Good Optimization Modeling Practices with Pyomo

All You Wanted to Know About Practical Optimization but Were Afraid to Ask

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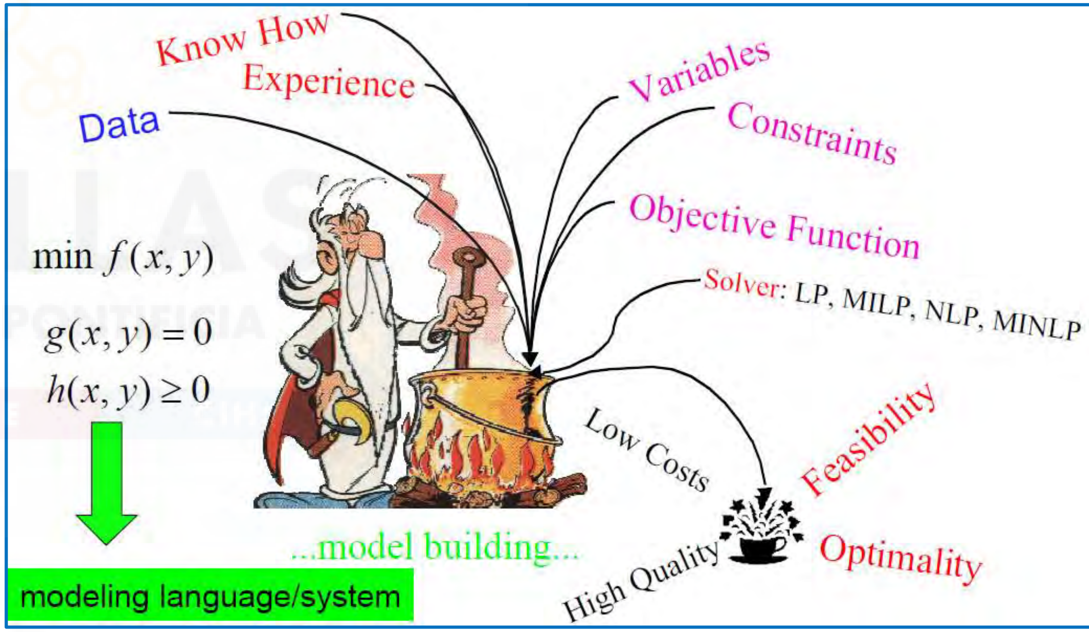
Do not confuse the ingredients of the recipe

- Mathematical formulation
  - LP, MIP, NLP, QCP, MCP
- Modeling language
  - GAMS, Pyomo
- Solver
  - CPLEX, Gurobi
- Optimization algorithm
  - Primal simplex, dual simplex, interior point
- Input/output interfaces
  - Text file, CSV, Microsoft Excel
- Operating system
  - Windows, Linux, macOS



Why Pyomo?

https://pyomo.readthedocs.io/en/stable/
https://groups.google.com/forum/?nomobile=true#!forum/pyomo-forum
https://mobook.github.io/MO-book/intro.html

- "Open-source optimization modeling language with a diverse set of optimization capabilities."
- No language license is required. Install

```
conda install -c conda-forge pyomo
```

- Allows the use of several solvers (open source –SCIP, GLPK, and CBC– or proprietary –Gurobi, CPLEX–)

```
pyomo help -s
```

GAMS

- Pros:
  - Consistency
  - Maturity. Everything has already been written
  - Documentation
  - Customer support

Pyomo

- Pros:
  - Flexibility, multiple choices
  - Powerful Python libraries to be used (e.g., input data, output results, visualization)
- Cons:
  - Documentation is a babel tower
  - Getting the duals

GAMS "Performance in Optimization Models: A Comparative Analysis of GAMS, Pyomo, GurobiPy, and JuMP" July 2023

Comparison between GAMS and Pyomo (by chatGPT)

1. GAMS has been around for longer than Pyomo, which means it has a more established user community and more extensive documentation and support.
2. GAMS is specifically designed for mathematical programming, whereas Pyomo is a general-purpose modeling tool that includes mathematical programming as one of its features.
3. GAMS provides a powerful, integrated modeling language that allows you to specify models using a concise syntax, while Pyomo requires you to write Python code to define your models.
4. GAMS has a wide range of solvers available, including commercial and open-source options, and it can seamlessly switch between solvers, whereas Pyomo requires more effort to switch between solvers.
5. GAMS includes built-in functionality for handling linear, nonlinear, and mixed-integer programming problems, whereas Pyomo requires additional libraries to handle some types of optimization problems.

1. Pyomo is open-source software, which means it is free to use and modify, while GAMS is a commercial software that requires a license to use.
2. Pyomo is based on Python, a popular general-purpose programming language that has a large and active user community, while GAMS has its own proprietary modeling language that can have a steeper learning curve.
3. Pyomo provides more flexibility than GAMS, allowing users to integrate their optimization models with other Python libraries and tools.
4. Pyomo can be used for a wide range of optimization problems, not just mathematical programming, such as stochastic programming, optimization under uncertainty, and mixed-integer nonlinear programming.
5. Pyomo has a more modular design that makes it easier to add new features or extensions, while GAMS has a more monolithic architecture that can be harder to customize.

Advantages/disadvantage of Jump (by ChatGPT)

1. High-performance optimization: Jump is built on the Julia programming language, which is known for its speed and efficiency. It leverages Julia's just-in-time (JIT) compilation to achieve high-performance optimization, making it suitable for solving large-scale and computationally intensive problems.
2. Modeling flexibility: Jump provides a flexible and intuitive modeling framework for mathematical optimization. It offers a wide range of modeling constructs and mathematical operators, allowing users to express complex optimization problems in a concise and natural manner. This flexibility enables rapid prototyping and experimentation.
3. Solver interoperability: Jump seamlessly integrates with a variety of solvers, including both open-source and commercial solvers. This allows users to leverage the strengths of different solvers and choose the most suitable one for their specific problem. Jump provides a unified interface for interacting with solvers, simplifying the process of switching between different solvers.
4. Support for advanced modeling techniques: Jump supports advanced modeling techniques such as constraint programming, mixed-integer nonlinear programming (MINLP), and stochastic programming. These capabilities enable the formulation and solution of more sophisticated optimization problems, including those with nonlinear objectives, integer variables, and uncertain parameters.
5. Active community and development: Jump benefits from an active and growing community of users and developers. This ensures ongoing development, frequent updates, and a rich ecosystem of contributed packages. The community provides support, examples, and documentation, making it easier for new users to get started and learn from others' experiences.

1. Learning curve: While Jump offers a powerful modeling framework, it may have a steeper learning curve compared to some other optimization libraries. The Julia language itself, although designed for ease of use, may require users to familiarize themselves with its syntax and concepts before fully leveraging Jump's capabilities.
2. Limited user base: Although the Julia language and Jump have gained popularity in recent years, their user base is still relatively smaller compared to more established optimization libraries. This means that finding specific examples, tutorials, or community support for certain niche topics or specialized domains may be more challenging.
3. Solver availability: Although Jump supports multiple solvers, the availability of certain solvers may be limited compared to other optimization libraries. Some specialized solvers or industry-specific solvers may not have native support in Jump, requiring additional effort to integrate or interface with them.
4. Documentation completeness: While Jump has documentation available, it may not be as comprehensive or extensive as that of other well-established optimization libraries. This can sometimes make it more difficult for users to find detailed explanations or examples for specific modeling techniques or functionalities.
5. Tool maturity: Julia and Jump are relatively newer technologies compared to some other optimization libraries, which have been around for several decades. While Julia has gained significant momentum, there may still be areas where Jump's toolset or functionality is less mature or refined compared to more established alternatives.

Advantages/disadvantage of Pyomo (by ChatGPT)

1. Extensive modeling capabilities: Pyomo offers a wide range of modeling components and constructs that allow users to represent complex optimization problems in a flexible and expressive manner. It supports a variety of mathematical formulations, including linear programming (LP), mixed-integer programming (MIP), and nonlinear programming (NLP).
2. Solver compatibility: Pyomo has built-in support for interfacing with a variety of optimization solvers, both open-source and commercial. This allows users to leverage the strengths of different solvers and choose the most suitable one for their problem. Pyomo provides a unified interface for interacting with solvers, making it easy to switch between different solver backends.
3. Python integration: Pyomo is implemented in Python, a widely-used and accessible programming language. This integration with Python provides several advantages, including a large ecosystem of libraries and tools, extensive documentation and support, and the ability to leverage Python's data manipulation and analysis capabilities.
4. Scalability: Pyomo is designed to handle large-scale optimization problems efficiently. It supports parallel computation and provides options for distributed computing, enabling users to solve computationally intensive problems more effectively. Additionally, Pyomo can leverage the performance benefits of optimization solvers to handle large models and datasets.
5. Active development and community support: Pyomo benefits from an active development community, ensuring regular updates, bug fixes, and improvements. It also has an active user community that provides support, shares examples, and contributes to the development of additional libraries and extensions, making it easier for users to get started and find solutions to their optimization problems.

