

# SIPLIB 2.0

Stochastic Integer Programming Library version 2

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- 2 Two-Stage Stochastic Integer Programming
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- 4 Implementation of a Julia package: **Siplib.jl**
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# What is SIPLIB?

<sup>1</sup>SIPLIB: A Stochastic Integer Programming Test Problem Library

- SIPLIB is a collection of test problems to facilitate computational and algorithmic research in stochastic integer programming (SIP).
- The test problem data is provided in the standard SMPS format unless otherwise mentioned.
- Where available, information on the underlying problem formulation and known solution is also included.

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<sup>1</sup> Available at: <https://www2.isye.gatech.edu/sahmed/siplib/>

# Limitation of the former SIPLIB

## ① Number of the instances

- Researchers in this field need more test set.

## ② Variation of problem types

- Current SIPLIB provides only 5 different variations in terms of variable types: continuous, binary, integer.
- 24 types exist in total for two-stage SIP.

## ③ Contribution rule

- Different problem provides different information.
- For some problems, only limited information is available.

# Contribution of SIPLIB 2.0

## **SIPLIB 2.0** provides

- richer pre-generated instances accompanied with analytic & computational information
- a **Julia package** to support computational research studies for SIP
  - generating new instances in SMPS format
  - analyzing the instances (size, sparsity)
  - solving the instances to get some known bounds
- all the details about the problems
  - formulation, deterministic & random parameters
  - parameterized modeling scripts

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# Problem of interest

## **Two-Stage Stochastic Integer Programming (TSSIP)**

- Considers only **two stages**.
  - **Present** (first-stage) and **Future** (second-stage)
- First-stage decision must be made **for now**.
- Second-stage decision can be made **after the future is realized** (called *recourse action*).
- First-stage decision affects the second-stage decision as well.

# Mathematical formulation

## TSSIP:

$$\min_{x \in X} \{c^T x + Q(x) : Ax \geq b\} \quad (1)$$

- $X \subseteq \mathbb{R}^{n_1-k_1} \times \mathbb{Z}^{k_1}$
- $c \in \mathbb{R}^{n_1}$
- $A \in \mathbb{R}^{m_1 \times n_1}$
- $b \in \mathbb{R}^{m_1}$
- $Q(x) := \mathbb{E}_{\xi}[Q(x, \xi)]$  (expected recourse function)
- $\xi$  is a random element defined on a probability triple  $(\Xi, \mathcal{F}, \mathbb{P})$

**Recourse function**  $Q(\cdot, \cdot)$ :

$$Q(x, \xi_s) := \min_{y \in Y} \{q(\xi_s)^T y : W(\xi_s)y \geq h(\xi_s) - T(\xi_s)x\} \quad (2)$$

- $\xi_s$  is a realized random element (called *scenario*)
- $Y \subseteq \mathbb{R}^{n_2-k_2} \times \mathbb{Z}^{k_2}$
- $q(\xi_s) \in \mathbb{R}^{n_2}$
- $W(\xi_s) \in \mathbb{R}^{m_2 \times n_2}$
- $h(\xi_s) \in \mathbb{R}^{m_2}$
- $T(\xi_s) \in \mathbb{R}^{m_2 \times n_1}$

