



Pyomo: Python Optimization Modeling Objects

William E. Hart
Sandia National Laboratories

wehart@sandia.gov



Pyomo

Idea: support mathematical modeling of integer programs in Python

- Support for MINLP is a longer-term goal

Why Math Modeling?

- Provide a natural syntax to describe mathematical models
- Can formulate large models with a concise syntax
- Separate modeling and data declarations
- Support sophisticated data indexing to facilitate modeling with structured data
- Support data import and export in commonly used formats
- Include tools for debugging a model

Examples: AMPL, GAMS, OptimJ, AIMMS, FlopCPP, ...



Requirements

Open Source

- Transparency and reliability
- Customizable capability
- Flexible licensing

Flexible Modeling Language

- Extensibility and robustness
- Documentation
- Standard libraries
- Support for standard programming language features
 - Classes, functions

Portability

- Linux, MS Windows, Mac OS

Solver Integration

- Tight integration: solvers linked into modeling language
- Loose integration: solver launched separately

Abstract Models

- Symbolic representation of objectives and constraints



Why Python?

Open Source License

Features

- A clean syntax, a rich set of data types, support for object oriented programming, namespaces, exceptions, dynamic loading, etc.

Support and Stability

- Highly stable and well-supported

Documentation

- Extensive online documentation and several excellent books

Standard Library

- Includes a large number of useful modules.

Extendability and Customization

- Simple model for loading Python code developed by a user
- Can easily integrate libraries that optimize compute kernels
- Python can dynamically integrate libraries

Portability

- Widely available on many platforms



Other Programming Languages

.Net

- Only available on MS Windows

Ruby

- A widely used scripting language with strong support
- More complicated syntax than Python

C++

- Requires explicit compilation
- No interactive interpreter

Java

- Meets most of the requirements outlined previously
- No interactive interpreter (?)
- Python's dynamic typing and concise syntax makes software development quick and easy



AMPL Example: Model

```
set P;
```

```
param a {j in P};
```

```
param b ;
```

```
param c {j in P};
```

```
param u {j in P};
```

```
var X {j in P};
```

```
maximize Total_Profit : sum {j in P} c[j] * X[j];
```

```
subject to Time : sum {j in P} (1/ a[j]) * X[j] <= b;
```

```
subject to Limit {j in P}: 0 <= X[j] <= u[j];
```



AMPL Example: Data

```
data;
```

```
set P := bands coils;
```

```
param:      a      c      u      :=  
  bands    200    25    6000  
  coils    140    30    4000 ;
```

```
param b := 40;
```

Pyomo Example: Model

(1)

```
#
# Coopr import
#
from coopr.pyomo import *
#
# Setup the model
#
model = Model()
#
# Declare sets, parameters and variables
#
model.P = Set()
model.a = Param(model.P)
model.b = Param()
model.c = Param(model.P)
model.u = Param(model.P)
model.X = Var(model.P)
```

Pyomo Example: Model

(2)

```
#  
# Declare objective rule and create objective object  
#  
def Objective_rule(model):  
    ans = 0  
    for j in model.P:  
        ans = ans + model.c[j] * model.X[j]  
    return ans  
  
model.Total_Profit = Objective(rule=Objective_rule,  
                               sense=maximize)
```

Pyomo Example: Model

(3)

```
#
# Declare constraint rules and create objective objects
#
# Time
#
def Time_rule(model):
    ans = 0
    for j in model.P:
        ans = ans + (model.X[j]/model.a[j])
    return ans < model.b

model.Time = Constraint(rule=Time_rule)
#
# Limit
#
def Limit_rule(j, model):
    return(0, model.X[j], model.u[j])

model.Limit = Constraint(model.P, rule=Limit_rule)
```



AMPL Example: Solving Model

```
% ampl
ampl: model prod.mod;
ampl: data prod.dat;
option solver PICO;
solve;
No integer variables... solving the LP normally.
    LP value= 192000
    CPU RunTime=          0
    CPU TotalTime=       0.109
    WallClock TotalTime= 0.109375
PICO Solver: final f = 192000.000000
```

Pyomo Example: Solving Model

(1)

```
% pyomo prod.py prod.dat
```

```
=====
--- Solver Results ---
```

```
=====
----- Problem Information -----
```

```
name: None
num_constraints: 5
num_nonzeros: 6
num_objectives: 1
num_variables: 2
sense: maximize
upper_bound: 192000
```