1. Learning curve: Pyomo's powerful modeling capabilities come with a learning curve, especially for users who are new to mathematical optimization or programming in Python. Understanding the syntax, constructs, and best practices of Pyomo may require some initial effort and familiarity with optimization modeling concepts.
2. Limited solver support: While Pyomo supports interfacing with multiple solvers, the availability of specific solvers may be limited compared to other optimization libraries. Some specialized or proprietary solvers may not have direct support in Pyomo, requiring additional effort to integrate or interface with them.
3. Performance overhead: Pyomo's flexibility and generality in modeling can sometimes come with a performance overhead. Depending on the complexity of the model and the chosen solver, Pyomo may not always achieve the same level of performance as more specialized modeling languages or libraries.
4. Documentation completeness: While Pyomo has documentation available, it may not cover all aspects of the library or provide in-depth explanations for specific modeling techniques or functionalities. Users may need to refer to external resources or rely on community support to find detailed information on certain topics.
5. Tool maturity: Pyomo, like other optimization libraries, has undergone significant development over the years. However, it may still be considered less mature compared to some other well-established optimization libraries. This means that there may be areas where Pyomo's toolset or functionality is less refined or lacks certain advanced features available in other libraries.

GAMSPy (https://gamspy.readthedocs.io/en/latest/index.html)

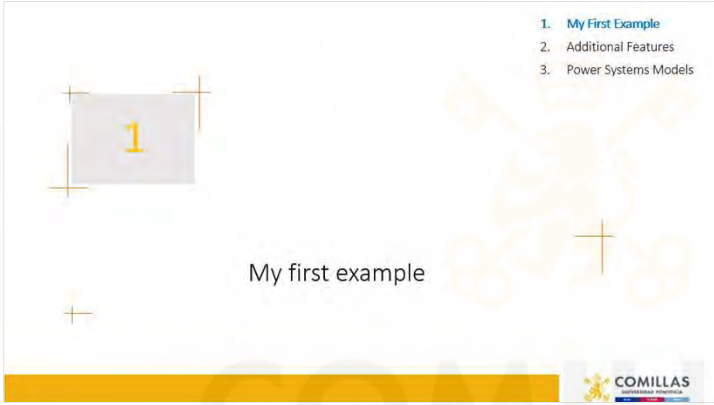
- Combines the high-performance GAMS execution system with the flexible Python language, creating a powerful mathematical optimization package
- Acts as a bridge between the expressive Python language and the robust GAMS system, allowing you to create complex mathematical models effortlessly.

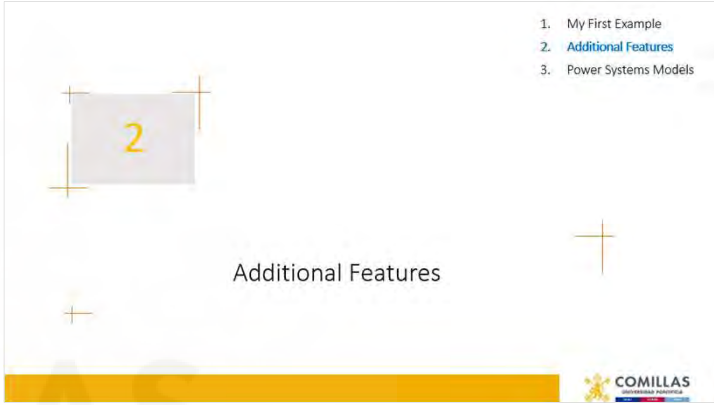
A Transportation Problem

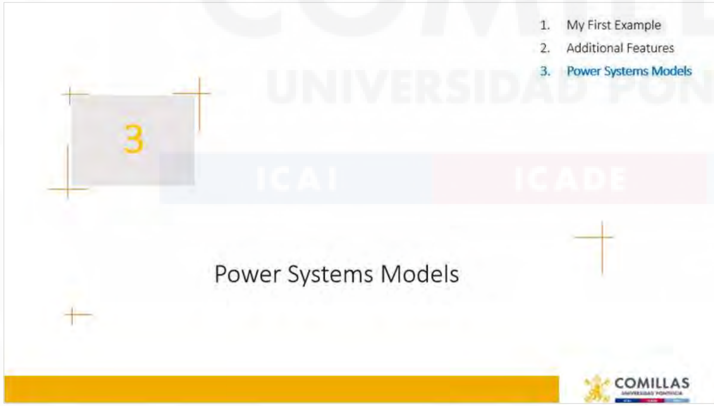
```python
import pandas as pd
capacities = pd.DataFrame(
    [["seattle", 350], ["san-diego", 600]], columns=["city", "capacity"]
).set_index("city")
demands = pd.DataFrame(
    [["new-york", 325], ["chicago", 300], ["topeka", 275]], columns=["city", "demand"]
).set_index("city")
distances = pd.DataFrame(
    [
        ["seattle", "new-york", 2.5],
        ["seattle", "chicago", 1.7],
        ["seattle", "topeka", 1.8],
        ["san-diego", "new-york", 2.5],
        ["san-diego", "chicago", 1.8],
        ["san-diego", "topeka", 1.4],
    ],
    columns=["from", "to", "distance"],
).set_index(["from", "to"])
freight_cost = 90
from gamspy import Container, Set, Parameter, Variable, Equation, Model, Sum, Sense
m = Container()
i = Set(container=m, name="i", description="plants")
i.setRecords(capacities.index)
j = Set(container=m, name="j", description="markets", records=demands.index)
a = Parameter(
    container=m,
    name="a",
    domain=i,
    description="supply of commodity at plant i (in cases)",
    records=capacities.reset_index(),
)
b = Parameter(
    container=m,
    name="b",
    domain=j,
    description="demand for commodity at market j (in cases)",
    records=demands.reset_index(),
)
```

```python
c = Parameter(
    container=m,
    name="c",
    domain=[i, j],
    description="cost per unit of shipment between plant i and market j",
)
cost = freight_cost * distances / 1000
c.setRecords(cost.reset_index())
x = Variable(
    container=m,
    name="x",
    domain=[i, j],
    type="Positive",
    description="amount of commodity to ship from plant i to market j",
)
supply = Equation(
    container=m, name="supply", domain=i, description="observe supply limit at plant i"
)
demand = Equation(
    container=m, name="demand", domain=j, description="satisfy demand at market j"
)
obj = Sum((i, j), c[i, j] * x[i, j])
transport = Model(
    m,
    name="transport",
    equations=[supply, demand],
    problem="LP",
    sense=Sense.MIN,
    objective=obj,
)
import sys
transport.solve(output=sys.stdout)
x.records.set_index(["i", "j"])
transport.objective_value
```

https://gamspy.readthedocs.io/en/latest/user/notebooks/trnsport.html







Good Optimizatic

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My first example

Code conventions

- Must be defined in blocks. For example, a set and all its subsets should constitute one block in the sets section.
- Names are intended to be meaningful. Follow conventions
  - Items with the same name represent the same concept in different models
  - Units should be used in all definitions
  - Parameters are named pParameterName (e.g., pOperReserveDw)
  - Variables are named vVariableName (e.g., vReserveDown)
  - Equations are named eEquationName (e.g., eOperReserveDw)
  - Use short set names (one or two letters) for easier reading
- Equations are laid out as clearly as possible

Transportation model

There are i can factories and j consumption markets. Each factory has a maximum capacity of a_i cases, and each market demands a quantity of b_j cases (it is assumed that the total production capacity is greater than the total market demand for the problem to be feasible). The transportation cost between each factory i and each market j for each case is c_{ij}. The demand must be satisfied at a minimum cost.

The decision variables of the problem will be cases transported between each factory i and each market j, x_{ij}.