# Mathematical formulation

**Extensive Form** (EF):

$$\min_{x,y} c^T x + \sum_{s=1}^r \mathbb{P}(s) (q_s^T y_s) \quad (3a)$$

$$\text{s.t. } Ax \geq b, \quad (3b)$$

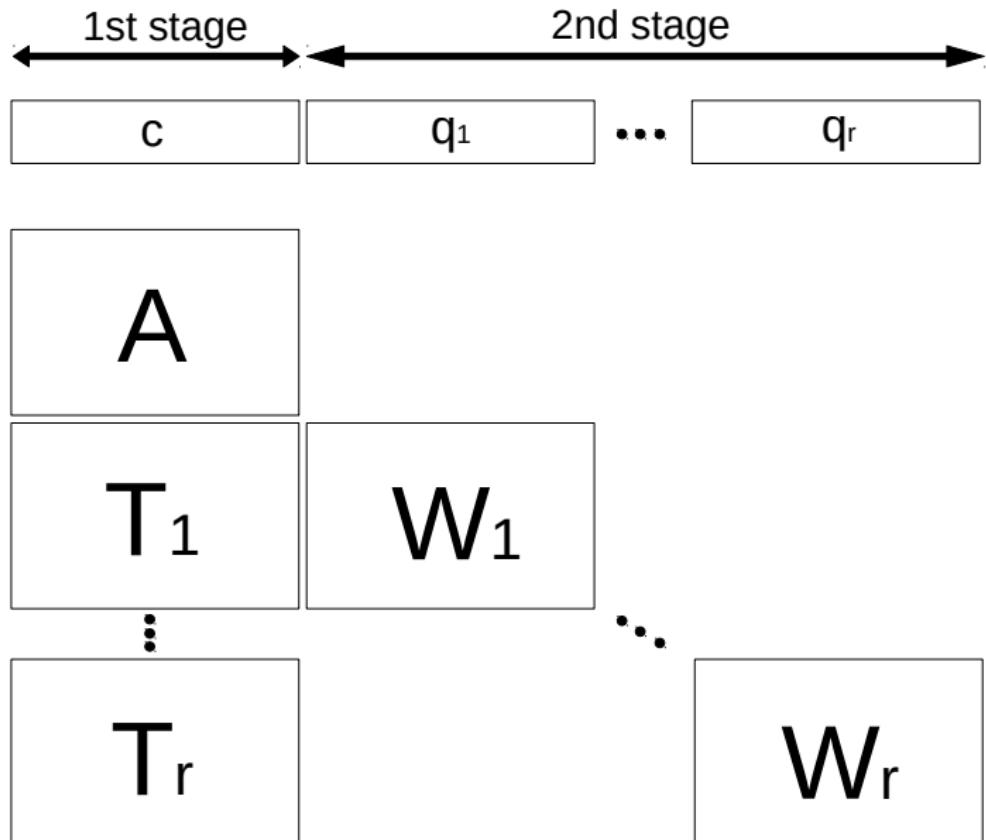
$$T_s x + W_s y_s \geq h_s, \quad \forall s \in \{1, \dots, r\}, \quad (3c)$$

$$x \in X, \quad (3d)$$

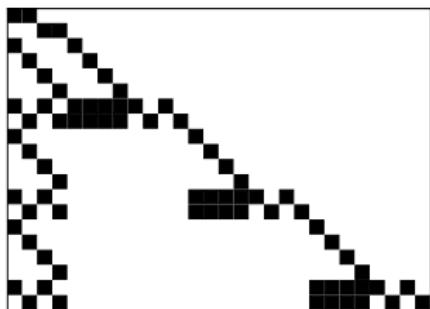
$$y_s \in Y, \quad \forall s \in \{1, \dots, r\}. \quad (3e)$$

- $y := \{y_1, y_2, \dots, y_r\}$
- $q_s := q(\xi_s)$
- $W_s := W(\xi_s)$
- $h_s := h(\xi_s)$
- $T_s := T(\xi_s)$

