
    if i > 0:
        if j > 0:
            t.append((i - 1, j - 1, DOWN_DIAG, i - 1, j - 1))
        if j < n - 1:
            t.append((i - 1, j, UP_DIAG, i - 1, j + 1))
    if i < n - 1:
        if j > 0:
            t.append((i, j - 1, UP_DIAG, i + 1, j - 1))
        if j < n - 1:
            t.append((i, j, DOWN_DIAG, i + 1, j + 1))
    return t

nodes = [(i, j) for i in range(n) for j in range(n)]
connections = [connections_of(i, j) for i, j in nodes]

satisfy(
    # computing the number of neighbors
    [x[i][j] == Sum(e[k][l] == a for (k,l,a,_,_) in connections_of(i, j)) for i, j in nodes],

    # isolated nodes are roots (are at distance 0)
    [If(x[i][j] == 0, Then=d[i][j] == 0) for i, j in nodes],

    # nodes with at least 2 neighbors cannot be roots (be at distance 0)
    [If(x[i][j] > 1, Then=d[i][j] != 0) for i, j in nodes],

    # nodes with at least 2 neighbors have exactly 1 parent (node with the same distance - 1)
    [If(x[i][j] > 1, Then=Count(both(e[k][l] == a, d[i][j] == d[ii][jj] + 1)
        for (k, l, a, ii, jj) in connections_of(i, j)) == 1) for i, j in nodes],

    # the distance between any two neighbors is always 1
    [If(e[k][l] == a, Then=abs(d[i][j] - d[ii][jj]) == 1) for i, j in nodes
        for (k, l, a, ii, jj) in connections_of(i, j)]
)

```

This problem involves 3 array of variables and 3 type of constraints: Sum, Intension and Count. A series of 10 instances (with data coming from LPCP'22) has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python Slant.py -data=instance01.in -parser=Slant_Parser.py
```

where 'instance01.in' is a data file and 'Slant_Parser.py' is a parser (i.e., a Python file allowing us to load data that are not directly given in JSON format). Note that for saving data in JSON files, you can add the option '-export' (or '-dataexport').

2.1.16 Soccer

Description. Soccer computational problems have been studied in [11], and several instances have been submitted to Minizinc challenges 2018 and 2020. This is related to SABIO [12], an interactive platform that can be used to represent several soccer computational problems using CP, and notably, “position in ranking”, which let users to impose constraints about the positions of the teams at the end of a tournament.

Data. As an illustration of data specifying an instance of the “position in ranking” problem, we have:

```
{
  "games": [[1, 0], [2, 0], [2, 1], ..., [23, 22]],
  "initial_points": [21, 21, 21, ...16],
  "positions": [[0, 21], [1, 19], [2, 17], ..., [13, 3]]
}
```

Model. The PyCSP³ model, in a file ‘Soccer.py’, based on the model submitted by Robinson Duque, Alejandro Arbelaez, and Juan Francisco Díaz to the Minizinc challenges 2018 and 2020, and used for the competition is:

 **PyCSP³ Model 12**

```
from pycsp3 import *

games, iPoints, positions = data
nGames, nTeams, nPositions = len(games), len(iPoints), len(positions)

pt = [0, 1, 3]

lb_score = min(iPoints[i] + sum(min(pt) for j in range(nGames) if i in games[j])
               for i in range(nTeams))
ub_score = max(iPoints[i] + sum(max(pt) for j in range(nGames) if i in games[j])
               for i in range(nTeams))

# points[j] are the points for the two teams (indexes 0 and 1) of the jth game
points = VarArray(size=[nGames, 2], dom=pt)

# score[i] is the final score of the ith team
score = VarArray(size=nTeams, dom=range(lb_score, ub_score + 1))

# fp[i] is the final position of the ith team
fp = VarArray(size=nTeams, dom=range(1, nTeams + 1))

# bp[i] is the best possible position of the ith team
bp = VarArray(size=nTeams, dom=range(1, nTeams + 1))

# wp[i] is the worst possible position of the ith team
wp = VarArray(size=nTeams, dom=range(1, nTeams + 1))

satisfy(
  # assigning rights points for each game
  [(points[j][0], points[j][1]) in {(0, 3), (1, 1), (3, 0)} for j in range(nGames)],

  # computing final points
  [score[i] - Sum(points[j][0 if i == games[j][0] else 1] for j in range(nGames) if i in
                  games[j]) == iPoints[i] for i in range(nTeams)],

  # computing worst positions (the number of teams with greater total points)
  [wp[i] == Sum(score[j] >= score[i] for j in range(nTeams)) for i in range(nTeams)],

  # computing best positions (from worst positions and number of teams with equal points)
  [bp[i] == wp[i] - Sum(score[j] == score[i] for j in range(nTeams) if i != j)
   for i in range(nTeams)],

  # bounding final positions
  (
    [fp[i] >= bp[i] for i in range(nTeams)],
    [fp[i] <= wp[i] for i in range(nTeams)]
  ),
)
```

```

# ensuring different positions
AllDifferent(fp),

# applying rules from specified positions
(
  [fp[i] == p for i, p in positions],
  [Sum(score[j] > score[i] for j in range(nTeams) if j != i) < p for i, p in positions],
  [Sum(score[j] < score[i] for j in range(nTeams) if j != i) <= nTeams + 1 - p
   for i, p in positions]
)
)

```

This problem involves 5 array of variables and 4 type of constraints: **Extension**, **Sum**, **Intension** and **AllDiferent**. A series of 10 instances (data having courteously been provided by R. Duque) has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python Soccer.py -data=30-20-24-1.json
```

where ‘30-20-24-1.json’ is a data file in JSON format.

2.1.17 Square Packing Suite

Description. The Square packing problem involves packing all squares with sizes 1×1 to $n \times n$ into an enclosing container [22, 26].

Data. Only one integer is required to specify a specific instance: the order n (i.e., the largest square to be packed). The values of n used for generating the 2023 competition instances are:

15, 18, 20, 21, 22, 23, 24, 25, 26, 27

Model. The PyCSP³ model, in a file ‘SquarePackingSuite.py’, used for the competition is:

PyCSP³ Model 13

```

from pycsp3 import *

n = data
assert 6 <= n <= 27 # for data (containers) below, as given in papers mentioned above

containers = [[9, 11], [7, 22], [14, 15], [15, 20], [15, 27], [19, 27], [23, 29], [22, 38],
              [23, 45], [23, 55], [27, 56], [39, 46], [31, 69], [47, 53], [34, 85], [38, 88], [39,
              98], [64, 68], [56, 88], [43, 129], [70, 89], [47, 148]] # indices from 6 to 27

# initial reduction as indicated in the CP'08 paper
t = [[], [1, 2], [2, 3], [2]] + [[3]] * 4 + [[4]] * 3 + [[5]] * 6 + [[6]] * 4
    + [[7]] * 8 + [[8]] * 5 + [[9]] * 11 + [[10]]

width, height = containers[n - 6]

# x[i] is the x-coordinate where is put the ith rectangle
x = VarArray(size=n, dom=lambda i: range(width - i))

# y[i] is the y-coordinate where is put the ith rectangle
y = VarArray(size=n, dom=lambda i: range(height - i))

satisfy(
  # no overlap on boxes

```

```

NoOverlap(origins=[(x[i],y[i]) for i in range(n)], lengths=[(i+1,i+1) for i in range(n)]),

# tag(redundant-constraints)
[
    Cumulative(
        Task(origin=x[i], length=i + 1, height=i + 1) for i in range(n)
    ) <= height,

    Cumulative(
        Task(origin=y[i], length=i + 1, height=i + 1) for i in range(n)
    ) <= width
],

# tag(symmetry-breaking)
(
    [x[-1] <= (width - n) // 2, y[-1] <= (height - n) // 2],
    [x[i] != v for i in range(n) for v in t[i]],
    [y[i] != v for i in range(n) for v in t[i]]
)
)

```

This model involves 2 array of variables, and 3 type of constraints: `NoOverlap`, `Cumulative`, and `Intension`. A series of 10 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python SquirePackingSuite.py -data=20
```

2.1.18 Word Design (for DNA Computing on Surfaces)

This is Problem [033](#) on CSPLib.

Description (excerpt from CSPLib). This problem (proposed by M. Van Dongen) on CSPLib has its roots in Bioinformatics and Coding Theory. It is to find as large as possible a set S of strings (words) of length 8 over the alphabet $W = \{A, C, G, T\}$ with the following properties:

- each word in S contains 4 occurrences of symbols from $\{C, G\}$,
- each pair of distinct words in S differ in at least 4 positions,
- each pair of words x and y in S (where x and y may be identical) are such that x^R and y^C differ in at least 4 positions; Here, $(x_1, \dots, x_8)^R = (x_8, \dots, x_1)$ is the reverse of $(x_1 \dots, x_8)$ and $(y_1 \dots, y_8)^C$ is the Watson-Crick complement of $(y_1 \dots, y_8)$, i.e. the word where each A is replaced by a T and vice versa and each C is replaced by a G and vice versa.

Data. A first invariant JSON file, called ‘words.json’, indicates the possible words (each word has 4 symbols from $\{1, 2\} = \{C, G\}$) and is such that its reverse and Watson-Crick complement differ in at least 4 positions):

```

{
  "words": [
    [0,0,0,0,1,1,1,1],
    [0,0,0,0,1,1,1,2],
    [0,0,0,0,1,1,2,1],
    [0,0,0,0,1,1,2,2],
    ...
  ]
}

```

```

]
}

```

A second invariant JSON, called ‘mdd.json’, indicates the transitions of a MDD that can be used to enforce the restrictions on pairs of words (it will be used for a second model):

```

{
  "transitions":[
    ["root",0,"n3"],
    ["root",1,"n286276"],
    ["root",2,"n430777"],
    ...
  ]
}

```

Finally, CSP instances can be generated by setting the size n of the set S . The values of n used for generating the 2023 competition instances are:

5, 15, 25, 35, 45, 55, 65, 75, 85, 100

Model. A first PyCSP³ model, in a file ‘WordDesign1.py’, used for the competition is:



PyCSP³ Model 14

```

from pycsp3 import *

words, n = data

# x[i][k] is the kth letter (0-A, 1-C, 2-G, 3-T) of the ith word
x = VarArray(size=[n, 8], dom=range(4))

# y[i][k] is the kth letter of the Watson-Crick complement of the ith word (in x)
y = VarArray(size=[n, 8], dom=range(4))

satisfy(
  # computing the Watson-Crick complement of words
  [x[i][k] + y[i][k] == 3 for i in range(n) for k in range(8)],

  # each word must be well formed
  [x[i] in words for i in range(n)],

  # ordering words tag(symmetry-breaking)
  LexIncreasing(x, strict=True),

  # each pair of distinct words differ in at least 4 positions
  [Sum(x[i][k] != x[j][k] for k in range(8)) >= 4 for i, j in combinations(n, 2)],

  # each pair of distinct words are such that the reverse of the former and the Watson-Crick
  # complement of the latter differ in at least 4 positions
  [Sum(x[i][7 - k] != y[j][k] for k in range(8)) >= 4 for i in range(n) for j in range(n)
   if i != j]
)

```

This first model involves 2 arrays of variables and 4 types of constraints: *Intension*, *Extension*, *LexIncreasing* and *Sum*. A series of 10 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python WordDesign1.py -data=[words.json,n=15]
```

Note how we can append a specific parameter to the data coming from a JSON file.

A second PyCSP³ model, in a file ‘WordDesign2.py’, used for the competition is:



PyCSP³ Model 15

```

from pycsp3 import *

words, transitions, n = data
M = MDD(transitions)

# x[i][k] is the kth letter (0-A, 1-C, 2-G, 3-T) of the ith word
x = VarArray(size=[n, 8], dom=range(4))

satisfy(
    # each word must be well-formed
    [x[i] in words for i in range(n)],

    # ordering words tag(symmetry-breaking)
    LexIncreasing(x, strict=True),

    # ensuring the validity of any pair of words
    [x[i] + x[j] in M for i, j in combinations(n, 2)]
)

```

This second model involves 1 array of variables and 3 types of constraints: **Extension**, **LexIncreasing** and **MDD**. A series of 10 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python WordDesign2.py -data=[words.json,mdd.json,n=15]
```

Note how we can append a specific parameter to the data coming from two JSON files.

2.2 COP

2.2.1 Aircraft Assembly Line

Description. This problem has been proposed by Stéphanie Roussel from ONERA (Toulouse), and comes from an aircraft manufacturer. The objective is to schedule tasks on an aircraft assembly line in order to minimize the overall number of operators required on the line. The schedule must satisfy several operational constraints, the main ones being:

- tasks are assigned on a unique workstation (on which specific machines are available);
- the takt-time, i.e., the duration during which the aircraft stays on each workstation, must be respected;
- capacity of aircraft zones in which operators perform the tasks must never be exceeded;
- zones can be neutralized by some tasks, i.e., it is not possible to work in those zones during the tasks execution.

Note that similar problems have been studied in [23], where the authors are interested in the design of assembly lines (with similar instances).