My first GAMS transportation model

```
sets
   I origins      / VIGO, ALGECIRAS /
   J destinations / MADRID, BARCELONA, VALENCIA /

parameters
   pA(i) origin capacity
       / VIGO      350
         ALGECIRAS 700 /

   pB(j) destination demand
       / MADRID    400
         BARCELONA 450
         VALENCIA  150 /

table pC(i,j) per unit transportation cost
          MADRID BARCELONA VALENCIA
VIGO       0.06     0.12     0.09
ALGECIRAS  0.05     0.15     0.11

variables
   vX(i,j) units transported
   vCost   transportation cost

positive variable vX

equations
   eCost        transportation cost
   eCapacity(i) maximum capacity of each origin
   eDemand   (j) demand supply at destination ;

eCost        .. sum[(i,j), pC(i,j) * vX(i,j)] =e= vCost ;
eCapacity(i) .. sum[   j ,           vX(i,j)] =l= pA(i) ;
eDemand   (j) .. sum[ i   ,           vX(i,j)] =g= pB(j) ;

model mTransport / all /
solve mTransport using LP minimizing vCost
```

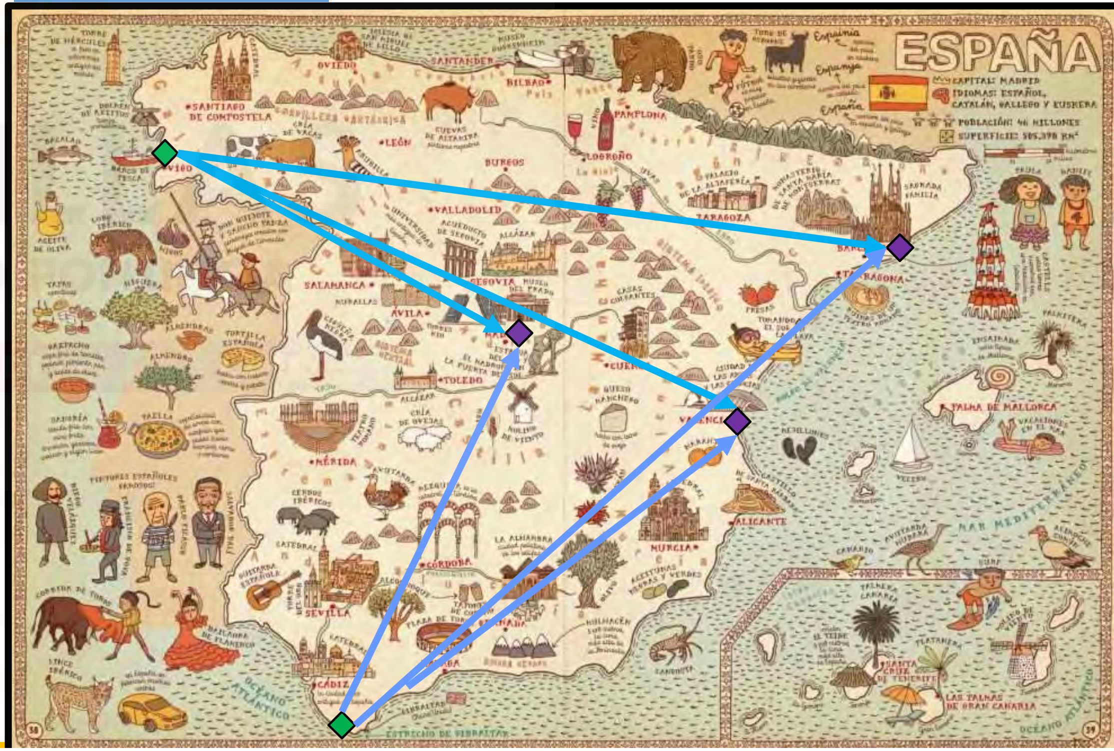
$$\min_{x_{ij}} \sum_{ij} c_{ij} x_{ij}$$

$$\sum_{j} x_{ij} \le a_i \quad \forall i$$

$$\sum_{i} x_{ij} \ge b_j \quad \forall j$$

$$x_{ij} \ge 0$$

A. Mizielinska y D. Mizielinski *Atlas del mundo: Un insólito viaje por las mil curiosidades y maravillas del mundo* Ed. Maeva 2015



My first Pyomo transportation model

```
import pyomo.environ as pyo
from   pyomo.environ import ConcreteModel, Set, Param, Var, NonNegativeReals, Constraint, Objective, minimize, Suffix
from   pyomo.opt     import SolverFactory

mTransport = ConcreteModel('Transportation Problem')

mTransport.i = Set(initialize=['Vigo',   'Algeciras'             ], doc='origins'     )
mTransport.j = Set(initialize=['Madrid', 'Barcelona', 'Valencia'], doc='destinations')

mTransport.pA = Param(mTransport.i, initialize={'Vigo'  : 350, 'Algeciras': 700                  }, doc='origin capacity'   )
mTransport.pB = Param(mTransport.j, initialize={'Madrid': 400, 'Barcelona': 450, 'Valencia': 150}, doc='destination demand')

TransportationCost = {
    ('Vigo',      'Madrid'   ): 0.06,
    ('Vigo',      'Barcelona'): 0.12,
    ('Vigo',      'Valencia' ): 0.09,
    ('Algeciras', 'Madrid'   ): 0.05,
    ('Algeciras', 'Barcelona'): 0.15,
    ('Algeciras', 'Valencia' ): 0.11,
    }

mTransport.pC = Param(mTransport.i, mTransport.j, initialize=TransportationCost, doc='per unit transportation cost')

mTransport.vX = Var  (mTransport.i, mTransport.j, bounds=(0.0,None), doc='units transported', within=NonNegativeReals)

def eCapacity(mTransport, i):
    return sum(mTransport.vX[i,j] for j in mTransport.j) <= mTransport.pA[i]
mTransport.eCapacity = Constraint(mTransport.i, rule=eCapacity, doc='maximum capacity of each origin')

def eDemand  (mTransport, j):
    return sum(mTransport.vX[i,j] for i in mTransport.i) >= mTransport.pB[j]
mTransport.eDemand   = Constraint(mTransport.j, rule=eDemand,   doc='demand supply at destination'   )

def eCost(mTransport):
    return sum(mTransport.pC[i,j]*mTransport.vX[i,j] for i,j in mTransport.i*mTransport.j)
mTransport.eCost = Objective(rule=eCost, sense=minimize, doc='transportation cost')

mTransport.write('mTransport.lp', io_options={'symbolic_solver_labels': True})

mTransport.dual = Suffix(direction=Suffix.IMPORT)

Solver = SolverFactory('gurobi')
Solver.options['LogFile'] = 'mTransport.log'
SolverResults = Solver.solve(mTransport, tee=True)

SolverResults.write()
mTransport.pprint()

mTransport.vX.display()
for j in mTransport.j:
    print(mTransport.dual[mTransport.eDemand[j]])
```

$$\min_{x_{ij}} \sum_{ij} c_{ij} x_{ij}$$

$$\sum_j x_{ij} \leq a_i \quad \forall i$$

$$\sum_i x_{ij} \geq b_j \quad \forall j$$

$$x_{ij} \geq 0$$

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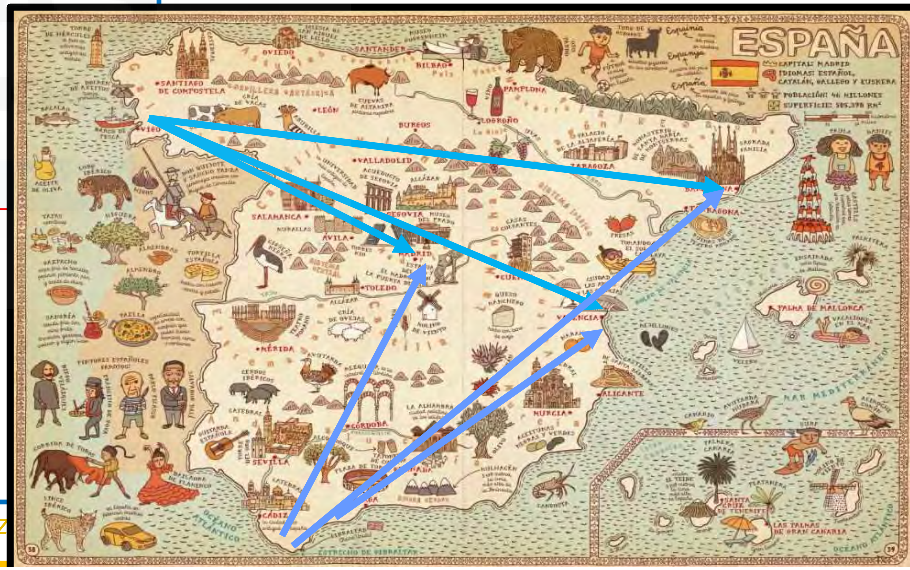