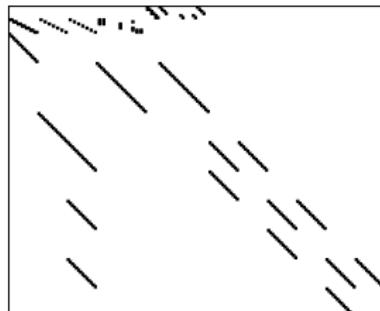
# EF: Block-diagonal structure



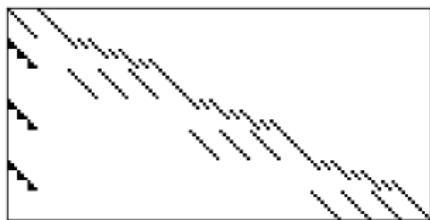
# EF: Block-diagonal structure



(a) AIRLIFT\_3



(b) CHEM\_3



(c) DCAP\_3\_3\_3\_3



(d) SS LP\_5\_10\_3

Figure: Example: Sparsity patterns in EF

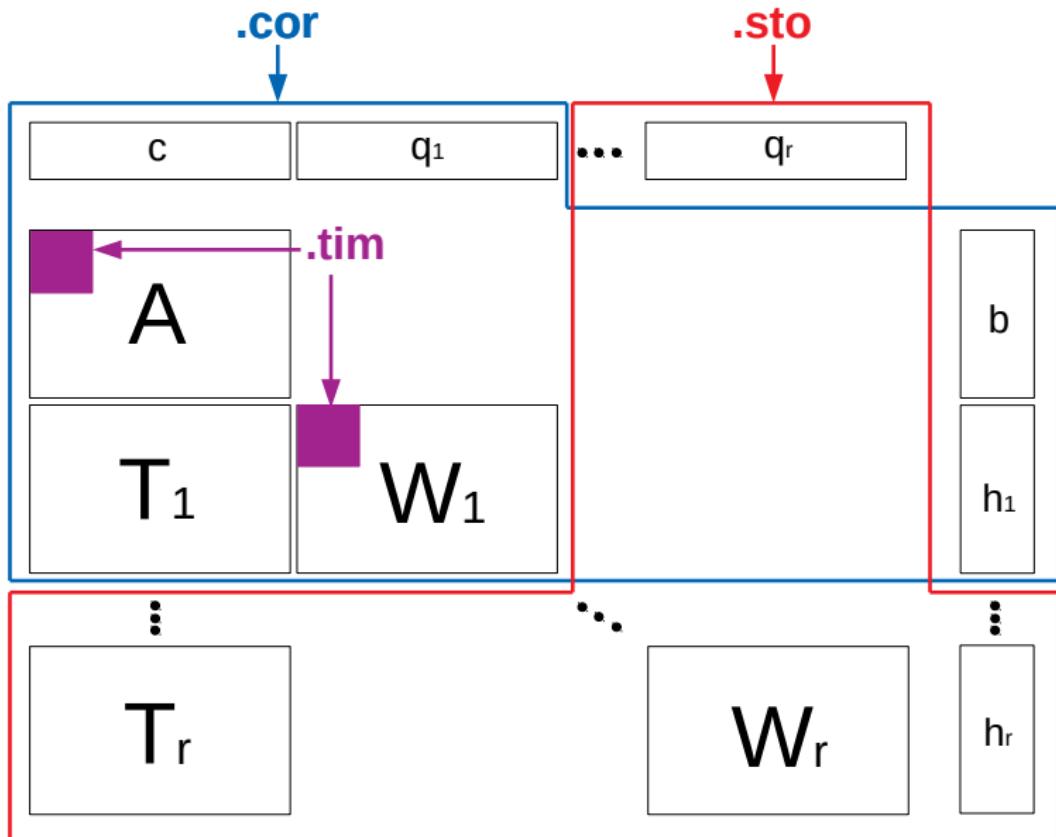
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**SMPS is a standard column-oriented data convention for the automatic input of multi-stage stochastic programs.**

- **(example)** Let DCAP\_3\_3\_3\_10 be the instance name.  
Then, SMPS format comprises
  - DCAP\_3\_3\_3\_10.cor
  - DCAP\_3\_3\_3\_10.tim
  - DCAP\_3\_3\_3\_10.sto
- The role of each file
  - **.cor:** Core file written in MPS format. This describes the fundamental problem structure and contains first-stage data and a single second-stage scenario data.
  - **.tim:** Time file which specifies the location where each stage begins.
  - **.sto:** Stoch file which contains remaining scenario data.

# SMPS format: Graphical description



# Julia language

<sup>2</sup>**Julia programming language is a flexible dynamic language, appropriate for scientific and numerical computing, with performance comparable to traditional statically-typed languages.**

## Julia in a Nutshell

### Julia is fast!

Julia was designed from the beginning for **high performance**. Julia programs compile to efficient native code for multiple platforms via LLVM.

### General

Julia uses multiple dispatch as a paradigm, making it easy to express many object-oriented and functional programming patterns. The standard library provides asynchronous I/O, process control, logging, profiling, a package manager, and more.

### Dynamic

Julia is dynamically-typed, feels like a scripting language, and has good support for interactive use.

### Technical

Julia excels at numerical computing. Its syntax is great for math, many numeric datatypes are supported, and parallelism is available out of the box. Julia's multiple dispatch is a natural fit for defining number and array-like datatypes.

### Optionally Typed

Julia has a rich language of descriptive datatypes, and type declarations can be used to clarify and solidify programs.

### Composable

Julia packages naturally work well together. Matrices of unit quantities, or data table columns of currencies and colors, just work — and with good performance.

<sup>2</sup> Available at: <https://julialang.org/>

# StructJuMP package

<sup>3</sup>**StructJuMP is a Julia package for modeling structured optimization models.**

- **StructJuMP** is an extension of **JuMP package**, a domain-specific modeling language for mathematical optimization embedded in Julia.
  - **JuMP** is generic, fast, and straightforward modeler.
- **StructJuMP** provides a parallel algebraic modeling framework for **block-structured optimization models** in Julia.
- **StructJuMP** constructs a **JuMP.Model-type object** that contains every information of an SIP instance.