Data. As an illustration of data specifying an instance of this problem, we have:

```
{
  "takt": 1440,
  "nTasks": 199,
  "nMachines": 5,
  "nAreas": 48,
  "areasCapacities": [1,1,...,1],
  "tasksPerMachine": [
    [49,50,51,52,53],
    ...,
    [197]
  ],
  "nMaxOpsPerStation": [10,10,10,10],
  "neutralizedAreas": [
    [12,15,24,28,31,37,39,46],
    ...,
    []
  ],
  "operators": [0,1,...,1],
  "tasksPerAreas": [
    [2,5,11,13],
    ...,
    [6,7,165,166,167]
  ],
  "usedAreas": [
    [0,0,...,0],
    ...,
    [0,0,...,0]
  ],
  "durations": [0,109,...,470],
  "precedences": [
    [8,9],
    ...,
    [198,190]
  ],
  "nStations": 4,
  "machines": [
    [0,0,0,0,0],
    ...,
    [0,0,1,1,1]
  ]
}
```

Model. The PyCSP³ model, in a file ‘AircraftAssemblyLine.py’, used for the competition is:

PyCSP³ Model 16

```
from pycsp3 import *

takt, areas, stations, tasks, tasksPerMachine, precedences = data
nAreas, nStations, nTasks = len(areas), len(stations), len(tasks)
nMachines = len(tasksPerMachine)
```

```

areaCapacities, areaTasks = zip(*areas) # nb of operators who can work, and tasks per area
stationMachines, stationMaxOperators = zip(*stations)
durations, operators, usedAreaRooms, neutralizedAreas = zip(*tasks)
usedAreas = [set(j for j in range(nAreas) if usedAreaRooms[i][j] > 0) for i in range(nTasks)]

def station_of_task(i):
    r = next((j for j in range(nMachines) if i in tasksPerMachine[j]), -1)
    return -1 if r == -1 else next(j for j in range(nStations) if stationMachines[j][r] == 1)

stationOfTasks = [station_of_task(i) for i in range(nTasks)] # -1 if can be everywhere

# x[i] is the starting time of the ith task
x = VarArray(size=nTasks, dom=range(takt * nStations + 1))

# z[j] is the number of operators at the jth station
z = VarArray(size=nStations, dom=lambda i: range(stationMaxOperators[i] + 1))

satisfy(
    # respecting the final deadline
    [x[i] + durations[i] <= takt * nStations for i in range(nTasks)],

    # ensuring that tasks start and finish in the same station
    [x[i] // takt == (x[i] + max(0, durations[i] - 1)) // takt
     for i in range(nTasks) if durations[i] != 0],

    # ensuring that tasks are put on the right stations (wrt needed machines)
    [x[i] // takt == stationOfTasks[i] for i in range(nTasks) if stationOfTasks[i] != -1],

    # respecting precedence relations
    [x[i] + durations[i] <= x[j] for (i, j) in precedences],

    # respecting limit capacities of areas
    [
        Cumulative(
            Task(origin=x[t], length=durations[t], height=usedAreaRooms[t][i])
            for t in areaTasks[i]
        ) <= areaCapacities[i] for i in range(nAreas) if len(areaTasks[i]) > 1
    ],

    # computing/restricting the number of operators at each station
    [
        Cumulative(
            Task(origin=x[t], length=durations[t], height=operators[t] * (x[t] // takt == j))
            for t in range(nTasks)
        ) <= z[j] for j in range(nStations)
    ],

    # no overlapping between some tasks
    [NoOverlap(tasks=[(x[i], durations[i]), (x[j], durations[j])])
     for i in range(nTasks) for j in range(nTasks)
     if i != j and len(usedAreas[i].intersection(neutralizedAreas[j])) > 0],

    # avoiding tasks using the same machine to overlap
    [NoOverlap(tasks=[(x[j], durations[j]) for j in tasksPerMachine[i]])
     for i in range(nMachines) if len(tasksPerMachine[i]) > 1]
    )

minimize(
    # minimizing the number of operators
    Sum(z)
)

```

This involves 2 arrays of variables and 3 types of constraints: Intension, Cumulative and

NoOverlap. A series of 20 instances has been selected from data files generated by Stéphanie Roussel from ONERA (Toulouse).

For generating an XCSP³ instance (file), you can execute for example:

```
python AircraftAssemblyLine.py -data=1-178.json -parser=Aircraft_Converter.py
```

where ‘1-178.json’ is a data file in JSON format, and ‘Aircraft_Converter.py’ is a converter tool allowing us to pass from one JSON format to another that is easier to handle (with respect to the model). See how the initial 15 data fields have been reduced to 6 data fields only. Note that for saving data in JSON files, you can add the option ‘-export’ (or ‘-dataexport’).

2.2.2 Beer Jugs

Description (from LP/CP Programming Contest 2022). From [LPCP’22](#): “Blue Meth, Blue Sky, Heisenberg Blue... movie directors often like to adapt scientific (or maybe scientific) concepts in their creations. You are asked to help some of those fellas, who were impressed by the water jugs riddle in Die Hard 3. They want to shoot a similar scene, but in a pub, using beer instead of water (obviously, no beer will be wasted, and a drop essentially means that the main actors drink all the beer from a jug). In order to do the scene as much comical as possible, they ask for the longest sequence of non-repeating configurations that can be achieved using two jugs. Given the capacities of the two jugs, A and B, the possible actions are the following:

- drop_a, to empty the first jug;
- drop_b, to empty the second jug;
- fill_a, to fill the first jug;
- fill_b, to fill the second jug;
- a.to.b, to pour the second jug with the content of the first jug (either until the second jug is full, or until the first jug is empty);
- b.to.a, to pour the first jug with the content of the second jug (either until the first jug is full, or until the second jug is empty).

Note that they don’t care if the final configuration can be achieved with a shorter sequence... no one will note, they’ll all be drunk for a while anyway.”

Data. Two integers are required to specify a specific instance: the capacities A and B of the two jugs. The values of (A, B) used for generating the 2023 competition instances are (some of the LPCP’22 contest):

(3,10), (9,10), (7,12), (11,12), (11,14), (11,16), (13,16), (15,16)

Model. The PyCSP³ model, in a file ‘BeerJugs.py’, used for the competition is:

PyCSP³ Model 17

```
from pycsp3 import *

A, B = data
MAX = 70

STOP, FILL_A, FILL_B, DROP_A, DROP_B, A_TO_B, B_TO_A = Actions = range(-1, 6)
```

```

def execute(q1, q2, action):
    if action == STOP:
        return -1, -1
    if action == FILL_A:
        return (A, q2) if q1 != A else None
    if action == FILL_B:
        return (q1, B) if q2 != B else None
    if action == DROP_A:
        return (0, q2) if q1 > 0 else None
    if action == DROP_B:
        return (q1, 0) if q2 > 0 else None
    if action == A_TO_B:
        pour = min(q1, B - q2)
        return (q1 - pour, q2 + pour) if pour > 0 else None
    if action == B_TO_A:
        pour = min(A - q1, q2)
        return (q1 + pour, q2 - pour) if pour > 0 else None

valid = [(q1, q2, a) for q1 in range(A + 1) for q2 in range(B + 1) for a in Actions
         if execute(q1, q2, a)]
T = [(-1, -1, -1, -1, -1)] + [(q1, q2, a, *execute(q1, q2, a)) for q1, q2, a in valid]

# x[t][i] is the quantity in the ith jug (i is equal to 0 for A and 1 for B) at time t
x = VarArray(size=[MAX+1,2], dom=lambda i,j: {0} if i==0 else range(-1,(A if j==0 else B)+1))

# y[t] is the action taken at time t (to t+1)
y = VarArray(size=MAX, dom=Actions)

# z is the time when the process is stopped
z = Var(range(MAX))

satisfy(
    # ensuring that the same state is never encountered several times
    If(
        s1[0] != -1,
        Then=either(s1[0] != s2[0], s1[1] != s2[1])
    ) for s1, s2 in combinations(x, 2),

    # computing the consequences of each action
    [(x[t][0], x[t][1], y[t], x[t + 1][0], x[t + 1][1]) in T for t in range(MAX)],

    # ensuring a stable state (-1, -1) when the process is finished
    [(t < z) == (y[t] != STOP) for t in range(MAX)]
)

maximize(
    # maximizing the length of the sequence of actions
    z
)

```

This problem involves 2 arrays of variables, a stand-alone variable and 2 type of constraints: **Intension** and **Extension**. A series of 8 instances (with data coming from LPCP'22) has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python BeerJugs.py -data=[9,10]
```

2.2.3 Benzenoide

Description. From [8]: “The benzenoid generation problem is defined as follows: given a set of structural properties P, generate all the benzenoids which satisfy each property of P.

For instance, these structural properties may deal with the number of carbons, the number of hexagons or a particular structure for the hexagon graph.” Here, we are interested in generating benzenoids with n hexagons (including benzenoids with ‘holes’).

Data. Only one integer is required to specify a specific instance: the order n of the coronenoide. The values of n used for generating the 2023 competition instances are:

6, 7, 8, 9, 10, 11, 12, 13, 14, 15

Model. The PyCSP³ model, in a file ‘Benzenoide.py’, used for the competition is:

```

 PyCSP3 Model 18

from pycsp3 import *

n = data # order of the coronenoide
w = 2 * n - 1 # maximal width
widths = [w - abs(n - i - 1) for i in range(w)]

symmetries = [sym.apply_on(n) for sym in TypeHexagonSymmetry]

def valid(*t):
    return [(i, j) for i, j in t if 0 <= i < w and 0 <= j < widths[i]]

neighbors = [[valid(
    (i, j - 1), (i, j + 1),
    (i - 1, j - (1 if i < n else 0)), (i - 1, j + (0 if i < n else 1)),
    (i + 1, j - (1 if i >= n - 1 else 0)), (i + 1, j + (0 if i >= n - 1 else 1)))
    for j in range(widths[i])] for i in range(w)]

def T1(i, j):
    r = len(neighbors[i][j])
    return [(0, 0, *[ANY] * r), (1, 1, *[ANY] * r)] +
           [(2, 1, *[1 if j == i else ANY for j in range(r)]) +
            [(v, 1, *[v - 1 if j == i else {0}.union(range(v - 1, n + 1)) for j in range(r)])
            for v in range(3, n + 1) for i in range(r)]

T2 = [(1,1,1,1,1,1,1)] + [(ANY, *[0 if j == i else ANY for j in range(6)]) for i in range(6)]

# x[i][j] is 1 iff the hexagon at row i and column j is selected
x = VarArray(size=[w, w], dom=lambda i, j: {0, 1} if j < widths[i] else None)

# y[i][j] is the distance (+1) wrt the root of the connected tree
y = VarArray(size=[w, w], dom=lambda i, j: range(n + 1) if j < widths[i] else None)

satisfy(
    # only one root
    Count(y, value=1) == 1,

    # ensuring connectedness
    [(y[i][j], x[i][j], y[neighbors[i][j]]) in T1(i, j)
     for i in range(w) for j in range(widths[i])],

    # exactly n hexagons
    Sum(x) == n,

    # ensuring no holes
    [(x[i][j], x[neighbors[i][j]]) in T2 for i in range(w)
     for j in range(widths[i]) if len(neighbors[i][j]) == 6],

```

```

# tag(symmetry-breaking)
[
  [LexDecreasing(x, [x[row] for row in sym]) for sym in symmetries],
  [Precedence(y, values=(1, v)) for v in range(2, n + 1)]
]
)

minimize(
  Sum(x[i][j] * ((n-i) * w + (n-j)) for i in range(w) for j in range(w) if j < widths[i])
)

```

This model involves 2 arrays of variables, and 5 types of constraints: **Count**, **Extension**, **Sum**, **LexDecreasing** and **Precedence**. A series of 10 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python Benzenoide.py -data=10
```

2.2.4 Carpet Cutting

Description. From [24]: “The carpet cutting problem is a two-dimensional cutting and packing problem in which carpet shapes (also called items or objects) are cut from a rectangular carpet roll with a fixed roll width and a sufficiently long roll length. The goal is to find a non-overlapping placement of all carpet shapes on the carpet roll, so that the waste is minimized or in other words the utilization of used carpet material is maximized while meeting all additional constraints. In our case the objective is to minimize the carpet roll length.”

Data. Twenty instances have been selected in several Minizinc challenges (in 2011, 2012, 2016 and 2021); see [minizinc-benchmarks](#). The structure of a data file in JSON format is as follows:

```

{
  "roll_wid": 315,
  "max_roll_len": 20000,
  "roomCarpets": [
    {
      "rectangleIds": [0],
      "possibleRotations": [0, 1],
      "maxLength": 181,
      "maxWidth": 131
    }, ...
  ],
  "rectangles": [
    {
      "length": 181,
      "width": 131,
      "xOffsets": [0, 0, -1, -1],
      "yOffsets": [0, 0, -1, -1]
    }, ...
  ],
  "stairCarpets": []
}

```

Model. The PyCSP³ model, in a file ‘CarpetCutting.py’, based on the [Minizinc model](#), used for the competition is:

 **PyCSP³ Model 19**

```

from pycsp3 import *

rollWidth, maxRollLength, roomCarpets, rectangles, stairCarpets = data
roomRectangles, possibleRotations, maxLengths, maxWidths = zip(*roomCarpets)
rectLengths, rectWidths, xOffsets, yOffsets = zip(*rectangles)
stairLengths, stairWidths, nCoveredSteps, minCutSteps, maxCuts = zip(*stairCarpets)
    if len(stairCarpets) > 0 else ([], [], [], [], [])
nRoomCarpets, nRectangles, nStairCarpets = len(roomCarpets), len(rectangles), len(stairCarpets)

RC, SC = range(nRoomCarpets), range(nStairCarpets)

R0, R90, R180, R270 = Rotations = range(4) # 0 - 0, 1 - 90, 2 - 180, and 3 - 270

stairOffsets = [sum(nCoveredSteps[:i]) for i in SC]
stairRanges = [range(sco, sco + nCoveredSteps[i]) for i, sco in enumerate(stairOffsets)]

nSteps = sum(nCoveredSteps)
stepLengths = [stairLengths[i]//nCoveredSteps[i] for i in SC for _ in range(nCoveredSteps[i])]
stepWidths = [stairWidths[i] for i in SC for _ in range(nCoveredSteps[i])]

totalArea = sum(l * w for (l, w, _, _) in rectangles) + sum(stairLengths[i] * stairWidths[i]
    for i in SC)
minRollLength = (totalArea // rollWidth) + (1 if totalArea % rollWidth > 0 else 0)
totalLength = sum(max(maxLengths[i], maxWidths[i]) for i in RC) + sum(stairLengths)
maxRollLength = min(maxRollLength, totalLength)

rectSizes = range(min(min(l, w) for (l, w, _, _) in rectangles), max(max(l, w)
    for (l, w, _, _) in rectangles) + 1)

nexts = [next(j for j in RC if i in roomRectangles[j]) for i in range(nRectangles)]

# z is the carpet roll length
z = Var(dom=range(minRollLength, maxRollLength + 1))

# x[i] is the x-coordinate of the ith room carpet
x = VarArray(size=nRoomCarpets, dom=range(maxRollLength + 1))

# y[i] is the y-coordinate of the ith room carpet
y = VarArray(size=nRoomCarpets, dom=range(rollWidth + 1))

# r[i] is the rotation of the ith room carpet
r = VarArray(size=nRoomCarpets, dom=Rotations)

# r0or180[is] is 1 if the rotation of the ith room carpet is 0 or 180 degrees
r0or180 = VarArray(size=nRoomCarpets, dom={0, 1})

# r0or90[is] is 1 if the rotation of the ith room carpet is 0 or 90 degrees
r0or90 = VarArray(size=nRoomCarpets, dom={0, 1})

# xr[j] is the x-coordinate of the jth rectangle
xr = VarArray(size=nRectangles, dom=range(maxRollLength + 1))

# yr[j] is the y-coordinate of the jth rectangle
yr = VarArray(size=nRectangles, dom=range(rollWidth + 1))

# lr[j] is the length of the jth rectangle (considering a possible rotation)
lr = VarArray(size=nRectangles, dom=rectSizes)

# wr[j] is the width of the jth rectangle (considering a possible rotation)
wr = VarArray(size=nRectangles, dom=rectSizes)