LP File: `mTransport.write('mTransport.lp', io_options={'symbolic_solver_labels': True})`

```
\* Source Pyomo model name=unknown *\

min
eCost:
+0.14999999999999999 vX(Algeciras_Barcelona)
+0.050000000000000003 vX(Algeciras_Madrid)
+0.11 vX(Algeciras_Valencia)
+0.12 vX(Vigo_Barcelona)
+0.059999999999999998 vX(Vigo_Madrid)
+0.089999999999999997 vX(Vigo_Valencia)

s.t.

c_u_eCapacity(Algeciras)_:
+1 vX(Algeciras_Barcelona)
+1 vX(Algeciras_Madrid)
+1 vX(Algeciras_Valencia)
<= 700

c_u_eCapacity(Vigo)_:
+1 vX(Vigo_Barcelona)
+1 vX(Vigo_Madrid)
+1 vX(Vigo_Valencia)
<= 350
```

```
c_l_eDemand(Barcelona)_:
+1 vX(Algeciras_Barcelona)
+1 vX(Vigo_Barcelona)
>= 450

c_l_eDemand(Madrid)_:
+1 vX(Algeciras_Madrid)
+1 vX(Vigo_Madrid)
>= 400

c_l_eDemand(Valencia)_:
+1 vX(Algeciras_Valencia)
+1 vX(Vigo_Valencia)
>= 150

c_e_ONE_VAR_CONSTANT:
ONE_VAR_CONSTANT = 1.0

bounds
   0 <= vX(Algeciras_Barcelona) <= +inf
   0 <= vX(Algeciras_Madrid) <= +inf
   0 <= vX(Algeciras_Valencia) <= +inf
   0 <= vX(Vigo_Barcelona) <= +inf
   0 <= vX(Vigo_Madrid) <= +inf
   0 <= vX(Vigo_Valencia) <= +inf
end
```

Problem summary: `SolverResults.write()`

```
# ==========================================================
# = Solver Results                                         =
# ==========================================================
# ----------------------------------------------------------
#   Problem Information
# ----------------------------------------------------------
Problem:
- Name: x7
  Lower bound: 93.5
  Upper bound: 93.5
  Number of objectives: 1
  Number of constraints: 6
  Number of variables: 7
  Number of binary variables: 0
  Number of integer variables: 0
  Number of continuous variables: 7
  Number of nonzeros: 13
  Sense: minimize
# ----------------------------------------------------------
#   Solver Information
# ----------------------------------------------------------
Solver:
- Status: ok
  Return code: 0
  Message: Model was solved to optimality (subject to tolerances), and an optimal solution is available.
  Termination condition: optimal
  Termination message: Model was solved to optimality (subject to tolerances), and an optimal solution is available.
  Wall time: 0.020067214965820312
  Error rc: 0
  Time: 0.30008649826049805
# ----------------------------------------------------------
#   Solution Information
# ----------------------------------------------------------
Solution:
- number of solutions: 0
  number of solutions displayed: 0
```

Optimal results: `mTransport.pprint()`

```
4 Set Declarations
    i : origins
        Dim=0, Dimen=1, Size=2, Domain=None, Ordered=False, Bounds=None
        ['Algecirass', 'Vigo']
    j : destinations
        Dim=0, Dimen=1, Size=3, Domain=None, Ordered=False, Bounds=None
        ['Barcelona', 'Madrid', 'Valencia']
    pC_index : Dim=0, Dimen=2, Size=6, Domain=None, Ordered=False, Bounds=None
        Virtual
    vX_index : Dim=0, Dimen=2, Size=6, Domain=None, Ordered=False, Bounds=None
        Virtual
3 Param Declarations
    pA : origin capacity
        Size=2, Index=i, Domain=Any, Default=None, Mutable=False
        Key       : Value
        Algeciras :   700
             Vigo :   350
    pB : destination demand
        Size=3, Index=j, Domain=Any, Default=None, Mutable=False
        Key       : Value
        Barcelona :   450
           Madrid :   400
         Valencia :   150
    pC : per unit transportation cost
        Size=6, Index=pC_index, Domain=Any, Default=None, Mutable=False
        Key                        : Value
        ('Algeciras', 'Barcelona') :  0.15
           ('Algeciras', 'Madrid') :  0.05
         ('Algeciras', 'Valencia') :  0.11
             ('Vigo', 'Barcelona') :  0.12
                ('Vigo', 'Madrid') :  0.06
              ('Vigo', 'Valencia') :  0.09
```

```
1 Var Declarations
    vX : units transported
        Size=6, Index=vX_index
        Key                        : Lower : Value : Upper : Fixed : Stale : Domain
        ('Algeciras', 'Barcelona') :   0.0 : 100.0 :  None : False : False :  Reals
           ('Algeciras', 'Madrid') :   0.0 : 400.0 :  None : False : False :  Reals
         ('Algeciras', 'Valencia') :   0.0 : 150.0 :  None : False : False :  Reals
             ('Vigo', 'Barcelona') :   0.0 : 350.0 :  None : False : False :  Reals
                ('Vigo', 'Madrid') :   0.0 :   0.0 :  None : False : False :  Reals
              ('Vigo', 'Valencia') :   0.0 :   0.0 :  None : False : False :  Reals
1 Objective Declarations
    eCost : transportation cost
        Size=1, Index=None, Active=True
        Key  : Active : Sense    : Expression
        None :   True : minimize : 0.06*vX[Vigo,Madrid] + 0.12*vX[Vigo,Barcelona] + 0.09*vX[Vigo,Valencia] +
0.05*vX[Algeciras,Madrid] + 0.15*vX[Algeciras,Barcelona] + 0.11*vX[Algeciras,Valencia]
2 Constraint Declarations
    eCapacity : maximum capacity of each origin
        Size=2, Index=i, Active=True
        Key       : Lower : Body                                                                     : Upper : Active
        Algeciras :  -Inf : vX[Algeciras,Madrid] + vX[Algeciras,Barcelona] + vX[Algeciras,Valencia] : 700.0 :   True
             Vigo :  -Inf :                     vX[Vigo,Madrid] + vX[Vigo,Barcelona] + vX[Vigo,Valencia] : 350.0 :   True
    eDemand : demand supply at destination
        Size=3, Index=j, Active=True
        Key       : Lower : Body                                           : Upper : Active
        Barcelona : 450.0 : vX[Vigo,Barcelona] + vX[Algeciras,Barcelona] :  +Inf :   True
           Madrid : 400.0 :       vX[Vigo,Madrid] + vX[Algeciras,Madrid] :  +Inf :   True
         Valencia : 150.0 :   vX[Vigo,Valencia] + vX[Algeciras,Valencia] :  +Inf :   True
11 Declarations: j pA pB pC_index pC vX_index vX eCapacity eDemand eCost i
```

2

Additional Features

Sets

Indices	
ω	Scenario
n	Load level
ν	Time step. Duration of each load level (e.g., 2 h, 3 h)
g	Generator (thermal or hydro unit or ESS)
t	Thermal unit
e	Energy Storage System (ESS)

- Subsets

```
mSDUC.g = Set(initialize=mSDUC.gg, ordered=False, doc='generating units', filter=lambda mSDUC,gg: gg in mSDUC.gg and pRatedMaxPower[gg] > 0)
mSDUC.t = Set(initialize=mSDUC.g , ordered=False, doc='thermal    units', filter=lambda mSDUC,g : g  in mSDUC.g  and pLinearVarCost [g] > 0)
```

- Lag and lead operators: `first/last`, `prev/next`

```
def eUCStrShut(mTEPES,sc,p,n,nr):
    if n == mTEPES.n.first():
        return mTEPES.vCommitment[sc,p,n,nr] - pInitialUC[nr]                              == mTEPES.vStartUp[sc,p,n,nr] - mTEPES.vShutDown[sc,p,n,nr]
    else:
        return mTEPES.vCommitment[sc,p,n,nr] - mTEPES.vCommitment[sc,p,mTEPES.n.prev(n),nr] == mTEPES.vStartUp[sc,p,n,nr] - mTEPES.vShutDown[sc,p,n,nr]
mTEPES.eUCStrShut = Constraint(mTEPES.sc, mTEPES.p, mTEPES.n, mTEPES.nr, rule=eUCStrShut, doc='relation among commitment startup and shutdown')
```

$$\boxed{uc_{ng} - uc_{n-\nu,g} = su_{ng} - sd_{ng} \quad \forall ng}$$

```
# fixing the ESS inventory at the last load level
for sc,p,es in mTEPES.sc*mTEPES.p*mTEPES.es:
    mTEPES.vESSInventory[sc,p,mTEPES.n.last(),es].fix(pESSInitialInventory[es])
```