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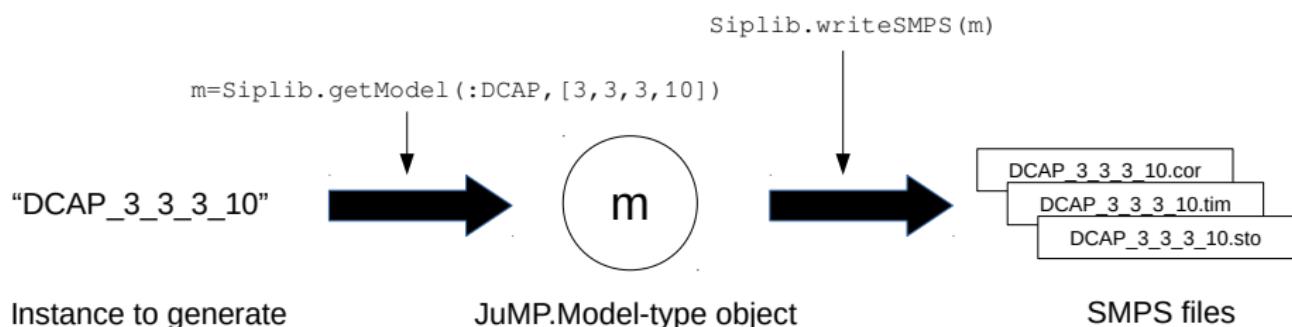
<sup>3</sup> Available at: <https://github.com/StructJuMP/StructJuMP.jl>

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# Core functionality of Siplib.jl

## Generating SMPS files of SIP instance:



# Problems available in SIPLIB 2.0

We implement Julia scripts for modeling 11 different problems from various sources and embed them into `Siplib.jl`.

Problem	Description	Main reference
AIRLIFT	Airlift operations scheduling	Midler and Wollmer (1969)
CARGO	Cargo network scheduling	Mulvey and Ruszczyński (1995)
CHEM	Design of batch chemical plants	Subrahmanyam et al. (1994)
DCAP	Dynamic capacity planning with stochastic demand	Ahmed and Garcia (2003)
MPTSPs	Multi-path traveling salesman problem with stochastic travel costs	Tadei et al. (2017)
PHONE	Telecommunication network planning	Sen et al. (2004)
SDCP	Stochastic data center placement	Kim et al. (2017)
SIZES	Optimal product substitution with stochastic demand	Jorjani et al. (1999)
SMKP	Stochastic multiple knapsack problem	Angulo et al. (2016)
SSLP	Stochastic server location problem	Ntiamo and Sen (2005)
SUC	Stochastic unit commitment problem	Papavasiliou and Oren (2013)

# Problems available in SIPLIB 2.0

We parameterize the problems to let users tailor the instances and generate SMPS files as they want.

Problem	Instance name	Remark
AIRLIFT	AIRLIFT_ $S$	$S$ : number of scenarios
CARGO	CARGO_ $S$	$S$ : number of scenarios
CHEM	CHEM_ $S$	$S$ : number of scenarios
DCAP	DCAP_ $R_N T_S$	$R$ : number of resources, $N$ : number of tasks, $T$ : number of time periods, $S$ : number of scenarios
MPTSPs	MPTSPs_ $d N S$	$d$ : node distribution strategy, $N$ : number of nodes, $S$ : number of scenarios
PHONE	PHONE_ $S$	$S$ : number of scenarios
SDCP	SDCP_ $k p d S$	$k$ : maximum number of dispatchable loads, $p$ : wind penetration level (%), $d$ : day type, $S$ : number of scenarios
SIZES	SIZES_ $S$	$S$ : number of scenarios
SMKP	SMKP_ $I S$	$I$ : number of types for item, $S$ : number of scenarios
SSLP	SSLP_ $I J S$	$I$ : number of clients, $J$ : number of server locations, $S$ : number of scenarios
SUC	SUC_ $d S$	$d$ : day type, $S$ : number of scenarios

# Components of the problems

We classify the problems based on their stage-wise variable types (continuous, binary, integer).

Problem	Variable	1st stage		2nd stage	
		Constraint	Variable	Constraint	Variable
AIRLIFT	I	IKN	C, I	BIN, GEN	
CARGO	I	IKN	C	GEN	
CHEM	C, I	VBD, GEN	C, B	GEN	
DCAP	C, B	VBD	B	PAR, M01	
MPTSPs	C, B	PAR, GEN	B	GEN	
PHONE	C	IVK	C, I	GEN	
SDCP	I	IKN	C	GEN	
SIZES	I	VBD, GEN	B, I	IKN	
SMKP	B	KNA	B	KNA	
SSLP	B	IVK, GEN	C, B	GEN	
SUC	C, B	VBD, GEN	C, B	VBD, GEN	

- C: continuous, B: binary, I: integer
- Constraint type notation is adopted from <sup>4</sup>MIPLIB 2010.