Pyomo Example: Solving Model

(2)

```
-----  
----- Solver Information -----  
-----
```

```
error_rc: 0  
nbounded: None  
ncreated: None  
status: ok  
systemtime: None  
usertime: None
```

```
-----  
----- Solution 0 -----  
-----
```

```
gap: 0.0  
status: optimal  
value: 192000  
Primal Variables  
    X_bands_          6000  
    X_coils_          1400  
Dual Variables  
    c_u_Limit_1      4  
    c_u_Time_0       4200
```



Solving a Pyomo Model within Python

```
#
# Imports
import prod
from coopr.pyomo import *
#
# Configure Coopr
coopr.opt.config().configure()
#
# Create the model instance
instance = prod.model.create("prod.dat")
#
# Setup the optimizer
opt = solvers.SolverFactory("glpk")
#
# Optimize
results = opt.solve(instance)
#
# Write the output
results.write(num=1)
```



AMPL/Pyomo Comparison

- Pyomo object/constraint declarations are more verbose
 - Typically requires the use of a temporary function
- Pyomo declarations explicitly refer to models
 - Can declare multiple models and model instances
- Pyomo can apply solvers that do not recognize the *.nl format
- Pyomo (currently) only supports linear models
 - Linear programs and mixed-integer linear programs
- Pyomo does not include preprocessing of LP/MILP instances
- Pyomo can work with a richer programming environment



Customizing Pyomo

- Adding diagnostic information during generation
- Generation of model instance (using custom generation method)
- Custom set/parameter definitions
- Data integration with external data sources
 - Databases, spreadsheets, Python classes, etc...

Note: the default generation process is sufficient for current Pyomo applications



Related Python Optimization Tools

Python Optimizer Packages

- CVXOPT
- SciPy
- OpenOpt
- NLPy
- Pyipopt

Python Optimization Modeling Packages

- PuLP
 - Direct construction of LP/MILP models
- POAMS
 - Symbolic representation of LP/MILP models



Coordinating with POAMS and PuLP

- Integration of Pyomo, POAMS and PuLP capabilities?
 - Tight integration may not happen
 - Developers have different design requirements and/or research goals
 - Idea: share common components and/or core infrastructure
- Plugin support for extensibility
 - Registration of optimizers
 - Registration of modeling tools

Example: preprocessing

- Broadly applicable to LP & MILP models
- Idea: leverage common 'instance' representation
- Idea: leverage plugins to customize preprocessing
 - Standard techniques
 - Application-specific techniques
- Challenge: map preprocessing changes into original model representations



Pyomo and Coopr

Pyomo is a Python package that is managed within the Coopr software.

Coopr:

- COMmon Optimization Python Repository
- Integrates a variety of optimization-related Python packages
- Designed to support the Acro software project

Coopr Opt

- Commonly-used optimization utilities
 - Solver results
 - Problem transformations
- Optimization solvers
 - Wrappers to external solvers
 - Python optimizers



Coopr Opt: Current Capabilities

LP/MILP Solvers

GLPK	Stable
PICO	Stable (using Acro 2.0)
CBC	In development (working on I/O issues)
CPLEX	In development

Problem formats

- NL, MPS, LP, MathProg
- Uses `glpsol` and Acro's `pico_convert` command to perform conversions
 - `pico_convert` uses COIN-OR and AMPL utilities



Future Directions

- Extensible plugin architecture
- Support for nonlinear models
 - Possible integration with SAGE to support AD
- Interfacing with Python optimization packages
 - E.g. interface with SciPy, OpenOpt, etc
- Solver interfaces
 - Direct solver interfaces
 - Support for the COIN-OR OS services
- Distributions
 - Windows installers
 - PyPi support (to enable use of the Python `easy_install` utility)



Related Talks

- Acro 2.0: A Common Respository for Optimizers
 - MB05
- Object-algebraic Modeling Using POAMS: Meta-algorithms
 - TA05
- SUCASA, Implementing a Facility for Exposing Mathematical Programming Language Names in Customized Integer Programming Codes
 - TB04
- Using SUCASA, Developing Integer Programming Solver Customizations Using Natural Names
 - TB04



Getting Started

Coopr 1.0 release has been recently finalized

Downloads:

<https://software.sandia.gov/trac/coopr/downloader>

Online Documentation

<https://software.sandia.gov/trac/coopr/wiki/Package/Pyomo>