- Circular indexes (`prew/nextw`)
- Union, intersection of sets

Sparse index sets in a network

- Set of lines (initial node, final node, circuit)

```
mTEPES.la = Set(initialize=mTEPES.ni*mTEPES.nf*mTEPES.cc, ordered=False, doc='all lines', filter=lambda mTEPES,ni,nf,cc:(ni,nf,cc) in pLineX)
```

- All the connections (`ni,nf,cc`) vs. real lines (`lc`)

```
def eInstalNetCap1(mTEPES,sc,p,n,ni,nf,cc):
    return mTEPES.vFlow[sc,p,n,ni,nf,cc] / mTEPES.pLineNTC[ni,nf,cc] >= - mTEPES.vNetworkInvest[ni,nf,cc]
mTEPES.eInstalNetCap1 = Constraint(mTEPES.sc, mTEPES.p, mTEPES.n, mTEPES.lc, rule=eInstalNetCap1, doc='maximum flow by installed network capacity [p.u.]')
```

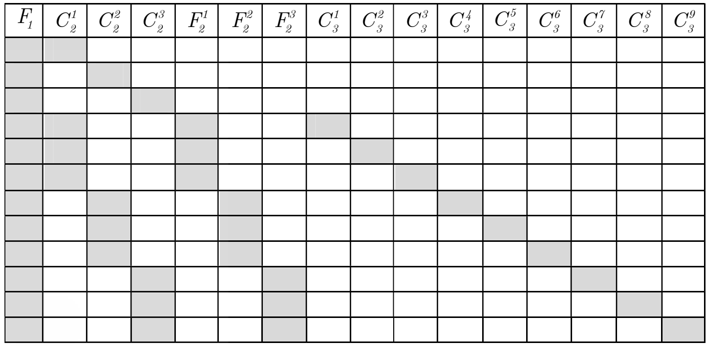
Constraint $\mathrm{l} \le Ax \le u$

```
#%% maximum angular difference between any two nodes
def eMaxThetaDiff(mTEPES,sc,p,n,ni,nf):
    if ni > nf and nf != mTEPES.pReferenceNode:
        return (-pMaxThetaDiff.loc[ni,nf], vTheta[sc,p,n,ni] - vTheta[sc,p,n,nf], pMaxThetaDiff.loc[ni,nf])
    else:
        return Constraint.Skip
mTEPES.eMaxThetaDiff = Constraint(mTEPES.sc, mTEPES.p, mTEPES.n, mTEPES.ni, mTEPES.nf, rule=eMaxThetaDiff, doc='maximum angle difference [rad]')
```

Sizing and timing

- Counting constraints

```
print('eBalance ... ', len(mTEPES.eBalance), ' rows’)
```



- Counting time

```
GeneratingRBITime = time.time() - StartTime
StartTime         = time.time()
print('Generating reserves/balance/inventory ... ', round(GeneratingRBITime), 's')
```

Boosting performance

- Threads

```
Solver.options['Threads'] = int((psutil.cpu_count(logical=True) +
psutil.cpu_count(logical=False))/2)
```

- Sensitivity analysis with persistent solvers
  - Sequential resolution of similar problems in memory

```
Solver.remove_constraint(model.ConstraintName)
model.del_component(model.SetName)
Solver.add_constraint(model.ConstraintName)
```

- Distributed computing
  - Create the problems and send them to be solved in parallel
  - Retrieve the solution once solved

```
model.ConstraintName.deactivate()
model.del_component(model.SetName)
model.ConstraintName.activate()
```

Modeling extensions

- Auto-Persistent Pyomo Solver Interfaces (APPSI). Sensitivity analysis
- Stochastic Programming
  - Equivalent to GAMS/EMP. Formulate the deterministic problem and define the scenario tree
- Bilevel Programming
- Dynamic Optimization with pyomo.DAE
- MPEC
- Generalized Disjunctive Programming
- Pyomo Network

Preprocessing by Gurobi Python shell

- Before and after presolve can help you in detecting improvements in the formulation
- Allows getting the optimization problem after the presolve

```
ModelName          = read("OriginalProblem.lp")
ModelNamePresolved = ModelName.presolve()
ModelNamePresolved.write("PresolvedProblem.lp")
```

- Gurobi Model Analyzer (`gurobi_modelanalyzer`) allows to detect numerical problems

Transportation Problem with demand scenarios Auto-Persistent Pyomo Solver Interfaces (APPSI)

```python
import numpy              as np
import pyomo.environ      as pyo
from   pyomo.environ      import ConcreteModel, Set, Param, Var, NonNegativeReals, Constraint, Objective, minimize, Suffix
from   pyomo.opt          import SolverFactory
from   pyomo.contrib      import appsi
from   pyomo.common.timing import HierarchicalTimer

# Developed by
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#    https://pascua.iit.comillas.edu/aramos/Ramos_CV.htm
#
#    May 8, 2023

mTransport = ConcreteModel('Transportation Problem with many demand scenarios')

mTransport.i = Set(initialize=['Vigo',   'Algeciras'             ], doc='origins'     )
mTransport.j = Set(initialize=['Madrid', 'Barcelona', 'Valencia'], doc='destinations')

mTransport.pA = Param(mTransport.i, initialize={'Vigo'  : 350, 'Algeciras': 700                 }, doc='origin capacity'   )
mTransport.pB = Param(mTransport.j, initialize={'Madrid': 400, 'Barcelona': 450, 'Valencia': 150}, doc='destination demand', mutable=True)
mTransport.pD = Param(mTransport.j, initialize={'Madrid': 400, 'Barcelona': 450, 'Valencia': 150}, doc='destination demand', mutable=True)

TransportationCost = {
    ('Vigo',      'Madrid'   ): 0.06,
    ('Vigo',      'Barcelona'): 0.12,
    ('Vigo',      'Valencia' ): 0.09,
    ('Algeciras', 'Madrid'   ): 0.05,
    ('Algeciras', 'Barcelona'): 0.15,
    ('Algeciras', 'Valencia' ): 0.11,
    }

mTransport.pC = Param(mTransport.i, mTransport.j, initialize=TransportationCost, doc='per unit transportation cost')

mTransport.vX = Var  (mTransport.i, mTransport.j, bounds=(0.0,None), doc='units transported', within=NonNegativeReals)

def eCapacity(mTransport, i):
    return sum(mTransport.vX[i,j] for j in mTransport.j) <= mTransport.pA[i]
mTransport.eCapacity = Constraint(mTransport.i, rule=eCapacity, doc='maximum capacity of each origin')

def eDemand  (mTransport, j):
    return sum(mTransport.vX[i,j] for i in mTransport.i) >= mTransport.pB[j]
mTransport.eDemand   = Constraint(mTransport.j, rule=eDemand,   doc='demand supply at destination'   )

def eCost(mTransport):
    return sum(mTransport.pC[i,j]*mTransport.vX[i,j] for i,j in mTransport.i*mTransport.j)
mTransport.eCost = Objective(rule=eCost, sense=minimize, doc='transportation cost')

mTransport.write('mTransport.lp', io_options={'symbolic_solver_labels': True})

mTransport.dual = Suffix(direction=Suffix.IMPORT)

opt = appsi.solvers.Gurobi()
timer = HierarchicalTimer()
for p_val in np.linspace(0.8, 1):
    for j in mTransport.j:
        mTransport.pB[j] = float(p_val)*mTransport.pD[j]
    res = opt.solve(mTransport, timer=timer)
    assert res.termination_condition == appsi.base.TerminationCondition.optimal
    print(mTransport.eCost.expr())
print(timer)
```

Fixed-Charge Transportation Problem (FCTP)

Flows
(second stage)

Investment decisions
(first stage)

Capacity of each origin

Demand of each destination

Flow can pass only for installed connections

Complete problem

$$\min_{x_{ij},y_{ij}} \sum_{ij} (f_{ij}y_{ij} + c_{ij}x_{ij})$$
$$\sum_j x_{ij} \le a_i \quad \forall i$$
$$\sum_i x_{ij} \ge b_j \quad \forall j$$
$$x_{ij} \le M_{ij}y_{ij} \quad \forall ij$$
$$x_{ij} \ge 0, y_{ij} \in \{0,1\}$$