<sup>4</sup> Available at: <http://miplib.zib.de/miplib2010.php>

# Structure of the package

```
Siplib
└─src
    └─problems
        └─AIRLIFT
            ├─DATA
            │   └─numerical_data.csv
            ├─AIRLIFT_model.jl
            └─AIRLIFT_data.jl
        └─CARGO
            └─CARGO_model.jl
        └─...
    └─Siplib.jl
    └─analyzer.jl
    └─generator.jl
    └─writer.jl
    └─solver.jl
    └─utility.jl
    └─problem_info.csv
```

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# Computing environment



Computing facility	<sup>5</sup> Bebop with each node - CPU: Intel Xeon Processor E5-2695 v4 (36 cores, 36 threads) - Clock speed: 2.10GHz (maximum 3.30GHz) - Memory: 128GB (45MB Smart cache)
Solver	General purpose MIP solver: CPLEX 12.8 Open-source Dual Decomposition based SIP solver: DSP
Multi-threading per instance	36
Time limit per instance	1 hours

# Computational report

Table: Computational report (template)

Instance	Objective value		Optimality gap		LP2-relax gap	REVPI	RVSS
	CPLEX (SD)	DSP (SD)	CPLEX (time)	DSP (time)			
AIRLIFT_200							
AIRLIFT_300							
AIRLIFT_500							
AIRLIFT_1000							
CARGO_10							
CARGO_50							
CARGO_100							

- DSP's optimality gap: Lagrangian duality gap
- LP2-relax gap: Relative gap between the EF and LP-relaxation (2nd stage only)
- REVPI: Relative Expected Value of Perfect Information
- RVSS: Relative Value of Stochastic Solution

*End of slide*  
*(next: demonstration)*

# Appendix: Deterministic Equivalent Form SIP

**Example:** DCAP (dynamic capacity planning with stochastic demand)

$$(DCAP) \min \sum_{t \in T} \sum_{i \in R} (\alpha_{it} x_{it} + \beta_{it} u_{it}) + \sum_{s \in S} \mathbb{P}(s) \sum_{t \in T} \sum_{i \in R \cup \{0\}} \sum_{j \in N} c_{ijt}^s y_{ijt}^s \quad (1a)$$

$$\text{s.t. } x_{it} \leq M u_{it}, \quad \forall i \in R, \forall t \in T, \quad (1b)$$

$$\sum_{j \in N} d_{jt}^s y_{ijt}^s \leq \sum_{\tau=1}^t x_{i\tau}, \quad \forall i \in R, \forall t \in T, \forall s \in S, \quad (1c)$$

$$\sum_{i \in R \cup \{0\}} y_{ijt}^s = 1, \quad \forall j \in N, \forall t \in T, \forall s \in S, \quad (1d)$$

$$x_{it} \geq 0, \quad \forall i \in R, \forall t \in T, \quad (1e)$$

$$u_{it} \in \{0, 1\}, \quad \forall i \in R, \forall t \in T, \quad (1f)$$

$$y_{ijt}^s \in \{0, 1\}, \quad \forall i \in R \cup \{0\}, \forall j \in N, \forall t \in T, \forall s \in S. \quad (1g)$$

# Appendix: Modeling an SIP using StructJuMP

## Example: DCAP(dynamic capacity planning with stochastic demand)

```
# construct JuMP.Model
model = StructuredModel(num_scenarios = nS)

## 1st stage
@variable(model, x[i=R,t=T] >= 0)
@variable(model, u[i=R,t=T], Bin)
@objective(model, Min, sum(a[i,t]*x[i,t] + b[i,t]*u[i,t] for i in R for t in T))
@constraint(model, [i=R,t=T], x[i,t] - u[i,t] <= 0)

## 2nd stage
for s in S
    sb = StructuredModel(parent=model, id = s, prob = Pr[s])
    @variable(sb, y[i=R, j=N, t=T], Bin)
    @variable(sb, z[j=N,t=T], Bin) # modify as SIPLIB 1.0
    @objective(sb, Min, sum(c[i,j,t,s]*y[i,j,t] for i in R for j in N for t in T) + sum(c0[j,t,s]*z[j,t] for j in N for t in T))
    @constraint(sb, [i=R, t=T], -sum(x[i,tau] for tau in 1:t) + sum(d[j,t,s]*y[i,j,t] for j in N) <= 0)
    @constraint(sb, [j=N, t=T], sum(y[i,j,t] for i in R) + z[j,t] == 1)
end
```