```

```

if nSteps > 0:
    # xs[k] is the x-coordinate of the kth step of the stair
    xs = VarArray(size=nSteps, dom=range(maxRollLength + 1))

    # ys[k] is the y-coordinate of the kth step of the stair
    ys = VarArray(size=nSteps, dom=range(rollWidth + 1))

    # lp[i][j] is 1 if the jth covered step by the ith stair carpet is the last step of a part
    # (of the partition of the stair carpet)
    lp = VarArray(size=[nStairCarpets, nCoveredSteps], dom={0, 1})

    ls, ws = stepLengths, stepWidths

else:
    xs = ys = lp = ls = ws = []

X, Y, L, W = xr + xs, yr + ys, lr + ls, wr + ws

satisfy(
    # computing lengths and widths of rectangles
    [
        (
            lr[i] == rectWidths[i] + (rectLengths[i] - rectWidths[i]) * r0or180[nexts[i]],
            wr[i] == rectLengths[i] + (rectWidths[i] - rectLengths[i]) * r0or180[nexts[i]]
        ) for i in range(nRectangles)
    ],

    # enforcing room carpets to stay within limits
    [
        (
            x[i] + maxWidths[i] + (maxLengths[i] - maxWidths[i]) * r0or180[i] <= z,
            y[i] + maxLengths[i] + (maxWidths[i] - maxLengths[i]) * r0or180[i] <= rollWidth
        ) for i in RC
    ],

    # enforcing rectangles (of room carpets) to stay within limits
    [
        (
            xr[j] + lr[j] <= z,
            yr[j] + wr[j] <= rollWidth
        ) for i in RC for j in roomRectangles[i]
    ],

    # handling possible rotations of room carpets
    [
        (
            r[i] in possibleRotations[i],
            r0or90[i] == (r[i] in {R0, R90}),
            r0or180[i] == (r[i] in {R0, R180})
        ) for i in RC
    ],

    # computing the coordinates of the rectangles in room carpets
    [
        (
            xr[j] == x[i] + xOffsets[j][r[i]],
            yr[j] == y[i] + yOffsets[j][r[i]]
        ) for i in RC for j in roomRectangles[i]
    ],

    # enforcing stair steps to stay within limits

```

```

[
  (
    xs[j] + stepLengths[j] <= z,
    ys[j] + stepWidths[j] <= rollWidth
  ) for i in SC for j in stairRanges[i]
],

# breaking symmetries between steps of a stair carpet tag(symmetry-breaking)
[
  (
    ys[j] <= ys[j + 1],
    If(ys[j] >= ys[j + 1], Then=xs[j] + stepLengths[j] <= xs[j + 1])
  ) for i in SC for j in stairRanges[i] if j + 1 in stairRanges[i]
],

# computing the last steps in the parts of the partitions of the stair carpets
[
  [lp[i][nCoveredSteps[i] - 1] == 1 for i in SC],

  [
    lp[i][j] == either(
      ys[k] < ys[k + 1],
      xs[k] + stepLengths[j] < xs[k + 1]
    ) for i, offset in enumerate(stairOffsets) for j in range(nCoveredSteps[i] - 1)
      if [k := j + offset]
  ],

  [
    If(
      xs[k] + 2 * stepLengths[k] > z,
      Then=lp[i][j]
    ) for i, offset in enumerate(stairOffsets) for j in range(nCoveredSteps[i])
      if [k := j + offset]
  ],

  [Sum(lp[i][:nCoveredSteps[i]]) <= maxCuts[i] + 1 for i in SC],

  [lp[i][j] == 0 for i in SC if minCutSteps[i] > 1 for j in range(minCutSteps[i] - 1)],

  [
    If(
      lp[i][j],
      Then=lp[i][k] == 0
    ) for i in SC if minCutSteps[i] > 1 for j in range(minCutSteps[i]-1,nCoveredSteps[i])
      for k in range(j - minCutSteps[i] + 1, j)
  ]
],

# respecting roll length
Cumulative(origins=X, lengths=L, heights=W) <= rollWidth,

# respecting roll width
Cumulative(origins=Y, lengths=W, heights=L) <= z,

# non-overlapping
NoOverlap(origins=zip(X, Y), lengths=zip(L, W))
)

minimize(
  # minimizing the carpet roll length
  z
)

```

This model involves many arrays of variables, and 5 types of constraints: Intension,

Extension, Cumulative, NoOverlap and Element. A series of 20 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python CarpetCutting.py -data=test01.json
```

where ‘test01.json’ is a data file in JSON format.

2.2.5 Generalised Balanced Academic Curriculum Problem (GBACP)

This is Problem 064 on CSPLib.

Description. From CSPLib: “This is a generalisation of the Balanced Academic Curriculum Problem (BACP) proposed by Marco Chiarandini, Luca Di Gaspero, Stefano Gualandi, and Andrea Schaerf at University of Udine. With respect to BACP, GBACP adds:

- several curricula that can share courses,
- soft constraints, in particular for teacher preferences for not teaching during some terms.

The detailed description, data, best results, and a solution validator can be found at oathub.uniud.it. See also [13].

Data. Ten historical instances come from the School of Engineering of University of Udine; see oathub.uniud.it. The structure of a data file in JSON format is as follows:

```
{
  "nYears": 3,
  "nPeriodsPerYear": 3,
  "loadBounds": {"min": 2, "max": 6},
  "courseLoads": [6, 5, 5, ..., 1],
  "curricula": ...,
  "precedences": [[121, 3], [121, 6], ...],
  "undesiredPeriods": [[257, 1], [240, 2], ...]
}
```

Model. The PyCSP³ model, in a file ‘GBACP.py’, used for the competition is:

PyCSP³ Model 20

```
from pycsp3 import *

nYears, nPeriodsPerYear, loadBounds, courseLoads, curricula, precedences, uPeriods = data
nPeriods, nCourses, nCurricula = nYears * nPeriodsPerYear, len(courseLoads), len(curricula)
loadRange = range(loadBounds.min, loadBounds.max + 1)

max_load = sum(courseLoads)
total_load = [sum(courseLoads[i] for i in c) for c in curricula]
ideal_floor = [total_load[c] // nPeriods for c in range(nCurricula)]
ideal_ceil = [ideal_floor[c] + (0 if total_load[c] % nPeriods == 0 else 1)
              for c in range(nCurricula)]
distinctCurricula = [curricula[i] for i in range(nCurricula)
                       if all(curricula[j] != curricula[i] for j in range(i))]

# x[i] is the period for the ith course
x = VarArray(size=nCourses, dom=range(nPeriods))
```

```

# y[c][p] is the load in period p of curriculum c
y = VarArray(size=[nCurricula, nPeriods], dom=range(max_load + 1))

# d[c][p] is the delta between the ideal and effective loads in period p of curriculum c
d = VarArray(size=[nCurricula, nPeriods], dom=range(max_load + 1))

satisfy(
    # respecting authorized loads of courses for all periods and curricula
    [Cardinality(x[crm], occurrences={p: loadRange for p in range(nPeriods)})
     for crm in distinctCurricula],

    # respecting prerequisites
    [x[i] < x[j] for i, j in precedences],

    # computing loads
    [BinPacking(x[crm], sizes=courseLoads[crm], loads=y[c]) for c, crm in enumerate(curricula)]
)

if not variant():
    satisfy(
        # computing deltas
        [d[c][p] == Maximum(y[c][p] - ideal_ceil[c], ideal_floor[c] - y[c][p])
         for c in range(nCurricula) for p in range(nPeriods)]
    )

elif variant("table"):
    T = [[(max(v - ideal_ceil[c], ideal_floor[c] - v), v) for v in range(max_load + 1)]
         for c in range(nCurricula)]

    satisfy(
        # computing deltas
        [(d[c][p], y[c][p]) in T[c] for c in range(nCurricula) for p in range(nPeriods)]
    )

minimize(
    # minimizing preference violations and unbalanced loads
    Sum(d[c][p] * d[c][p] for c in range(nCurricula) for p in range(nPeriods))
    + Sum(x[i] == v + k*nPeriodsPerYear for i, v in uPeriods for k in range(nPeriodsPerYear))
)

```

This model involves 3 arrays of variables, and 5 types of constraints: **Cardinality**, **Intension**, **BinPacking**, **Maximum** and **Extension**. Actually, depending on the chosen variant, either **Maximum** constraints are posted, or **Extension** constraints are posted. Note that $x[crm]$ is a shortcut for $[x[i] \text{ for } i \text{ in } crm]$.

A series of $2 * 10$ instances has been selected for the competition (10 per variant). For generating an XCSP³ instance (file), you can execute for example:

```
python GBACP.py -data=UD01.json
python GBACP.py -data=UD01.json -variant=table
```

where ‘UD01.json’ is a data file in JSON format. Note that when you omit to write ‘-variant=table’, you get the main variant.

2.2.6 Generalized MKP

Description (excerpt from Wikipedia). In this variation of the knapsack problem, the weight of knapsack item i is given by a D -dimensional vector $w_i = (w_{i_1}, \dots, w_{i_D})$ and the knapsack has a D -dimensional capacity vector (W_1, \dots, W_D) . The target is to maximize the sum of the values of the items in the knapsack so that the sum of weights in each dimension d does not exceed W_d . See [Wikipedia](#).

Data. As an illustration of data specifying an instance of this problem, we have:

```
{
  "profits": [504, 803, 667, ..., 632],
  "wmatrix": [
    [42, 41, 523, ..., 298],
    [509, 883, 229, ..., 850],
    [806, 361, 199, ..., 447],
    [404, 197, 817, ..., 322],
    [475, 36, 287, ..., 635]],
  "capacities": [11927, 13727, 11551, 13056, 13460],
  "pmatrix": [
    [866, 690, 813, ..., 717],
    [1022, 959, 510, ..., 813],
    [866, 1022, 654, ..., 625],
    [855, 853, 811, ..., 932],
    [826, 654, 636, ..., 640]]
}
```

Data are from the Chu and Beasley series coming from [ResearchGate](#).

Model. The PyCSP³ model, in a file ‘GeneralizedMKP.py’, used for the competition is:

 **PyCSP³ Model 21**

```
from pycsp3 import *

profits, WM, capacities, PM = data # Weight and Profit Matrices
nItems, nBins = len(profits), len(capacities)

# x[i] is 1 if the item i is packed
x = VarArray(size=nItems, dom={0, 1})

# w[j] is the total weight in the jth bin
w = VarArray(size=nBins, dom=lambda j: range(capacities[j] + 1))

# z is the general profit
z = Var(range(sum(profits) + 1))

satisfy(
    [Knapsack(x, weights=W, wlimit=w[j], profits=PM[j]) >= z for j, W in enumerate(WM)],

    # computing the objective value
    z == profits * x
)

maximize(
    # maximizing the profit of packed items
    z
)
```

This problem involves 2 arrays of variables, a stand-alone variable and 2 types of constraints: Knapsack, and Sum. A series of 15 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python GeneralizedMKP.py -data=OR05x100-25-1.json
```

where ‘OR05x100-25-1.json’ is a data file in JSON format.

2.2.7 HC Pizza

This is Pizza Practice Problem for [Hash Code 2017](#).

Description. From HC'17: “The pizza corresponds to a 2-dimensional grid of n rows and m columns. Each cell of the pizza contains either mushroom or tomato. A slice of pizza is a rectangular section of the pizza delimited by two rows and two columns, without holes. The slices we want to cut out must contain at least L cells of each ingredient and at most H cells of any kind in total. The slices being cut out cannot overlap, and do not need to cover the entire pizza. The goal is to cut correct slices out of the pizza maximizing the total number of cells in all slices.”

Data. As an illustration of data specifying an instance of this problem, we have:

```
{
  "minIngredients": 2,
  "maxSize": 6,
  "pizza": [
    [1, 1, 0, 1, 1, 1, 1, 1, 1, 0],
    [0, 1, 0, 0, 1, 0, 1, 0, 0, 1],
    ...,
    [1, 0, 0, 1, 0, 1, 1, 0, 0, 0]
  ]
}
```

Model. The PyCSP³ model, in a file ‘HCPizza.py’, used for the competition is:

PyCSP³ Model 22

```
from pycsp3 import *

minIngredients, maxSize, pizza = data
n, m = len(pizza), len(pizza[0]) # nRows and nColumns
patterns = [(i, j) for i in range(1, min(maxSize, n)+1) for j in range(1, min(maxSize, m)+1)
             if 2 * minIngredients <= i * j <= maxSize]
nPatterns = len(patterns)

def possible_slices():
    _overlaps = [[[] for _ in range(m)] for _ in range(n)]
    _possibles = [[[] for _ in range(nPatterns)] for _ in range(m)]
    for i, j, k in product(range(n), range(m), range(nPatterns)):
        height, width = patterns[k][0], patterns[k][1]
        n_mushrooms, n_tomatoes = 0, 0
        for ib, jb in product(range(i, min(i + height, n)), range(j, min(j + width, m))):
            if pizza[ib][jb] == 0:
                n_mushrooms += 1
            else:
                n_tomatoes += 1
        if n_mushrooms >= minIngredients and n_tomatoes >= minIngredients:
            _possibles[i][j][k] = True
            for ib, jb in product(range(i, min(i + height, n)), range(j, min(j + width, m))):
                _overlaps[ib][jb].append((i, j, k))
    return _overlaps, _possibles

overlaps, slices = possible_slices()
```

```

def pattern_size(i, j, k):
    return (min(i + patterns[k][0], n) - i) * (min(j + patterns[k][1], m) - j)

# x[i][j][k] is 1 iff the slice with left top cell at (i,j) and pattern k is selected
x = VarArray(size=[n, m, nPatterns],
             dom=lambda i, j, k: {0, 1} if slices[i][j][k] else None)

# s[i][j][k] is the size of the slice with left top cell at (i,j) and pattern k (0 if the
# slice is not selected)
s = VarArray(size=[n, m, nPatterns],
             dom=lambda i, j, k: {0, pattern_size(i, j, k)} if slices[i][j][k] else None)

# z is the number of selected pizza cells
z = Var(dom=range(n * m + 1))

satisfy(
    # computing sizes of selected slices
    [(x[i][j][k], s[i][j][k]) in {(0, 0), (1, pattern_size(i, j, k))}
     for i, j, k in product(range(n), range(m), range(nPatterns)) if slices[i][j][k]],

    # ensuring that no two slices overlap
    [Sum(x[t]) <= 1 for i in range(n) for j in range(m) if len(t:=overlaps[i][j]) > 1],

    # computing the number of selected pizza cells
    Sum(s) == z
)

maximize(
    # maximizing the number of selected pizza cells
    z
)