- Bd Relaxed Master

$$\min_{y_{ij},\theta} \sum_{ij} (f_{ij}y_{ij}) + \theta$$
$$\delta^l\theta - \theta^l \ge \sum_{ij} \pi_{ij}^l M_{ij}(y_{ij}^l - y_{ij}) \quad l = 1, \dots, k$$
$$y_{ij} \in \{0,1\}$$

O.F. of the subproblem at iteration l

Dual variables of linking constraints at iteration l

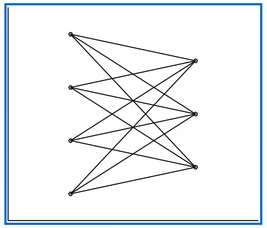
Master proposal at iteration l

- Bd Subproblem

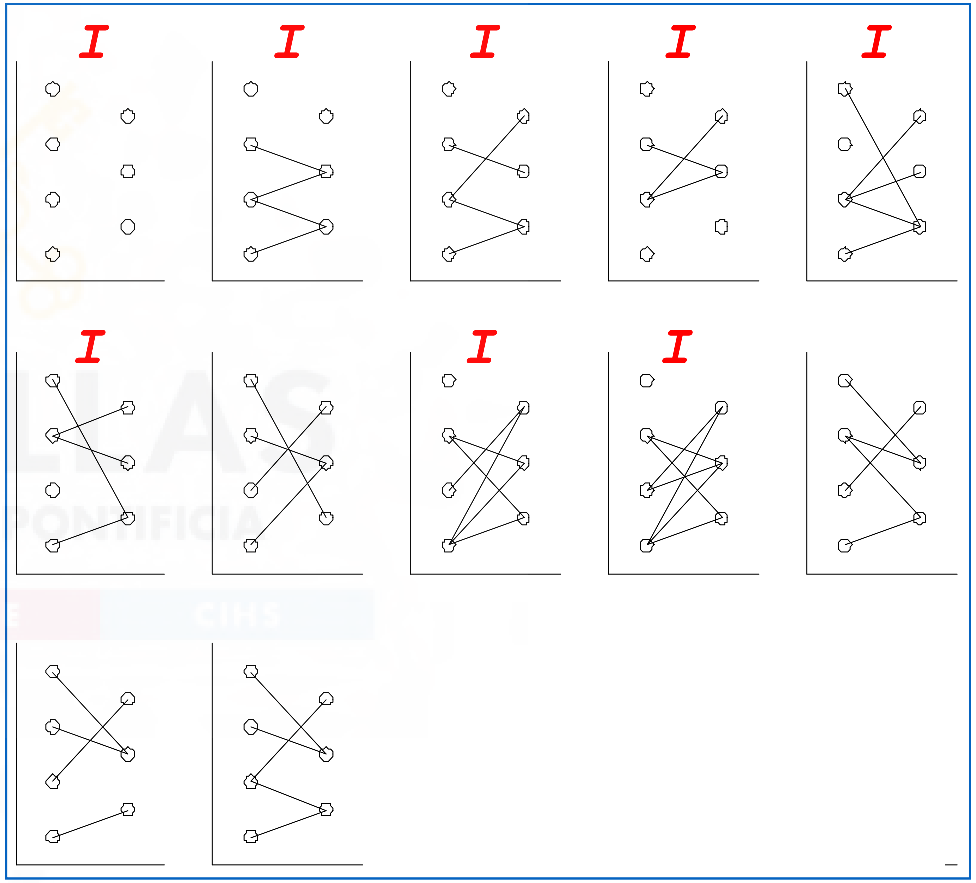
$$\min_{x_{ij}} \sum_{ij} (c_{ij}x_{ij})$$
$$\sum_j x_{ij} \le a_i \quad \forall i$$
$$\sum_i x_{ij} \ge b_j \quad \forall j$$
$$x_{ij} \le M_{ij}y_{ij}^k \quad \forall ij \quad : \pi_{ij}^k$$
$$x_{ij} \ge 0$$

Fixed-Charge Transportation Problem. Bd Solution

- Possible arcs

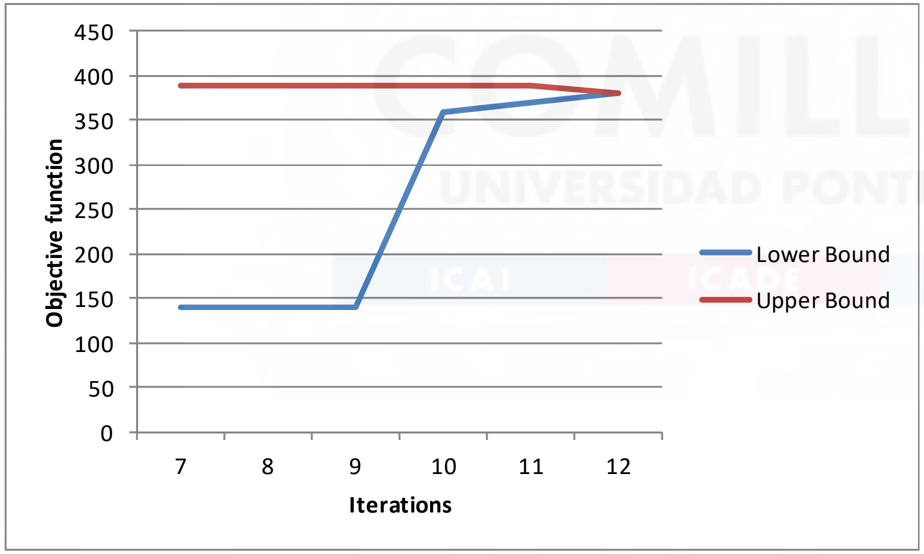


- Solutions along Benders decomposition iterations



Fixed-Charge Transportation Problem. Bd Convergence

Iteration	*Lower Bound*	*Upper Bound*
1 a 6	$-\infty$	∞
7	*140*	*390*
8	*140*	*390*
9	*140*	*390*
10	*360*	*390*
11	*370*	*390*
12	*380*	*380*



FCTP solved by Benders decomposition (i)

```
import pandas as pd
import pyomo.environ as pyo
from   pyomo.environ import ConcreteModel, Set, Param, Var, Binary, NonNegativeReals, RealSet, Constraint, Objective, minimize, Suffix, TerminationCondition
from   pyomo.opt     import SolverFactory

mFCTP      = ConcreteModel('Fixed-Charge Transportation Problem')
mMaster_Bd = ConcreteModel('Master problem')

mFCTP.i       = Set(initialize=['i1', 'i2', 'i3', 'i4'], doc='origins'      )
mFCTP.j       = Set(initialize=['j1', 'j2', 'j3'      ], doc='destinations')

mMaster_Bd.l  = Set(initialize=['it1', 'it2', 'it3', 'it4', 'it5', 'it6', 'it7', 'it8', 'it9', 'it10'], ordered=True, doc='iterations')
mMaster_Bd.ll = Set(                                                                                         doc='iterations')

mFCTP.pA      = Param(mFCTP.i, initialize={'i1': 20, 'i2': 30, 'i3': 40, 'i4': 20}, doc='origin capacity'   )
mFCTP.pB      = Param(mFCTP.j, initialize={'j1': 20, 'j2': 50, 'j3':30           }, doc='destination demand')

FixedCost = {
    ('i1', 'j1'): 10,
    ('i1', 'j2'): 20,
    ('i1', 'j3'): 30,
    ('i2', 'j1'): 20,
    ('i2', 'j2'): 30,
    ('i2', 'j3'): 40,
    ('i3', 'j1'): 30,
    ('i3', 'j2'): 40,
    ('i3', 'j3'): 50,
    ('i4', 'j1'): 40,
    ('i4', 'j2'): 50,
    ('i4', 'j3'): 60,
    }

TransportationCost = {
    ('i1', 'j1'): 1,
    ('i1', 'j2'): 2,
    ('i1', 'j3'): 3,
    ('i2', 'j1'): 3,
    ('i2', 'j2'): 2,
    ('i2', 'j3'): 1,
    ('i3', 'j1'): 2,
    ('i3', 'j2'): 3,
    ('i3', 'j3'): 4,
    ('i4', 'j1'): 4,
    ('i4', 'j2'): 3,
    ('i4', 'j3'): 2,
    }
```