```

This problem involves 2 arrays of variables, 1 stand-alone variable and 2 types of constraints Extension and Sum. A series of 10 (randomly generated) instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python HCPizza.py -data=10-10-2-6.json
```

where ‘10-10-2-6.json’ is a data file in JSON format.

Or, you can use the random generator ‘HCPizza_Random.py’:

```
python HCPizza.py -parser=HCPizza_Random.py 20 20 2 8 2
```

Note that for saving data in JSON files, you can add the option ‘-export’ (or ‘-dataexport’).

2.2.8 Hoist Scheduling Problem (HSP)

Description. From [2]: “we consider a facility with a single handling resource (a hoist). The hoist has to perform a sequence of moves in order to accomplish a set of jobs, with varying processing requirements, while satisfying processing and transport resource constraints. The objective is to determine a feasible schedule (i.e., a sequence) that minimizes the total processing time of a set of jobs (i.e., the makespan), while, at the same time, satisfying surface treatment constraints.” See also [30].

Data. As an illustration of data specifying an instance of this problem, we have:

```
{
  "cuves": [[50, 114], [80, 184], [60, 145], [80, 191], [28, 67]],
```

```

    "f": 12,
    "e": 8
}

```

Model. The PyCSP³ model, in a file ‘Hsp.py’, used for the competition is:

 **PyCSP³ Model 23**

```

from pycsp3 import *

intervals, ld, ud = data # loaded and unloaded time for one move

min_dips, max_dips = zip(*intervals) # min and max dip durations
nTanks = len(intervals) + 1
horizon = sum(min_dips) + ld * nTanks + ud * nTanks + 1

# t[i] is the time when the product is picked from the ith tank
t = VarArray(size=nTanks, dom=range(horizon - ld - ud))

# o[i] is the order in which the picking operation of the ith tank is executed
o = VarArray(size=nTanks, dom=range(nTanks))

# d[i] is the dip duration in the ith tank (plus ld)
d = VarArray(size=nTanks, dom=lambda i: range(min_dips[i - 1] + ld, max_dips[i - 1] + 1 + ld)
             if i != 0 else {0}) # i-1 because of special tank 0

# time of the cycle
z = Var(range(nTanks * (ld + ud), horizon))

def duration_limit(i, j, delta):
    return ld + ud * (abs(j - i) + delta)

satisfy(
    # we start the cycle by putting a product in the first tank
    [t[0] == 0, o[0] == 0],

    # taking into account the time of going back to tank 0
    [t[i] <= horizon - ld - (i + 1) * ud for i in range(1, nTanks)],

    # operations are executed in some order
    AllDifferent(o),

    # order of picking operations must be compatible with their picking times
    [(o[i] < o[j]) == (t[i] < t[j]) for i, j in combinations(nTanks, 2)],

    # ensuring a minimal duration between any two tanks
    NoOverlap(origins=t, lengths=ld + min(ud, min(min_dips))),

    # computing the time of the cycle
    z == Maximum(t[i] + ld + (i + 1) * ud for i in range(1, nTanks)),

    # ensuring a duration limit between any two tanks
    [
        (
            If(o[j] - o[i] == 1, Then=t[j] - t[i] >= duration_limit(i, j, -1)),
            If(o[i] - o[j] == 1, Then=t[i] - t[j] >= duration_limit(i, j, +1))
        ) for i, j in combinations(nTanks, 2)
    ]
)

```

```

if not variant():
    satisfy(
        # computing the dip duration of each product
        d[i] == ift(o[i] < o[i-1], z + t[i] - t[i-1], t[i] - t[i-1]) for i in range(1, nTanks)
    )
else:
    assert variant() in ("aux", "table")

    # g[i] is the gap (distance) between t[i] and t[i+1]
    g = VarArray(size=nTanks - 1, dom=range(-horizon, horizon))

    satisfy(
        # reducing the domain of auxiliary variables
        (
            g[i] < horizon - ld - (i + 2) * ud,
            g[i] > -horizon + ld + (i + 2) * ud
        ) for i in range(1, nTanks - 1)
    )

    if variant("aux"):

        satisfy(
            # computing the gap/distance between the picking time concerning two successive tanks
            [g[i] == t[i + 1] - t[i] for i in range(nTanks - 1)],

            # computing the dip duration of each product
            [d[i] == ift(g[i - 1] < 0, z + g[i - 1], g[i - 1]) for i in range(1, nTanks)]
        )

    elif variant("table"):

        T1 = [(v2 - v1, v2, v1) for v2 in t[2].dom for v1 in t[1].dom if v2 - v1 in g[1].dom]
        T2 = [(vt + vg if vg < 0 else vg, vg, vt) for vg in g[i - 1].dom for vt in z.dom
              if (vt + vg if vg < 0 else vg) in d[i].dom] for i in range(1, nTanks)]

        satisfy(
            # computing the gap/distance between two successive tanks
            [(g[i], t[i + 1], t[i]) in T1 for i in range(nTanks - 1)],

            # computing the dip duration of each product
            [(d[i], g[i - 1], z) in T2[i - 1] for i in range(1, nTanks)]
        )

    minimize(
        # minimizing the time of the cycle
        z
    )

```

This problem involves 3 arrays of variables, a stand-alone variable (z) and 5 types of constraints: Intension, AllDifferent, NoOverlap, Maximum and Extension. Actually, the constraints Extension are only posted when the chosen variant is 'table'. A series of 6*3 instances has been selected for the competition (6 per variant). For generating an XCSP³ instance (file), you can execute for example:

```

python Hsp.py -data=10405.json
python Hsp.py -data=10405.json -variant=aux
python Hsp.py -data=10405.json -variant=table

```

where '10405.json' is a data file in JSON format.

Note that when you omit to write '-variant=aux' or '-variant=table', you get the main variant.

2.2.9 Kidney Exchange

Description. From [Wikipedia](#): “Optimal kidney exchange is an optimization problem faced by programs for kidney paired donations (also called Kidney Exchange Programs). Such programs have large databases of patient-donor pairs, where the donor is willing to donate a kidney in order to help the patient, but cannot do so due to medical incompatibility. The centers try to arrange exchanges between such pairs. For example, the donor in pair A donates to the patient in pair B, the donor in pair B donates to the patient in pair C, and the donor in pair C donates to the patient in pair A. The objective is to find an optimal arrangement of such exchanges.”

Data. As an illustration of data specifying an instance of this problem, we have:

```
{
  "weights": [
    [-1, -1, -1, -1, 1, -1, 1, -1, -1, -1, -1, -1, -1, -1, -1, 0, -1],
    [-1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, 1, -1, 1, -1, 0, -1],
    ...,
    [-1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1]],
  "k": 4
}
```

The data files used for the competition were generated by John Dickerson (see [10]), and are available at [PrefLib](#).

Model. The PyCSP³ model, in a file ‘KidneyExchange.py’, used for the competition is:

 **PyCSP³ Model 24**

```

from pycsp3 import *

weights, k = data
n = len(weights)

# x[i] is the successor node of node i (in the cycle where i belongs)
x = VarArray(size=n, dom=range(n))

# y[i] is the cycle (index) where the node i belongs
y = VarArray(size=n, dom=range(n))

satisfy(
    AllDifferent(x),

    # ensuring correct cycles
    [y[i] == y[x[i]] for i in range(n)],

    # disabling infeasible arcs
    [x[i] != j for i in range(n) for j in range(n) if i != j and weights[i][j] < 0],

    # each cycle has k as maximum length
    BinPacking(y, sizes=1) <= k,

    # tag(symmetry-breaking)
    Precedence(y)
)

maximize(

```

```
# maximizing the sum of arc weights of selected cycles
Sum(weights[i][x[i]] for i in range(n))
)
```

Here, the model is equivalent to the one proposed by Edward Lam and Vicky H. Mak-Hau at the Minizinc challenge 2019. See also [21]. This model involves 2 arrays of variables and 5 types of constraints: `AllDifferent`, `Element`, `Intension BinPacking` and `Precedence`. A series of 18 instances has been selected for the competition (coming from data at [PrefLib](#)). For generating an XCSP³ instance (file), you can execute for example:

```
python KidneyExchange.py -data=4-001.json
```

where ‘4-001.json’ is a data file in JSON format.

2.2.10 K-Median Problem

Description. From [Wikipedia](#): “The k-median problem (with respect to the 1-norm) is the problem of finding k centers such that the clusters formed by them are the most compact. Formally, given a set of data points, the k centers c_i are to be chosen so as to minimize the sum of the distances from each data point to the nearest c_i .” See also [3], as well as the results in Chapter 11 of [29].

Data. As an illustration of data specifying an instance of this problem, we have:

```
{
  "distances": [
    [0, 30, 76, ..., 88],
    [30, 0, 46, ..., 118],
    ...
    [88, 118, 98, ..., 0]
  ],
  "k": 5
}
```

Model. The PyCSP³ model, in file ‘KMedian.py’, used for the competition is:

 **PyCSP³ Model 25**

```
from pycsp3 import *

distances, k = data
n = len(distances)

# x[i] is the ith selected node
x = VarArray(size=k, dom=range(n))

satisfy(
  # selected nodes must be all different
  AllDifferent(x),

  # tag(symmetry-breaking)
  Increasing(x, strict=True)
)

if not variant():
```

```

minimize(
    # minimizing the minimal distances between nodes and the selected ones
    Sum(Minimum(distances[c][j] for c in x) for j in range(n))
)

elif variant("aux"):

    # d[i][j] is the distance between the ith selected node and the jth node
    d = VarArray(size=[k, n], dom=distances)

    satisfy(
        # computing distances
        d[i][j] == distances[:, j][x[i]] for i in range(k) for j in range(n)
    )

    minimize(
        # minimizing the minimal distances between nodes and the selected ones
        Sum(Minimum(d[:, j]) for j in range(n))
    )

```

For the variant ‘aux’ (used for the competition), this model involves 2 arrays of variables and 5 types of constraints: `AllDifferent`, `Increasing`, `Element`, `Minimum` and `Sum`. A series of 15 instances has been selected for the competition, coming from the data set ‘p-median - uncapacitated’ at [OR-Library](#). For generating an XCSP³ instance (file), you can execute for example:

```
python KMedian.py -data=pmed01.json -variant=aux
```

where ‘pmed01.json’ is a data file in JSON format.

2.2.11 Large Scale Scheduling

Description. Large scale scheduling instances have been built to show the interest of a scalable time-table filtering algorithm for the `Cumulative Constraint` [14].

Data. As an illustration of data specifying an instance of this problem, we have:

```

{
  "limit": 100,
  "durations": [1460, 6048, 8129, ..., 12471],
  "heights": [17, 6, 40, ..., 19]
}

```

Data files can be found at [BeCool - Belgian Constraints Group @ UCLouvain](#).

Model. The PyCSP³ model, in a file ‘LargeScaleScheduling.py’, used for the competition is:

PyCSP³ Model 26

```

from pycsp3 import *

limit, durations, heights = data
nTasks = len(durations)

horizon = sum(durations) + 1 # Trivial upper bound on the horizon

# x[i] is the starting time of the ith task

```

```

x = VarArray(size=nTasks, dom=range(horizon))

satisfy(
    # resource cumulative constraint
    Cumulative(origins=x, lengths=durations, heights=heights) <= limit
)

minimize(
    Maximum(x[i] + durations[i] for i in range(nTasks))
)

```

This model involves 1 array of variables and 2 types of constraints: `Cumulative`, and `Maximum` (in the objective). A series of 9 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python LargeScaleScheduling.py -data=03200-0.json
```

where ‘03200-0.json’ is a data file in JSON format.

2.2.12 Progressive Party

This is Problem [013](#) on CSPLib.

Description (excerpt from CSPLib). “The problem is to timetable a party at a yacht club. Certain boats are to be designated hosts, and the crews of the remaining boats in turn visit the host boats for several successive half-hour periods. The crew of a host boat remains on board to act as hosts while the crew of a guest boat together visits several hosts. Every boat can only hold a limited number of people at a time (its capacity) and crew sizes are different. The total number of people aboard a boat, including the host crew and guest crews, must not exceed the capacity. A table with boat capacities and crew sizes can be found below; there were six time periods. A guest boat cannot not revisit a host and guest crews cannot meet more than once. The problem facing the rally organizer is that of minimizing the number of host boats.”

Data. As an illustration of data specifying an instance of this problem, we have:

```

{
  "nPeriods": 5,
  "boats": [
    {"capacity": 6, "crewSize": 2},
    {"capacity": 8, "crewSize": 2},
    ...,
    {"capacity": 10, "crewSize": 3}
  ]
}

```

Model. The PyCSP³ model, partly developed from [\[27\]](#), in a file ‘ProgressiveParty.py’, used for the competition is:

 **PyCSP³ Model 27**

```

from pycsp3 import *

nPeriods, boats = data
nBoats = len(boats)
capacities, crews = zip(*boats)

def minimal_number_of_hosts():
    nPersons = sum(crews)
    cnt, acc = 0, 0
    for capacity in sorted(capacities, reverse=True):
        if acc >= nPersons:
            return cnt
        acc += capacity
        cnt += 1

# h[b] indicates if the boat b is a host boat
h = VarArray(size=nBoats, dom={0, 1})

# s[b][p] is the scheduled (visited) boat by the crew of boat b at period p
s = VarArray(size=[nBoats, nPeriods], dom=range(nBoats))

# g[b1][p][b2] is 1 if s[b1][p] = b2
g = VarArray(size=[nBoats, nPeriods, nBoats], dom={0, 1})

satisfy(
    # identifying host boats
    [h[b] == (s[b][p] == b) for b in range(nBoats) for p in range(nPeriods)],

    # identifying host boats (from visitors)
    [h[s[b][p]] == 1 for b in range(nBoats) for p in range(nPeriods)],

    # channeling variables from arrays s and g
    [Channel(g[b][p], s[b][p]) for b in range(nBoats) for p in range(nPeriods)],

    # boat capacities must be respected
    [g[:, p, b] * crews <= capacities[b] for b in range(nBoats) for p in range(nPeriods)],

    # a guest boat cannot revisit a host
    [AllDifferent(s[b], excepting=b) for b in range(nBoats)],

    # guest crews cannot meet more than once
    [Sum(s[b1][p] == s[b2][p] for p in range(nPeriods)) <= 1
     for b1, b2 in combinations(nBoats, 2)],

    # tag(redundant-constraint)
    # ensuring a minimum number of hosts
    Sum(h) >= minimal_number_of_hosts()
)

minimize(
    # minimizing the number of host boats
    Sum(h)
)

```

This problem involves 3 arrays of variables and 5 types of constraints: `Intension`, `Element`, `Channel`, `Sum` and `AllDifferent`. A series of 7 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python ProgressiveParty.py -parser=ProgressiveParty_rally-red.py 42 12
```

where ‘ProgressiveParty_rally-red.py’ is a generator based on the instance ‘rally-red’ that allows

us to specify the number of boats and the number of periods. Note that for saving data in JSON files, you can add the option ‘-export’ (or ‘-dataexport’).

2.2.13 Pigment Sequencing Problem (PSP)

This is a particular case of the Discrete Lot Sizing Problem (DLSP); see Problem 058 on CSPLib.

Description (excerpt from CSPLib). “Discrete Lot Sizing and Scheduling Problem (DLSP) is a production planning problem which consists of determining a minimal cost production schedule (production costs, setup costs, changeover costs, stocking costs, etc.), such that machine capacity restrictions are not violated, and demand for all products is satisfied. The planning horizon is discrete and finite. The variant PSP is a multi-item, single machine problem with capacity of production limited to one per period. There are storage costs and sequence-dependent changeover costs, respecting the triangle inequality. Each order consisting of one unit of a particular item has a due date and must be produced at latest by its due date. The stocking (inventory) cost of an order is proportional to the number of periods between the due date and the production period. The changeover cost $q_{i,j}$ is induced when passing from the production of item i to another one j with $q_{i,i} = 0, \forall i$. The objective is to assign a production period for each order respecting its due date and the machine capacity constraint so as to minimize the sum of stocking costs and changeover costs.”

See [16, 15].

Data. As an illustration of data specifying an instance of this problem, we have:

```
{
  "nOrders": 50,
  "changeCosts": [
    [0, 45, 10, 34, 36, 37, 10, 13, 35, 26],
    [18, 0, 47, 32, 30, 32, 49, 30, 40, 31],
    ...,
    [26, 21, 34, 22, 48, 45, 31, 25, 22, 0]
  ],
  "stockingCosts": [21, 38, 25, 10, 48, 42, 22, 24, 44, 38],
  "demands": [
    [0, 0, 0, ..., 1],
    [0, 0, 0, ..., 1],
    ...,
    [0, 0, 0, ..., 0]
  ]
}
```

Model. A first PyCSP³ model, in a file ‘PSP1.py’, used for the competition is:

PyCSP³ Model 28

```
from pycsp3 import *

nOrders, changeCosts, stockingCosts, demands = data
nItems, horizon = len(demands), len(demands[0])

# x[t][i] is 1 when item i is produced at time t
```

```

x = VarArray(size=[horizon, nItems], dom={0, 1})

# y[t][i] is 1 if the machine is ready to produce i at time t
y = VarArray(size=[horizon, nItems], dom={0, 1})

# c[t][i] is 1 if the configuration changes from i to j at time t
c = VarArray(size=[horizon, nItems, nItems], dom=lambda t, i, j: {0, 1} if t != 0 and i != j
              else None)

# s[t][i] is the number of items of type i stored at time t
s = VarArray(size=[horizon + 1, nItems], dom=lambda t, i: range(sum(demands[i]) + 1))

satisfy(
    # the stock of every item is empty at startup
    s[0] == 0,

    # when an item is produced, it is either delivered or stocked for later delivery
    [x[t][i] + s[t][i] == demands[i][t] + s[t + 1][i] for t in range(horizon)
     for i in range(nItems)],

    # consistency between production and machine setup
    [x[t][i] <= y[t][i] for t in range(horizon) for i in range(nItems)],

    # only 1 unit of one item is produced at each time
    [Sum(y[t]) == 1 for t in range(horizon)],

    # consistency between machine setup and changeover
    [c[t][i][j] >= y[t - 1][i] + y[t][j] - 1 for t in range(1, horizon) for i in range(nItems)
     for j in range(nItems) if i != j]
)

minimize(
    Sum(changeCosts[i][j] * Sum(c[:, i, j])
        for i in range(nItems) for j in range(nItems) if i != j)
    + Sum(stockingCosts[i] * Sum(s[:, i]) for i in range(nItems))
)

```

A second PyCSP³ model, in a file ‘PSP2.py’, used for the competition is:

PyCSP³ Model 29

```

from pycsp3 import *

nOrders, changeCosts, stockingCosts, demands = data
nItems, horizon = len(demands), len(demands[0])

required = [[sum(demands[i][:t + 1]) for t in range(horizon)] for i in range(nItems)]

# x[t] is the item produced at time t
x = VarArray(size=horizon, dom=range(nItems))

# p[i][t] is 1 if the ith item is produced at time t
p = VarArray(size=[nItems, horizon], dom={0, 1})

# z[t] is the changeover cost incurred at time t
z = VarArray(size=horizon - 1, dom=changeCosts)

satisfy(
    # channeling variables
    [p[i][t] == (x[t] == i) for i in range(nItems) for t in range(horizon)],

```

```

# ensuring that deadlines of demands are respected
[Sum(p[i][:t + 1]) >= required[i][t] for i in range(nItems) for t in range(horizon)
 if t == 0 or required[i][t - 1] != required[i][t]],

# computing changeover costs
[z[t] == changeCosts[x[t], x[t + 1]] for t in range(horizon - 1)],

# tag(redundant-constraints)
[Count(x, value=i) >= required[i][-1] for i in range(nItems)]
)

minimize(
    Sum(stockingCosts[i] * (Sum(p[i][:t + 1]) - required[i][t])
      for i in range(nItems) for t in range(horizon))
    + Sum(z)
)

```

These models can be, e.g., compared to the one written by Xavier Gillard; see [GitHub](#). The second model above involves 3 arrays of variables and 4 types of constraints: `Intension`, `Sum`, `Element` and `Count`. A series of $8 * 2$ instances has been selected for the competition (8 per model), from data files available in the [Supplementary Material](#) of paper [15]. For generating an XCSP³ instance (file), you can execute for example:

```
python PSP1.py -data=001.json
python PSP2.py -data=001.json
```

where ‘001.json’ is a data file in JSON format.

2.2.14 Resource Investment Problem (RIP)

The Resource Investment Problem (RIP) is also known as the Resource Availability Cost Problem (RACP).

Description From [OR&S Research Group at Ghent University](#): “The RIP assumes that the level of renewable resources can be varied at a certain cost and aims at minimizing this total cost of the (unlimited) renewable resources required to complete the project by a pre-specified project deadline.” See also [18].

Data. As an illustration of data specifying an instance of this problem, we have:

```

{
  "horizon": 96,
  "costs": [7, 7, 1, 5],
  "jobs": [
    {"duration": 8, "successors": [3, 8, 13], "requirements": [10, 0, 0, 0]},
    {"duration": 1, "successors": [5, 12, 27], "requirements": [0, 1, 0, 0]},
    {"duration": 10, "successors": [6, 10, 14], "requirements": [0, 9, 0, 0]},
    ...,
    {"duration": 1, "successors": [], "requirements": [0, 0, 0, 1]}
  ]
}

```

Model. The PyCSP³ model, in a file ‘RIP.py’, used for the competition is:

 **PyCSP³ Model 30**

```

from pycsp3 import *

horizon, costs, tasks = data
durations, successors, requirements = zip(*tasks)
nResources, nTasks = len(costs), len(tasks)
requirements = [[r[k] for r in requirements] for k in range(nResources)]

lb_usage = [max(row) for row in requirements]
ub_usage = [sum(row) for row in requirements]

# s[i] is the starting time of the ith task
s = VarArray(size=nTasks, dom=range(horizon + 1))

# u[k] is the maximal usage (at any time) of the kth resource
u = VarArray(size=nResources, dom=lambda k: range(lb_usage[k], ub_usage[k] + 1))

satisfy(
    # ending tasks before the given horizon
    [s[i] + durations[i] <= horizon for i in range(nTasks)],

    # respecting precedence relations
    [s[i] + durations[i] <= s[j] for i in range(nTasks) for j in successors[i]],

    # cumulative resource constraints
    [Cumulative(origins=s, lengths=durations, heights=requirements[k]) <= u[k]
     for k in range(nResources)]
)

minimize(
    # minimizing weighted usage of resources
    costs * u
)

```

The model involves 2 arrays of variables, and 2 types of constraints: **Intension** and **Cumulative**. A series of 12 instances has been selected for the competition: they correspond to applying some random perturbation on classical RCPSP instances. For generating an XCSP³ instance (file), you can execute for example:

```

python RIP.py -data=25-3-j060-01-01.json
python RIP.py -data=[25,3,j060-30-01] -parser=RIP_Parser.py

```

where ‘25-0-j060-01-01.json’ is a data file in JSON format, whereas ‘j060-30-01’ is a data file in tabular text format and ‘RIP_Parser.py’ is a parser (i.e., a Python file allowing us to load data that are not directly given in JSON format). Note that for saving data in JSON files, you can add the option ‘-export’ (or ‘-dataexport’).

2.2.15 Rule Mining

This series of instances has been generated by Nicolas Szczepanski from the classification rule mining problem, which is a problem over (discrete and) imbalanced data whose distribution greatly varies over the classes. A series of 9 instances has been selected for the competition.

2.2.16 Sonet

This is Problem [064](#) on CSPLib, called Synchronous Optical Networking Problem (SONET).

Description. From CSPLib: “In the SONET problem we are given a set of nodes, and for each pair of nodes we are given the demand (which is the number of channels required to carry network traffic between the two nodes). The demand may be zero, in which case the two nodes do not need to be connected. A SONET ring connects a set of nodes. A node is installed on a ring using a piece of equipment called an add-drop multiplexer (ADM). Each node may be installed on more than one ring. Network traffic can be transmitted from one node to another only if they are both installed on the same ring. Each ring has an upper limit on the number of nodes, and a limit on the number of channels. The demand of a pair of nodes may be split between multiple rings. The objective is to minimize the total number of ADMs used while satisfying all demands.”

Data. As an illustration of data specifying an instance of this problem, we have:

```
{
  "n":6,
  "m":10,
  "r":3,
  "connections":[[0,1],[0,2],[0,3],[2,3],[2,5],[4,5]]
}
```

Model. The PyCSP³ model, in a file ‘Sonet.py’, used for the competition is:

 **PyCSP³ Model 31**

```

from pycsp3 import *

n, m, r, connections = data

# x[i][j] is 1 if the ith ring contains the jth node
x = VarArray(size=[m, n], dom={0, 1})

T = {tuple(1 if j // 2 == i else ANY for j in range(2 * m)) for i in range(m)}

satisfy(
  [(x[i][conn] for i in range(m)) in T for conn in connections],

  # respecting the capacity of rings
  [Sum(x[i]) <= r for i in range(m)],

  # tag(symmetry-breaking)
  LexIncreasing(x)
)

minimize(
  # minimizing the number of nodes installed on rings
  Sum(x)
)

```

This problem involves 1 array of variables and 3 types of constraints: **Extension**, **Sum** and **LexIncreasing**. A series of 16 instances has been selected for the competition, from data files corresponding to parameters for Conjure [1]. For generating an XCSP³ instance (file), you can execute for example:

```
python Sonet.py -data=s3ring03.json
```

where ‘s3ring03.json’ is a data file in JSON format.

2.2.17 Single-Row Facility Layout Problem (SRFLP)

Description. from [9]: “The Single-Row Facility Layout Problem (SRFLP) is an ordering problem considering a set of departments in a facility, with given lengths and pairwise traffic intensities. Its goal is to find a linear ordering of the departments minimizing the weighted sum of the distances between department pairs”

Data. As an illustration of data specifying an instance of this problem, we have:

```
{
  "lengths": [40, 20, 50, 30, 10, 50, 80],
  "traffics": [
    [0, 5, 2, 4, 1, 0, 0],
    [5, 0, 3, 0, 2, 2, 2],
    ...,
    [0, 2, 5, 2, 0, 5, 0]
  ]
}
```

Model. The PyCSP³ model, in a file ‘SRFLP.py’, used for the competition is:

PyCSP³ Model 32

```
from pycsp3 import *

lengths, traffics = data
n = len(lengths)

ordered_lengths = sorted(lengths)

pairs = [(i, j) for i, j in combinations(n, 2) if i + 1 < j]

# x[i] is the department at the ith position
x = VarArray(size=n, dom=range(n))

# y[i] is the length of the department at the ith position
y = VarArray(size=n, dom=lengths)

# d[i][j] is the end-to-start distance between the ith and the jth departments
d = VarArray(size=[n, n], dom=lambda i, j: range(sum(ordered_lengths[:j - i - 1]), sum(
    ordered_lengths[i - j + 1:] + 1) if i + 1 < j else None))

satisfy(
    # ensuring a linear ordering of the departments
    AllDifferent(x),

    # computing lengths
    [(x[i], y[i]) in [(j, lengths[j]) for j in range(n)] for i in range(n)],

    # computing distances
    [d[i][j] == Sum(y[i + 1:j]) for i, j in pairs]
)

minimize(
    # minimizing weighted end-to-start distances
    Sum(d[i][j] * traffics[x[i], x[j]] for i, j in pairs)
)
```

This model involves 3 arrays of variables and 3 type of constraints: `AllDifferent`, `Extension` and `Sum`. A series of 15 instances has been selected for the competition, from data files in the [Supplemental Material](#) of Paper [9]. For generating an XCSP³ instance (file), you can execute for example:

```
python SRFLP.py -data=C112.json
```

where ‘C112.json’ is a data file in JSON format.

2.2.18 TSPTW

Description. Traveling Salesman Problem with Time Windows (TSPTW) is a popular variant of the TSP where the salesman’s customers must be visited within given time windows.

Data. As an illustration of data specifying an instance of this problem, we have:

```
{
  "distances": [
    [0, 19, 17, ..., 12],
    [19, 0, 10, ..., 31],
    ...,
    [12, 31, 29, ..., 0]
  ],
  "windows": [[0, 408], [62, 68], [181, 205], ..., [275, 300]]
}
```

Model. A first PyCSP³ model, in a file ‘TSPTW1.py’, used for the competition is:

 **PyCSP³ Model 33**

```

from pycsp3 import *

distances, windows = data
Earliest, Latest = cp_array(zip(*windows))
horizon = max(Latest) + 1
n = len(distances)

# x[i] is the customer (node) visited in the ith position
x = VarArray(size=n + 1, dom=range(n))

# a[i] is the time when is visited the customer in the ith position
a = VarArray(size=n, dom=range(horizon))

satisfy(
  # making it a tour while starting and ending at city 0
  [x[0] == 0, x[-1] == 0, a[0] == 0],

  AllDifferent(x[:-1]),

  # enforcing time windows
  [
    [Earliest[x[i]] <= a[x[i]] for i in range(n)],
    [a[x[i]] <= Latest[x[i]] for i in range(n)],
    [a[x[i + 1]] >= a[x[i]] + distances[x[i], x[i + 1]] for i in range(n - 1)]
  ]
)

```

```

minimize(
    # minimizing travelled distance
    Sum(distances[x[i], x[(i + 1) % n]] for i in range(n))
)

```

A second PyCSP³ model, in a file ‘TSPTW2.py’, used for the competition is:

PyCSP³ Model 34

```

from pycsp3 import *

distances, windows = data
horizon = max(latest for (_, latest) in windows) + 1
n = len(distances)

# x[i] is the node succeeding to the ith node
x = VarArray(size=n, dom=range(n))

# a[i] is the time when is visited the ith node
a = VarArray(size=n, dom=lambda i: range(windows[i][0], windows[i][1] + 1))

satisfy(
    # making it a tour while starting and ending at city 0
    a[0] == 0,

    # avoiding self-loops
    [x[i] != i for i in range(n)],

    # forming a circuit
    Circuit(x),

    # enforcing time windows
    [
        If(
            x[i] != 0,
            Then=a[x[i]] >= a[i] + distances[i][x[i]]
        ) for i in range(n)
    ]
)

minimize(
    # minimizing travelled distance
    Sum(distances[i, x[i]] for i in range(n))
)

```

A series of 2 * 8 instances has been selected for the competition (8 per model), from data files available in the [Supplementary Material](#) of paper [15]. For generating an XCSP³ instance (file), you can execute for example:

```

python TSPTW1.py -data=n020w020-1.json
python TSPTW2.py -data=n020w020-1.json

```

where ‘n020w020-1.json’ is a data file in JSON format.

Chapter 3

Solvers

In this chapter, we introduce the solvers and teams having participated to the XCSP³ Competition 2023.

- ACE (Christophe Lecoutre)
- BTD, miniBTD (Mohamed Sami Cherif, Djamel Habet, Philippe Jégou, H el ene Kanso, Cyril Terrioux)
- Choco (Charles Prud’homme)
- CoSoCo (Gilles Audemard)
- Exchequer (Martin Mariusz Lester)
- Fun-sCOP (Takehide Soh, Daniel Le Berre, Hidetomo Nabeshima, Mutsunori Banbara, Naoyuki Tamura)
- MiniCPBP (Gilles Pesant and Auguste Burlats)
- Mistral (Emmanuel Hebrard and Mohamed Siala)
- Nacre (Ga el Glorian)
- Picat (Neng-Fa Zhou)
- RBO, miniRBO (Mohamed Sami Cherif, Djamel Habet, Cyril Terrioux)
- Sat4j-CSP-PB (extension of Sat4j by Thibault Falque and Romain Wallon)
- SeaPearl (Max Bourgeat, Axel Navarro, L eo Boisvert, Tom Marty, Louis-Martin Rousseau, Quentin Cappart)
- toulbar2 (David Allouche et al.)

ACE at XCSP³ Competition 2023



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Version 2.1.1 – May 23, 2023

ACE [7] is an open-source constraint solver, developed in Java. ACE focuses on:

- integer variables, including 0/1 (Boolean) variables,
- state-of-the-art table constraints, including ordinary, starred, and hybrid table constraints,
- popular global constraints (AllDifferent, Count, Element, Cardinality, Cumulative, etc.),
- search heuristics, as e.g., wdeg [3, 11], last-conflict [8], BIVS [6], solution-saving [10], and pick/dom [2],
- mono-criterion optimization

ACE is derived from the constraint solver AbsCon that has been used as a research platform in our team at CRIL during many years. Many (more or less promising) ideas and algorithms have been discarded from AbsCon, so as to get a constraint solver of reasonable size and understanding.

Important: ACE is not an official competitor for the 2023 XCSP³ competition because I conducted the selection of instances. Note also that ACE is run with its default behaviour without any mechanism that could have been used to improve its performances (e.g., local search in a preprocessing step, use of several heuristics to improve diversification of search, etc.).

With the right classpath (after having cloned the code from Github), you can run the solver on any XCSP³ [5, 1, 4] instance (file) by executing:

```
java ace <xcsp3_file> [options]
```

with:

- <xcsp3_file>: an XCSP³ file representing a CSP or COP instance
- [options]: possible options to be used when running the solver

Of course, for generating XCSP³ instances, just write and compile models with the Python library PyCSP³ [9]; see <http://pycsp.org/>.

Licence. ACE is licensed under the [MIT License](#)

Code. ACE code is available

- on Github: <https://github.com/xcsp3team/ace>

Acknowledgements

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BTD and miniBTD

A Tree-decomposition based Approach

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(mini)BTD (Backtracking on Tree-Decomposition) is an open-source constraint solver which exploits the structure of CSP instances thanks to the notion of tree-decomposition [5]. It is written in C++ and implements the algorithm BTD-MAC+RST+Merge [3].

For the competition, we have made the following choices:

- The variable heuristic relies on Last Conflict [4] combined with a multi-armed bandit with 9 arms [1]. The i -th arm is based on CHS (for Conflict History Search [2]) with $\alpha = 0.1 * i$ and $\delta = 10^{-4}$. Note that the variable heuristic is only exploited for ordering the variables inside a cluster.
- *lexico* is used as value ordering heuristic.
- Generalized arc-consistency is enforced by a propagation-based system exploiting events.
- (mini)BTD relies on restarts performed according to a geometric restart policy based on the number of conflicts with an initial cutoff set to 50 and an increasing factor set to 1.05,
- The tree-decomposition is computed thanks to the heuristic H₅-TD-WT [3].
- The first root cluster is the cluster having the maximum ratio number of constraints to its size minus one and then, at each restart, the selected root cluster is one which maximizes the sum of the weights of the constraints whose scope intersects the cluster.

(mini)BTD is able to handle all the constraints used in the competition.

Licence. (mini)BTD is licensed under the [MIT License](#).

Code. The source code is available on Github: <https://github.com/Terrioux/BTD-RBO>.

Command line. (mini)BTD can be launched thanks to the following command line:

```
SOLVER TIMELIMIT BENCHMARK
```

where:

- SOLVER is the path to the executable BTD or miniBTD,
- TIMELIMIT is the number of seconds allowed for solving the instance,
- BENCHMARK is the name of the XML file representing the instance we want to solve.

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Choco solver
a free open-source Java library for CP



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Version 4.10.13 – July, 2023

Choco solver already has a long history : the first line of code was written in 1999 [11]. Since then, the code has been frequently re-engineered and released, up to version 4.0.8, the last current released [12]. It contains numerous variables, many (global) constraints and search procedures, to provide wide modeling perspectives.

Choco solver is used by the academy for teaching and research and by the industry to solve real-world problems, such as program verification, data center management, timetabling, scheduling and routing.

Several useful extra features are also available such as an extension that deals with graph variables, parsers to XCSP3 and FlatZinc or a minimalist profiler.

1 A Modeling API

Choco solver comes with the commonly used types of variables: integer vari-

ables with either bounded domain or enumerated one, Boolean variables, set variables and graph variables. Views [13] but also arithmetical, relational and logical expressions are supported.

Up to 100 constraints –and more than 150 propagators– are provided : from classic ones, such as arithmetical constraints, to must-have global constraints, such as ALLDIFFERENT or CUMULATIVE, and include less common even though useful ones, such as TREE. One can pick some existing propagators to compose a new constraint or create its own one in a straightforward way by implementing a filtering algorithm and a satisfaction checker.

The library supports natively real variables and constraints also, and relies on Ibex [3] to solve the continuous part of the problem [4].

2 Resolution Toolbox

Choco solver has been carefully designed to offer wide range of resolution configurations and good resolution performances. Backtrackable primitives and structures are based on trailing. The propagation engine deals with seven priority levels and manage either fine or coarse grain events which enables to get efficient incremental constraint propagators.

The search algorithm relies on three components *Propagate, Learn and Move* depicted in [8]. Such a generic search algorithm is then instantiated to DFS, LNS [14], LDS [7], DDS [15] or HBFS [1].

The search process can also be greatly improved by various built-in search strategies such as Dom/WDeg [2] and CACD variant [16], ABS [10], Failure-based searches [9], BIVS [5], first-fail [6], etc., and by creating a problem-adapted search strategy.

One can solve a problem in many ways : checking satisfaction, finding one or all solutions, optimizing one or more objectives and solving on one or more thread, or simply propagating. The search process itself is observable and extensible.

3 The code and the dev team

Structurally, **Choco solver** is made of 573 Java classes which represents roughly 53k source code lines. The source code is hosted on [GitHub](#) under a [BSD 4-clause licence](#). The project is mainly developed and maintained by [Charles Prud'homme](#) and [Jean-Guillaume Fages](#), they can count on [attentive contributors](#). [Tutorials](#), [Javadoc](#) and a [user guide](#) can be referred to, as long as a [Google group](#).

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CoSoCo 2.2

XCSP3 Competition 2023

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CoSoCo is a constraint solver written in C++. The main goal is to build a simple, but efficient constraint solver. Indeed, the main part of the solver contains less than 4,000 lines of code (including headers). CoSoCo is available on [github](#). CoSoCo recognizes XCSP3 [2] by using the C++ parser that can be downloaded at <https://github.com/xcsp3team/XCSP3-CPP-Parser>. It can deal with all XCSP3 Core constraints. The part related to all constraint propagators contains around 5,500 lines of codes (including headers). This is the fifth participation of CoSoCo to XCSP competitions. This year new additional features are embedded:

- Nogoods from restarts [4]
- a new heuristic pick/dom (see CP 2023 paper [1]).

CoSoCo performs backtrack search, enforcing (generalized) arc consistency at each node (when possible). The main components are :

- *lexico* as value ordering heuristic;
- lc(1), last-conflict reasoning with a collecting parameter k set to 1, as described in [5];
- a geometric restart policy;
- a variable-oriented propagation scheme [6], where a queue Q records all variables with recently reduced domains (see Chapter 4 in [3]).
- The solution saving technique [7].

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Exchequer

Solving XCSP3 problems using `xcsp2c` and CBMC

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Version 1.1.0 – June 1, 2023

Exchequer is a solver for constraint satisfaction and optimisation problems expressed in the XCSP3-Core format. This version is submitted to the Mini Solver tracks of the XCSP3 Competition 2023. Thus only a subset of XCSP3-Core is supported.

The solver works by translating an XCSP3 instance into a C program, which violates an assertion only if the values of the variables in the program give a solution to the instance. Then it uses the bounded model-checker CBMC [2] to attempt to verify absence of assertion violations. If CBMC finds an assertion violation, it reports back a counterexample trace, which Exchequer turns into an instance solution. If it finds no assertion violation, Exchequer reports that the instance is unsatisfiable.

Despite the naive approach, Exchequer 1.0.1 won the Mini CSP track in the XCSP3 Competition 2022. We attribute this to two main factors. Firstly, the version of CBMC we used was built with CaDiCaL as the integrated SAT solver; this is much faster on harder problems than the default solver MiniSat. Secondly, we contributed the *Crypto* benchmark set, which encodes the problem of breaking a stream cipher. These instances were produced by taking a low-level SAT encoding and translating it back into the intermediate level XCSP3 format. The resulting encoding is fairly easy for any SAT-based solver to handle, but not necessarily for solvers based on other techniques.

Building on this success, for Exchequer 1.1.0, we have included the latest version of CBMC and an updated SAT solver. CBMC now supports calling an external SAT solver. We use Kissat (SAT Competition 2022 Bulky version) [1], which solved most instances in the SAT Competition 2022 Anniversary track. On harder problems, this performs slightly better than CaDiCaL (used in Exchequer 1.0.1) and significantly better than MiniSAT (default solver in CBMC).

We have also submitted a new benchmark set, which encodes the optimisation problem of designing a tournament timetable for a round robin sports tournament with the minimum number of breaks. (A break is when a team plays two consecutive “home” games or two consecutive “away” games.) This follows the encoding by Zhang and others [6], which we reproduced in JavaScript [4]. The encoding uses pseudo-Boolean constraints, which are higher level than SAT, but still relatively low-level. Again, we have translated this back into XCSP3.

Apart from that, Exchequer 1.1.0 has a few small but important improvements. Support for optimisation problems was present in Exchequer 1.0.1, but it was poorly tested and there were errors in the encoding of the objective function; these should now have been fixed. We have turned on handling of large text nodes in XML files in the XML parser library, as these are used in some benchmark instances. We have also switched from using logical AND/OR to bitwise AND/OR for encoding some constraints; this seems to improve performance in some cases, although the improvement is not consistent. Otherwise, Exchequer has the same limitations as before. It struggles with large `extension` constraints used as a template. For larger problems, CBMC spends most of its time

generating the SAT instance, not running the SAT solver. For a more in-depth examination of the effectiveness of using C and CBMC for modelling and solving constraint problems, see our work on the CoPTIC constraint programming system [3].

Implementation details. Exchequer is implemented as two Perl scripts: `xcsp2c.pl` [5] performs the translation, while `exchequer.pl` is a wrapper that calls `xcsp2c.pl` and CBMC. Exchequer also uses XCSP3 Tools to validate solutions before returning them.

For constraint optimisation (COP) problems, Exchequer simply calls CBMC repeatedly, trying to find a solution incrementally better than the previous one each time. When a better solution cannot be found, we know this is the optimum. The actual value of the objective for each solution is calculated using XCSP3 Tools.

Usage. Download from <https://gitlab.act.reading.ac.uk/ta918887/exchequer> and run:

```
perl DIR/tool/exchequer.pl --tmpdir=TMPDIR BENCHMARK
```

where:

- DIR is the extracted release archive directory;
- BENCHMARK is the XML file encoding the XCSP3 instance;
- TMPDIR is the optional temporary directory to use.

If no temporary directory is given, Exchequer will use the directory containing the instance. In any case, it will write the following files:

- a `.c` file encoding the instance;
- a `.log` file recording the output from CBMC;
- a `.sol.xml` file containing the solution.

For optimisation problems, it will write multiple `.log` and `.sol.xml` files.

Licence. Exchequer, Kissat and XCSP3 Tools are distributed under the MIT License. CBMC is distributed under a BSD-style 4-clause licence.

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Fun-sCOP

XCSP3 Competition 2023

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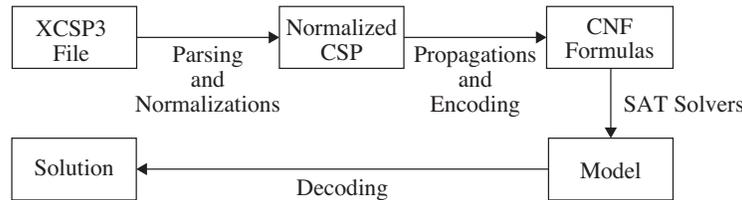
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1 Overview

Fun-sCOP is a SAT-based constraint programming system written in Scala, which aims to be a re-implementation of Sugar [3] written in Java. Compared to the previous version named scop, Fun-sCOP equips the hybrid encoding integrating the order and log encodings [2]. The following figure shows the framework of Fun-sCOP. We explain each part of this framework in the remaining of this paper.



2 Parsing and Normalizations

Parsing is done by using the official tool XCSP3-Java-Tools⁵. Fun-sCOP accepts constraints in the XCSP3-core language⁶.

Normalizations are executed as follows:

- **Global Constraints** are decomposed into intensional constraints. We use extra pigeon hole constraints [3] for alldifferent constraints.
- **Extensional constraints** are translated into intensional constraints by using a variant of multi-valued decision diagrams. This is a difference to ones in Sugar.
- **Intensional Constraints** are normalized to be in the form of a conjunction of disjunctions of linear comparisons $\sum_i a_i x_i \geq k$ where a_i 's are integer coefficients, x_i 's are integer variables and k is an integer constant. Tseitin transformation is used to avoid the combinatorial explosion.

⁵ <https://github.com/xcsp3team/XCSP3-Java-Tools>

⁶ <http://www.xcsp.org/specifications>

3 Propagations and Encoding Methods

Constraint propagations are executed to the normalized CSP (clausal CSP, i.e., in the form of CNF over linear comparisons $\sum_i a_i x_i \geq k$) to remove redundant values, variables, and linear comparisons. It is done by using an AC3 like algorithm.

Encoding methods are as follows:

- **Order Encoding** [5, 4] is an encoding method using propositional variables $p_{x \geq d}$'s meaning $x \geq d$ for each domain value d of each integer variable x . To encode linear comparisons, Algorithm 1 of the literature [4] is used in Fun-sCOP.
- **Hybrid Encoding** [2] is an encoding method integrating the order and log encodings without channeling constraints. In the hybrid encoding, each variable is encoded by either the order encoding or the log encoding, and each constraint is encoded according to its variables' encoding. The degree of hybridization can be controlled by classifying the order-encoded and log-encoded variables. Fun-sCOP uses the criterion *domain product* to classify variables as same as in [2].

4 SAT Solvers

GlueMiniSat [1] is used for the order encoding. It is a winning solver in the SAT solver competitions, and the submitted version of GlueMiniSat uses a special propagator for the axiom clauses of the order encoding.

Kissat ⁷ is used for the hybrid encoding. It is also a winning solver in the recent SAT solver competitions, and shows a good performance in our preliminary evaluation.

⁷ <https://github.com/arminbiere/kissat>

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MiniCPBP

A Constraint Solver Propagating Beliefs

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August 2023

MiniCPBP is an open-source constraint solver¹ used as a research platform by our team. It is developed in Java on top of MiniCP[4] and extends constraint propagation with belief propagation[5]. Among other things, it can use this extra information to guide search while solving combinatorial problems and to interface with neural networks while building neuro-symbolic AI systems[3]. MiniCPBP features integer variables, including 0/1 (Boolean) variables, most simple constraints and their reification, a growing list of global constraints, dedicated *weighted counting algorithms* for most of these constraints in order to propagate beliefs, and novel branching heuristics exploiting the propagated beliefs about variable-value assignments (e.g. minEntropy, maxMarginal, maxMarginalStrength)[2, 1].

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¹<https://github.com/PesantGilles/MiniCPBP>

Mistral

Mistral **IS** a **T**errific **R**ecursive **A**cronym for a **L**ibrary

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July 31, 2023

Abstract

Mistral is an open source constraint programming library written in C++ and available on GitHub. It implements a modelling API, however, it can also read instance files in XCSP3¹ or FlatZinc format. Moreover, it is fully interfaced with Numberjack [6] which provides a Python API for modelling and solving combinatorial optimization problems using several back-end solvers.

Solver Engine

The solver engine relies on standard mechanisms, using a priority constraint queue and a domain event stack to implement the propagation procedure. Moreover, it supports dynamic type change for variables: domains are initially implemented using intervals or Boolean types whenever possible, and can be changed to (bit)sets during search when a propagator requires it. The backtracking mechanism is implemented using a trail in a standard way.

Propagators

Several classic global constraints are implemented, such as LEXORDERING [4], bound consistency propagator for ALLDIFFERENT [10] and GCC [9]. Moreover, less standard constraints were implemented within the context of research articles on constraint propagation, such as the ATMOSTSEQCARD constraint for car-sequencing [12] or a VERTEXCOVER constraint [3] to reason about cliques, independant set or vertex covers. Search Strategy The search heuristic used for the XCSP3 competition is based on *Last Conflict* [8], using a variant of *Weighted Degree* [2] as default strategy: in the case of failure raised by a propagator of a global constraint, an explanation of the conflict is computed and only the weight of the variables participating in the conflict is incremented. This heuristic is fully described in [7]. Moreover, given the next variable x to branch

¹Using Gilles Audemard's parser.

on, the solver chooses the value that was assigned to x in the best solution found so far, if possible, or the minimum value in the domain of x otherwise.

Applications of Mistral

Mistral was used to implement a state-of-the-art method for disjunctive scheduling which improved several best known results on classic benchmarks [5]. More recently, some clause learning methods were implemented in Mistral, still improving the results on disjunctive scheduling [11] and car-sequencing problems [1]. These methods were not used within the context of the XCSP3 competition.

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Nacre

Nogood And Clause Reasoning Engine

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Version 1.0.6 – May, 2023

Nacre [3, 4] is a constraint solver written in C++. The main purpose of this solver is to experiment nogood recording (with a clause reasoning engine) in Constraint Programming (CP). In particular, the data structures of the solver have been carefully designed to play around nogoods and clauses.

Usage. You can compile and run Nacre using the following lines:

```
cd core && make -j  
  
./nacre_mini_release <xmsp3_file> method [options]
```

with:

- <xmsp3_file>: a xcp3 file representing a CSP instance
- method: the method to use for solving the CSP instance. Possible values are:
 - -complete: Simple complete search
 - -incng: Complete search with Increasing Nogoods [6]
 - -nld: Complete search with Negative last-decision nogoods [5]
 - -ca: Hybrid solving with conflict analysis, SAT-based lazy explanations [1, 2]
- [options]: possible options to be used when running the solver (e.g. `-l100` for Luby sequence where every terms is multiplied by 100 as restart policy; `-cm` for competition verbose mode)

Competition. Nacre is enlisted in the **Minitrack - CSP** ; line used for the competition:

```
./nacre_mini_release BENCHNAME -ca -l100 -cm
```

Licence. Nacre is licensed under the [GNU General Public License v3.0](#).

Code. Nacre code is available online at github.com/gglorian/Nacre¹.

¹New official Nacre repository, forked from [previous competition sources](#).

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An XCSP3 Solver in Picat

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Abstract. This short paper gives an overview of the XCSP3 solver implemented in Picat. Picat provides several constraint modules, and the Picat XCSP3 solver uses the `sat` module. The XCSP3 solver mainly consists of a parser implemented in Picat, which converts constraints from XCSP3 format to Picat. The solver demonstrates the strengths of Picat, a logic-based language, in parsing, modeling, and encoding constraints into SAT. The solver submitted to the 2022 XCSP competition is based on the one that won the 2019 XCSP competition. The high performance of the solver also demonstrates the viability of using a SAT solver to solve general constraint satisfaction and optimization problems.

XCSP3

XCSP3 [1] is an XML-based domain specific language for describing constraint satisfaction and optimization problems (CSP). XCSP3 is positioned as an intermediate language for CSPs. It does not provide high-level constructs as seen in modeling languages. However, XCSP3 is significantly more complex than a canonical-form language, like FlatZinc [4]. A constraint can sometimes be described in either the standard format or simplified format. The advanced format, which is used by group and matrix constraints, allows more compact description of constraints.

Picat

Picat [10] is a simple, and yet powerful, logic-based multi-paradigm programming language. Picat is a Prolog-like rule-based language, in which predicates, functions, and actors are defined with pattern-matching rules. Picat incorporates many declarative language features for better productivity of software development, including explicit non-determinism, explicit unification, functions, list comprehensions, constraints, and tabling. Picat also provides imperative language constructs, such as assignments and loops, for programming everyday things. Picat provides facilities for solving combinatorial search problems, including a common interface with CP, SAT, MIP, and SMT solvers, tabling for dynamic programming, and a module for planning. Picat uses, in the XCSP3 solver, the SAT module, which generally performs better than the CP, MIP, and SMT modules on competition benchmarks.

Parsing

The availability of different formats in XCSP3 makes it a challenge to parse the XCSP3 language. A parser implemented in C++ by the XCSP3 designers has more than 10,000 lines of code. The entire Picat implementation of XCSP3 has about 2,000 lines of code, two-thirds of which is devoted to parsing and syntax-directed translation. As illustrated in the following example, Picat is well suited to parsing.

```
% E -> T E'
ex(Si,So) => term(Si,S1), ex_prime(S1,So).

% E' -> + T E' | - T E' | e
ex_prime(['+'|Si],So) =>
    term(Si,S1),
    ex_prime(S1,So).
ex_prime(['-'|Si],So) =>
    term(Si,S1),
    ex_prime(S1,So).
ex_prime(Si,So) => So = Si.
```

The parser follows the framework for translating context-free grammar into Prolog [5]: a non-terminal is encoded as a predicate that takes an input string (*Si*) and an output string (*So*), and when the predicate succeeds, the difference *Si-So* constitutes a string that matches the nonterminal. Unlike in Prolog, pattern-matching rules in Picat are fully indexed, which facilitates selecting right rules based on look-ahead tokens.

Modeling

It is well known that loops and list comprehensions are a necessity for modeling CSPs. The following Picat example illustrates the convenience of these language constructs for modeling.

```
post_constr(allDifferentMatrix(Matrix)) =>
    NRows = len(Matrix),
    NCols = len(Matrix[1]),
    foreach (I in 1..NRows)
        all_different(Matrix[I])
    end,
    foreach (J in 1..NCols)
        all_different([Matrix[I,J] : I in 1..NRows])
    end.
```

The `allDifferentMatrix(Matrix)` constraint takes a matrix that is represented as a two-dimensional array, and posts an `all_different` constraint for each row and each column of the matrix.

SAT Encoding

Picat adopts the log encoding [2] for domain variables. While log encoding had been perceived to be unsuited to arithmetic constraints due to its hindrance to propagation [3], we have shown that log encoding can be made competitive with optimizations [8]. There are hundreds of optimizations implemented in Picat, and they are described easily as pattern-matching rules in Picat. We have also shown that, with specialization, the binary adder encoding is not only compact, but

also generally more efficient than BDD encodings for PB constraints [9]. Picat adopts specialized decomposition algorithms for some of the global constraints, such as the circuit and reachability constraints [6, 7].

SAT Solving

Picat uses the kissat SAT solver.¹ For a satisfiability problem, Picat calls the SAT solver, and converts the SAT solution to a solution for the decision variables if the problem is satisfiable. For an optimization problem, Picat uses a branch-and-bound algorithm to find the best solution, and calls the SAT solver each time a domain bound of the objective variable is narrowed. The kissat generally outperforms the Maple solver, which is used in the Picat XCSP3 solver submitted to the 2019 competition.

A Note on the 2023 Edition

In addition to the addition of the required global constraints, namely, **precedence**, **knapsack**, and **binPacking**, the 2023 edition also incorporates several improvements, including stronger inferences of equivalences.

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RBO and miniRBO

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(mini)RBO (Restart Based Optimizer) is an open-source constraint solver for COP instances. It is written in C++ and implements a variant of the algorithm MAC+RST [3].

For the competition, we have made the following choices:

- The variable heuristic relies on Last Conflict [4] combined with a multi-armed bandit with 9 arms [1]. The i -th arm is based on CHS (for Conflict History Search [2]) with $\alpha = 0.1 * i$ and $\delta = 10^{-4}$.
- Solution-saving [5] combined with *lexico* is used as value ordering heuristic.
- Generalized arc-consistency is enforced by a propagation-based system exploiting events.
- (mini)RBO relies on restarts performed according to a geometric restart policy based on the number of conflicts with an initial cutoff set to 50 and an increasing factor set to 1.05,

(mini)RBO is able to handle all the constraints and objective functions used in the competition.

Licence. (mini)RBO is licensed under the [MIT License](#).

Code. The source code is available on Github: <https://github.com/Terrioux/BTD-RBO>.

Command line. (mini)RBO can be launched thanks to the following command line:

```
SOLVER TIMELIMIT BENCHNAME
```

where:

- SOLVER is the path to the executable BTD or miniBTD,
- TIMELIMIT is the number of seconds allowed for solving the instance,
- BENCHNAME is the name of the XML file representing the instance we want to solve.

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Sat4j-CSP-PB

A Pseudo-Boolean-Based Constraint Solver

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XCSP'23 - August 2023

Sat4j-CSP-PB is a CSP solver based on the pseudo-Boolean solver Sat4j [4].

1 Description of the solving approach

Sat4j-CSP-PB encodes the constraints it receives as pseudo-Boolean (PB) constraints of the form $\sum_{i=1}^n \alpha_i l_i \Delta \delta$, where n is a positive integer, the *weights* (or *coefficients*) α_i and the *degree* δ are integers, l_i are literals and $\Delta \in \{<, \leq, =, \geq, >\}$. This allows to exploit the reasoning power of PB solvers based on the *cutting planes* proof system [2, 3, 5].

For some constraints, using a PB encoding is particularly convenient as it is more natural and more succinct than the clausal encodings that would be used by regular SAT solvers. This is particularly the case for the constraints `all-different`, `bin-packing`, `cardinality`, `cumulative`, `count`, `knapsack`, `n-values`, and `sum`.

As PB solvers are extensions of SAT solvers, we can also use clausal encodings for other constraints to encode, even though this often prevents PB solvers to benefit from the full inference power of the cutting planes proof system.

There are however some constraints that are not supported yet, and will lead the solver to output `s UNSUPPORTED` if one of the following features appears in the input instance:

- symbolic variables
- bin packing with an array of Condition
- circuit
- element
- “smart” extension
- intension constraints using pow
- mdd
- precedence
- regular
- stretch

2 Variants of the underlying PB solver

Sat4j-CSP-PB uses one of the PB solvers implemented by Sat4j to solve the PB encoding used to represent the input problem. The variants submitted to the competition are:

- `sat4j-csp-resolution`, which implements a resolution-based conflict analysis (PB constraints are lazily encoded as clauses during conflict analysis),
- `sat4j+roundingsat`, which delegates the resolution of the PB instance to the original implementation of `Roundingsat` [1],
- `sat4j-csp-both`, which uses a portfolio of `sat4j-cp` and `sat4j-resolution`.

3 Running Sat4j-CSP-PB

Sat4j-CSP-PB is written in *Java 11* and uses the *Jigsaw* modular system. *Java 11* is thus required to compile and execute this solver. To compile Sat4j-CSP-PB, you may run the following command at the root of the project:

```
./gradlew csp
```

Then, you will be able to run the solver using the wrapper bash script provided along with the solver:

```
./exec/sat4j-csp.sh [options] <path/to/instance.xml>
```

where

- `<path/to/instance.xml>` is an XCSP3 file representing a CSP or COP instance, and
- `[options]` are the possible options to be used when running the solver.

4 License

Sat4j-CSP-PB is licensed under the [GNU Lesser General Public License](#).

5 Code

The source code of Sat4j-CSP-PB is available on [OW2's GitLab](#).

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SeaPearl - XCSP 2023 Competition (miniTrack)

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Abstract

SeaPearl is a flexible, research-oriented, and open-source constraint programming solver dedicated to help the development of learning-based approaches inside the solving process. It is implemented in Julia and takes its inspiration from MiniCP. The development is still active and all the functionalities required for handling all the requirements of the contest are not yet fulfilled. For its first participation, only a standard solving process, without learning involved, has been submitted. The code is available on Github¹.

1 Motivation behind SeaPearl

Previous works have shown the promise to use learning-based methods inside combinatorial solvers. This has been proposed for integer programming [Gasse *et al.*, 2019], SAT solving [Selsam and Bjørner, 2019], and also for constraint programming [Cappart *et al.*, 2021]. However, integrating a learning component inside a solver is a tricky task as standard solvers do not have support for that in a native way. To tackle this issue, researchers have developed new tools to ease this integration. For instance, Ecole [Prouvost *et al.*, 2020] is a library dedicated to work in cooperation with mixed integer linear programming solvers. No such tool was available for constraint programming, and SeaPearl [Chalumeau *et al.*, 2021] has been introduced for addressing this challenge. It is a flexible, research-oriented, and open-source constraint programming (CP) solver dedicated to help the development of learning-based approaches inside the solving process. It is implemented in Julia [Bezanson *et al.*, 2012] and has been greatly influenced by MiniCP [Michel *et al.*, 2021]. The design choice of considering Julia is that this language offer support for both mathematical computation and learning. Besides, it is high-level and achieves good performances.

2 Main Characteristics

This section describes the core functionalities of SeaPearl, that has been used for this competition. Specifically, no learning-based algorithm is used.

¹<https://github.com/corail-research/SeaPearl.jl>

Solver Engine The solver is trailed-based. The fix-point algorithm is executed on each node of the tree search.

Propagation Notable propagators used are compactable [Demeulenaere *et al.*, 2016] for the extensional constraint, and Régin’s algorithm [Régin, 1994] for allDifferent.

Search Strategy A standard backtracking depth-first search is used. For optimization problems, Each time a solution is obtained, a new constraint enforcing that better solutions must be found is added. The variable selection follows the first-fail principle, and the value selection heuristic consists in taking the minimum value available in the variable’s domain.

3 Conclusion

For its first participation, our goal is not to obtain state-of-the-art results but to analyze the robustness and the efficiency of SeaPearl, when facing a large range of combinatorial problems, both for satisfaction and optimization. Besides other mechanisms (such as an iterated limited discrepancy search strategy) are currently available in the solver. For the next year, we plan to integrate our first learning components for the competition.

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toulbar2 and lintoulbar2

An exact cost function network solver
Version 1.3 – July 6, 2023



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Introduction

toulbar2 is an open-source C++ solver for cost function networks (CFN). It is available at <https://github.com/toulbar2/toulbar2>, with an MIT license and a documentation describing its interfaces with C++ and python.

The constraints and objective function are factorized in local functions on discrete variables. Each function returns a cost for any assignment of its variables. Constraints are represented as functions with costs in $\{0, \top\}$ where \top is an upper bound cost associated with forbidden assignments. toulbar2 looks for a non-forbidden assignment of all variables that minimizes the sum of all functions. In general, this problem is NP-hard [8].

Using on the fly translation, toulbar2 can also directly solve optimization problems on other graphical models such as Maximum probability Explanation on Bayesian networks, and Maximum A Posteriori on Markov random fields [13, 7]. It can also read partial weighted MaxSAT problems, (quadratic) pseudo-Boolean optimization problems as well as constrained satisfaction and optimization problems (COP in XCSP3 format).

toulbar2 provides and uses by default an *anytime* hybrid best-first branch-and-bound algorithm (HBFS) [1] that tries to quickly provide good solutions together with an upper bound on the gap between the cost of each solution and the (unknown) optimal cost. Thus, even when it is unable to prove optimality, it will bound the quality of the solution provided. It can also apply a variable neighborhood search algorithm exploiting a problem decomposition [19]. Both algorithms are complete (if enough CPU-time is given) and they can be run in parallel using OpenMPI [3, 19]. The variable ordering heuristic is *dom/wdeg* [5] combined with *last conflict* [15]. The value ordering heuristic exploits the last solution found if any [11] or else EDAC existential value [10]. EDAC is also used as soft local consistency during search to provide lower bounds and prune forbidden values [6]. A weaker relaxed version is used for pseudo-Boolean linear constraints [17]. Stronger soft local consistencies (VAC [6] and VPWC [16]) can be applied in preprocessing or during search. Variable elimination is performed during search and restricted to variables with at most two neighbors [14]. More preprocessing techniques such as cost function decomposition [12] and relaxation-aware probing heuristic (RASPS [21]) are or can be done before search and pruning by dominance is also applied during search [9].

Beyond the service of providing optimal solutions, toulbar2 can also find a sequence of diverse solutions [20] or exhaustively enumerate solutions below a cost threshold and perform guaranteed approximate weighted counting

of solutions. For stochastic graphical models, this means that `toulbar2` will compute the partition function (or the normalizing constant). These problems being #P-complete, `toulbar2` runtimes can quickly increase on such problems.

`toulbar2` was originally developed by Toulouse (INRAE, MIAT) and Barcelona (UPC, IIIA-CSIC) teams, hence the name of the solver. Additional contributions by:

- Caen University, France (GREYC) and University of Oran, Algeria for (parallel) variable neighborhood search methods [19] ;
- The Chinese University of Hong Kong and Caen University, France (GREYC) for global cost functions [2] ;
- Marseille University, France (LSIS) for tree decomposition heuristics ;
- Ecole des Ponts ParisTech, France (CERMICS/LIGM) for INCOP local search solver [18] ;
- Université de Toulouse (IRIT) and Université du Littoral Côte d’Opale, France for iterated local search with partition crossover [4] ;
- Artois University, France (CRIL) for the XCSP3 format reader of CSP and COP instances.

XCSP’2023 Competition Configuration Settings

For the XCSP’2023 competition, we used the following settings for `toulbar2`:

- For *COP sequential and mini COP* tracks, HBFS [1] was used with default settings ; command line:
`DIR/toulbar2 -timer=TIMELIMIT -v=-1 BENCHNAME`
- For *COP parallel* track, parallel HBFS [3] was used with the available number of cores and MPI compilation settings ; command line:
`mpirun -n NBCORE DIR/toulbar2mpi -timer=TIMELIMIT -v=-1 BENCHNAME`

For `lintoulbar2` (available at <https://forgemia.inra.fr/pierre.montalbano/lintoulbar2>), which extends `toulbar2` by allowing VAC on pseudo-Boolean linear constraints and sorting periodically (every 1,000 open nodes) its HBFS best-first priority queue with *dom/wdeg* heuristic values to break ties, we used the following settings:

- For *COP sequential and mini COP* tracks, the modified HBFS was used with VAC and RASPS [21] in preprocessing ; command line:
`DIR/toulbar2 -timer=TIMELIMIT -A -rasps -raspsini -v=-1 BENCHNAME`

Acknowledgements

`toulbar2` has been partly funded by the French Agence Nationale de la Recherche (projects STAL-DEC-OPT from 2006 to 2008, ANR-10-BLA-0214 Ficolofa from 2011 to 2014, and ANR-16-CE40-0028 DemoGraph from 2017 to 2021) and a PHC PROCORE project number 28680VH (from 2013 to 2015). It is currently supported by ANITI ANR-19-P3IA-0004.

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Chapter 4

Results

In this chapter, rankings for the various tracks of the XCSP³ Competition 2023 are given. Importantly, remember that you can find all detailed results, including all traces of solvers at <https://www.cril.univ-artois.fr/XCSP23/>.

4.1 Context

Remember that the tracks of the competition are given by Table 4.1 and Table 4.2.

Problem	Goal	Exploration	Timeout
CSP	one solution	sequential	40 minutes
COP	best solution	sequential	40 minutes
Fast COP	best solution	sequential	4 minutes
// COP	best solution	parallel	40 minutes

Table 4.1: Standard Tracks.

Problem	Goal	Exploration	Timeout
Mini CSP	one solution	sequential	40 minutes
Mini COP	best solution	sequential	40 minutes

Table 4.2: Mini-Solver Tracks.

Also, note that:

- the cluster was provided by CRIL and is composed of nodes with two quad-cores (Intel Xeon CPU E5-2637 v4 @ 3.50GHz, each equipped with 64 GiB RAM).
- Hyperthreading was disabled.
- Each solver was allocated a CPU and 64 GiB of RAM, independently from the tracks.
- Timeouts were set accordingly to the tracks through the tool `runsolver`:

- sequential solvers in the fast COP track were allocated 4 min of CPU time and 12 min of Wall Clock time,
- other sequential solvers were allocated 40 min of CPU time and 120 min of Wall Clock time,
- parallel solvers were allocated 160 min of CPU time and 120 min of Wall Clock time.
- The selection of instances for the Standard tracks was composed of 200 CSP instances and 250 COP instances.
- The selection of instances for the Mini-solver tracks was composed of 150 CSP instances and 155 COP instances.

About Scoring. The number of points won by a solver S is decided as follows:

- for CSP, this is the number of times S is able to solve an instance, i.e., to decide the satisfiability of an instance (either exhibiting a solution, or indicating that the instance is unsatisfiable)
- for COP, this is, roughly speaking, the number of times S gives the best known result, compared to its competitors. More specifically, for each instance I :
 - if I is unsatisfiable, 1 point is won by S if S indicates that the instance I is unsatisfiable, 0 otherwise,
 - if S provides a solution whose bound is less good than another one (found by another competing solver), 0 point is won by S ,
 - if S provides an optimal solution, while indicating that it is indeed the optimality, 1 point is won by S ,
 - if S provides (a solution with) the best found bound among all competitors, this being possibly shared by some other solver(s), while indicating no information about optimality: 1 point is won by S if no other solver proved that this bound was optimal, 0.5 otherwise.

Off-competition Solvers. Some solvers were run while not officially entering the competition: we call them *off-competition* solvers. ACE is one of them because its author (C. Lecoutre) conducted the selection of instances, which is a very strong bias. Also, when two variants (by the same competing team) of a same solver compete in a same track, only the best one is ranked (and the second one considered as being off-competition). This is why, for example, Fun-sCOP-glue was considered as off-competition in the CSP track.

4.2 Rankings

Recall that, concerning ranking, two new rules are used when necessary:

- In case a team submits the same solver to both the main track and the mini-track for the same problem (CSP or COP), the solver will be ranked in the mini-track only if the solver is not one of the three best solvers in the main track.
- In case several teams submit variations of the same solver to the same track, only the team who developed the solver and the best other team with that solver will be ranked (possibly, a second best other team, if the jury thinks that it is relevant)

The algorithm used in practice for establishing the ranking is:

1. first, off-competition solvers are discarded (this is the case for ACE in 2023)
2. second, in mini-tracks, solvers that are ranked 1st, 2nd or 3rd in the corresponding main track are discarded (for example, in 2023, this is the case for Choco and Mistral in the mini COP track)
3. third, any worse variation of the same solver (submitted by the same team) is discarded (for example, this is the case of lintoulbar2 and sa4j-resolution in the 2023 miniCOP track)

Here are the rankings¹ for the 6 tracks.

CSP		Picat	COP		Mistral
		Fun-sCOP			Choco
		Choco			CoSoCo
Fast COP		Choco	// COP		Choco
		Mistral			Toulbar2
		CoSoCo			–
Mini CSP		Exchequer	Mini COP		Toulbar2
		miniBTD			Exchequer
		Nacre			Sat4j-both

¹The images of medals come from freesvg.org

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