FCTP solved by Benders decomposition (ii)

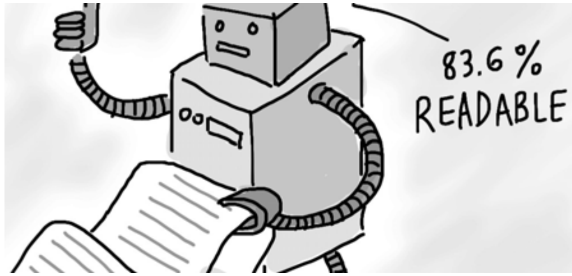
```
mFCTP.pF      = Param(mFCTP.i, mFCTP.j, initialize=FixedCost,          doc='fixed investment cost'       )
mFCTP.pC      = Param(mFCTP.i, mFCTP.j, initialize=TransportationCost, doc='per unit transportation cost')

mFCTP.vY      = Var  (mFCTP.i, mFCTP.j, bounds=(0,1), doc='units transported', within=Binary)
mMaster_Bd.vY = Var  (mFCTP.i, mFCTP.j, bounds=(0,1), doc='units transported', within=Binary)

mMaster_Bd.vTheta = Var(doc='transportation cost', within=RealSet)

mFCTP.vX      = Var  (mFCTP.i, mFCTP.j, bounds=(0.0,None), doc='units transported', within=NonNegativeReals)
mFCTP.vDNS    = Var  (         mFCTP.j, bounds=(0.0,None), doc='demand not served', within=NonNegativeReals)

def eCostMst(mMaster_Bd):
    return sum(mFCTP.pF[i,j]*mMaster_Bd.vY[i,j] for i,j in mFCTP.i*mFCTP.j) + mMaster_Bd.vTheta
mMaster_Bd.eCostMst = Objective(rule=eCostMst, sense=minimize, doc='total cost')

def eBd_Cuts(mMaster_Bd, ll):
    return mMaster_Bd.vTheta - Z2_L[ll] >= - sum(PI_L[ll,i,j] * min(mFCTP.pA[i],mFCTP.pB[j]) * (Y_L[ll,i,j] - mMaster_Bd.vY[i,j]) for i,j in mFCTP.i*mFCTP.j)

def eCostSubp(mFCTP):
    return sum(mFCTP.pC[i,j]*mFCTP.vX[i,j] for i,j in mFCTP.i*mFCTP.j) + sum(mFCTP.vDNS[j]*1000 for j in mFCTP.j)
mFCTP.eCostSubp = Objective(rule=eCostSubp, sense=minimize, doc='transportation cost')

def eCapacity(mFCTP, i):
    return sum(mFCTP.vX[i,j] for j in mFCTP.j) <= mFCTP.pA[i]
mFCTP.eCapacity  = Constraint(mFCTP.i,        rule=eCapacity,  doc='maximum capacity of each origin')

def eDemand  (mFCTP, j):
    return sum(mFCTP.vX[i,j] for i in mFCTP.i) + mFCTP.vDNS[j] >= mFCTP.pB[j]
mFCTP.eDemand    = Constraint(        mFCTP.j, rule=eDemand,    doc='demand supply at destination'    )

def eFlowLimit(mFCTP, i, j):
    return mFCTP.vX[i,j] <= min(mFCTP.pA[i],mFCTP.pB[j])*mFCTP.vY[i,j]
mFCTP.eFlowLimit = Constraint(mFCTP.i*mFCTP.j, rule=eFlowLimit, doc='arc flow limit'                  )

Solver = SolverFactory('gurobi')
Solver.options['LogFile'] = 'mFCTP.log'
mFCTP.dual = Suffix(direction=Suffix.IMPORT)

# initialization
Z_Lower = float('-inf')
Z_Upper = float(' inf')
BdTol   = 1e-6

Y_L   = pd.Series([0 ]*len(mMaster_Bd.l*mFCTP.i*mFCTP.j), index=pd.MultiIndex.from_tuples(mMaster_Bd.l*mFCTP.i*mFCTP.j))
PI_L  = pd.Series([0.]*len(mMaster_Bd.l*mFCTP.i*mFCTP.j), index=pd.MultiIndex.from_tuples(mMaster_Bd.l*mFCTP.i*mFCTP.j))
Z2_L  = pd.Series([0.]*len(mMaster_Bd.l                ), index=mMaster_Bd.l)
Delta = pd.Series([0 ]*len(mMaster_Bd.l                ), index=mMaster_Bd.l)
```

FCTP solved by Benders decomposition (iii)

```python
# Benders algorithm
mMaster_Bd.vTheta.fix(0)
for l in mMaster_Bd.l:
    if abs(1-Z_Lower/Z_Upper) > BdTol or l == mMaster_Bd.l.first():

        # solving master problem
        SolverResultsMst = Solver.solve(mMaster_Bd)
        Z1               = mMaster_Bd.eCostMst.expr()

        for i,j in mFCTP.i*mFCTP.j:
            # storing the master solution
            Y_L[l,i,j] = mMaster_Bd.vY[i,j]()
            # fix investment decision for the subproblem
            mFCTP.vY[i,j].fix(Y_L[l,i,j])

        # solving subproblem
        SolverResultsSbp    = Solver.solve(mFCTP)
        Z2                  = mFCTP.eCostSubp.expr()
        Z2_L[l]             = Z2

        # storing parameters to build a new Benders cut
        if SolverResultsSbp.solver.termination_condition == TerminationCondition.infeasible:
            # the problem has to be feasible because I am not able to obtain the sum of infeasibilities of the phase I
            Delta[l] =  0
        else:
            # updating lower and upper bound
            Z_Lower =               Z1
            Z_Upper = min(Z_Upper, Z1 - mMaster_Bd.vTheta() + Z2)
            print('Iteration ', l, ' Z_Lower ... ', Z_Lower)
            print('Iteration ', l, ' Z_Upper ... ', Z_Upper)

            mMaster_Bd.vTheta.free()

            Delta[l] =  1

        for i,j in mFCTP.i*mFCTP.j:
            PI_L[l,i,j] = mFCTP.dual[mFCTP.eFlowLimit[i,j]]

        mMaster_Bd.vY.unfix()

        # add one cut
        mMaster_Bd.ll.add(l)
        ll = mMaster_Bd.ll
        mMaster_Bd.eBd_Cuts = Constraint(mMaster_Bd.ll, rule=eBd_Cuts, doc='Benders cuts')

mFCTP.eCostSubp.deactivate()
mFCTP.vY.unfix()

def eCost(mFCTP):
    return sum(mFCTP.pF[i,j]*mFCTP.vY[i,j] for i,j in mFCTP.i*mFCTP.j) + sum(mFCTP.pC[i,j]*mFCTP.vX[i,j] for i,j in mFCTP.i*mFCTP.j) + sum(mFCTP.vDNS[j]*1000 for j in mFCTP.j)
mFCTP.eCost = Objective(rule=eCost, sense=minimize, doc='total cost')

SolverResults = Solver.solve(mFCTP, tee=True)
SolverResults.write()
```

3

Power Systems Models



Simplicity and transparency

- Replicating the GAMS structure and elegance in Python/Pyomo
- Separation between
  - Dictionaries of sets
  - Parameters
  - Variables
  - Equations
  - Solve
  - Output results
- Input data and output results in text format (csv)

openSDUC

https://opensduc.readthedocs.io/en/latest/index.html
https://github.com/IIT-EnergySystemModels/openSDUC

- Open Stochastic Daily Unit Commitment of Thermal and ESS Units
  - Web page created with `sphinx`

The openSDUC code is provided under the [GNU General Public License](#):
•the code can't become part of a closed-source commercial software product
•any future changes and improvements to the code remain free and open

Disclaimer:
This model is a work in progress and will be updated accordingly.

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```
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#                        Version 3, 29 June 2007
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# authors of previous versions.
#
#   Some devices are designed to deny users access to install or run
# modified versions of the software inside them, although the manufacturer
# can do so.  This is fundamentally incompatible with the aim of
# protecting users' freedom to change the software.  The systematic
# pattern of such abuse occurs in the area of products for individuals to
# use, which is precisely where it is most unacceptable.  Therefore, we
# have designed this version of the GPL to prohibit the practice for those
# products.  If such problems arise substantially in other domains, we
# stand ready to extend this provision to those domains in future versions
# of the GPL, as needed to protect the freedom of users.
#
#   Finally, every program is threatened constantly by software patents.
# States should not allow patents to restrict development and use of
# software on general-purpose computers, but in those that do, we wish to
# avoid the special danger that patents applied to a free program could
# make it effectively proprietary.  To prevent this, the GPL assures that
# patents cannot be used to render the program non-free.
```

SDUC (i)

```
# Open Stochastic Daily Unit Commitment of Thermal and Hydro Units (openSDUC) - Version 1.3.24 - January 24, 2021
# simplicity and transparency in power systems planning

# Developed by

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#    with the very valuable collaboration from David Dominguez (david.dominguez@comillas.edu) and Alejandro Rodriguez (argallego@comillas.edu), our local Python gurus

#%% Libraries
import pandas        as pd
import time          # count clock time
import psutil        # access the number of CPUs
import pyomo.environ as pyo
from   pyomo.environ import Set, Var, Binary, NonNegativeReals, RealSet, Constraint, ConcreteModel, Objective, minimize, Suffix, DataPortal
from   pyomo.opt     import SolverFactory

import matplotlib.pyplot as plt

StartTime = time.time()

CaseName   = '16g'                           # To select the case
SolverName = 'gurobi'

#%% model declaration
mSDUC = ConcreteModel('Open Stochastic Daily Unit Commitment of Thermal and Hydro Units (openSDUC) - Version 1.3.24 - January 24, 2021')
```

SDUC (ii)

```
#%% reading the sets
dictSets = DataPortal()
dictSets.load(filename='oUC_Dict_Scenario_'  +CaseName+'.csv', set='sc', format='set')
dictSets.load(filename='oUC_Dict_LoadLevel_' +CaseName+'.csv', set='n' , format='set')
dictSets.load(filename='oUC_Dict_Generation_'+CaseName+'.csv', set='g' , format='set')
dictSets.load(filename='oUC_Dict_Storage_'   +CaseName+'.csv', set='st', format='set')
dictSets.load(filename='oUC_Dict_Technology_'+CaseName+'.csv', set='gt', format='set')
dictSets.load(filename='oUC_Dict_Company_'   +CaseName+'.csv', set='co', format='set')

mSDUC.sc = Set(initialize=dictSets['sc'], ordered=True,  doc='scenarios'   )
mSDUC.nn = Set(initialize=dictSets['n' ], ordered=True,  doc='load levels' )
mSDUC.gg = Set(initialize=dictSets['g' ], ordered=False, doc='units'       )
mSDUC.gt = Set(initialize=dictSets['gt'], ordered=False, doc='technologies')
mSDUC.co = Set(initialize=dictSets['co'], ordered=False, doc='companies'   )
mSDUC.st = Set(initialize=dictSets['st'], ordered=False, doc='ESS types'   )

#%% reading data from CSV files
dfParameter          = pd.read_csv('oUC_Data_Parameter_'          +CaseName+'.csv', index_col=[0  ])
dfDuration           = pd.read_csv('oUC_Data_Duration_'           +CaseName+'.csv', index_col=[0  ])
dfScenario           = pd.read_csv('oUC_Data_Scenario_'           +CaseName+'.csv', index_col=[0  ])
dfDemand             = pd.read_csv('oUC_Data_Demand_'             +CaseName+'.csv', index_col=[0,1])
dfOperatingReserve   = pd.read_csv('oUC_Data_OperatingReserve_'   +CaseName+'.csv', index_col=[0,1])
dfGeneration         = pd.read_csv('oUC_Data_Generation_'         +CaseName+'.csv', index_col=[0  ])
dfVariableMaxPower   = pd.read_csv('oUC_Data_VariableGeneration_' +CaseName+'.csv', index_col=[0,1])
dfVariableMinStorage = pd.read_csv('oUC_Data_MinimumStorage_'     +CaseName+'.csv', index_col=[0,1])
dfVariableMaxStorage = pd.read_csv('oUC_Data_MaximumStorage_'     +CaseName+'.csv', index_col=[0,1])
dfEnergyInflows      = pd.read_csv('oUC_Data_EnergyInflows_'      +CaseName+'.csv', index_col=[0,1])

# substitute NaN by 0
dfParameter.fillna          (0.0, inplace=True)
dfDuration.fillna           (0.0, inplace=True)
dfScenario.fillna           (0.0, inplace=True)
dfDemand.fillna             (0.0, inplace=True)
dfOperatingReserve.fillna   (0.0, inplace=True)
dfGeneration.fillna         (0.0, inplace=True)
dfVariableMaxPower.fillna   (0.0, inplace=True)
dfVariableMinStorage.fillna(0.0, inplace=True)
dfVariableMaxStorage.fillna(0.0, inplace=True)
dfEnergyInflows.fillna      (0.0, inplace=True)
```

SDUC (iii)

```
#%% general parameters
pENSCost            = dfParameter['ENSCost' ][0] * 1e-3                                                                                 # cost of energy not served       [MEUR/GWh]
pCO2Cost            = dfParameter['CO2Cost' ][0]                                                                                        # cost of CO2 emission            [EUR/CO2
ton]
pTimeStep           = dfParameter['TimeStep'][0].astype('int')                                                                          # duration of the unit time step  [h]

pDuration           = dfDuration          ['Duration'    ] * pTimeStep                                                                  # duration of load levels         [h]
pScenProb           = dfScenario          ['Probability' ]                                                                              # probabilities of scenarios      [p.u.]
pDemand             = dfDemand            ['Demand'      ] * 1e-3                                                                       # demand                          [GW]
pOperReserveUp      = dfOperatingReserve  ['Up'          ] * 1e-3                                                                       # operating reserve up            [GW]
pOperReserveDw      = dfOperatingReserve  ['Down'        ] * 1e-3                                                                       # operating reserve down          [GW]
pVariableMaxPower   = dfVariableMaxPower  [list(mSDUC.gg)] * 1e-3                                                                       # dynamic variable maximum power  [GW]
pVariableMinStorage = dfVariableMinStorage[list(mSDUC.gg)]                                                                              # dynamic variable minimum storage [GWh]
pVariableMaxStorage = dfVariableMaxStorage[list(mSDUC.gg)]                                                                              # dynamic variable maximum storage [GWh]
pEnergyInflows      = dfEnergyInflows     [list(mSDUC.gg)] * 1e-3                                                                       # dynamic energy inflows          [GW]

# compute the demand as the mean over the time step load levels and assign it to active load levels. Idem for operating reserve, variable max power, variable min and max
storage capacity and inflows
pDemand             = pDemand.rolling            (pTimeStep).mean()
pOperReserveUp      = pOperReserveUp.rolling     (pTimeStep).mean()
pOperReserveDw      = pOperReserveDw.rolling     (pTimeStep).mean()
pVariableMaxPower   = pVariableMaxPower.rolling  (pTimeStep).mean()
pVariableMinStorage = pVariableMinStorage.rolling(pTimeStep).mean()
pVariableMaxStorage = pVariableMaxStorage.rolling(pTimeStep).mean()
pEnergyInflows      = pEnergyInflows.rolling     (pTimeStep).mean()

pDemand.fillna             (0.0, inplace=True)
pOperReserveUp.fillna      (0.0, inplace=True)
pOperReserveDw.fillna      (0.0, inplace=True)
pVariableMaxPower.fillna   (0.0, inplace=True)
pVariableMinStorage.fillna(0.0, inplace=True)
pVariableMaxStorage.fillna(0.0, inplace=True)
pEnergyInflows.fillna      (0.0, inplace=True)
```

SDUC (iv)

```
if pTimeStep > 1:
    # assign duration 0 to load levels not being considered, active load levels are at the end of every pTimeStep
    for i in range(pTimeStep-2,-1,-1):
        pDuration[range(i,len(mSDUC.nn),pTimeStep)] = 0
    # drop levels with duration 0
    pDemand            = pDemand.loc            [pDemand.index            [range(pTimeStep-1,len(mSDUC.sc*mSDUC.nn),pTimeStep)]]
    pOperReserveUp     = pOperReserveUp.loc     [pOperReserveUp.index     [range(pTimeStep-1,len(mSDUC.sc*mSDUC.nn),pTimeStep)]]
    pOperReserveDw     = pOperReserveDw.loc     [pOperReserveDw.index     [range(pTimeStep-1,len(mSDUC.sc*mSDUC.nn),pTimeStep)]]
    pVariableMaxPower  = pVariableMaxPower.loc  [pVariableMaxPower.index  [range(pTimeStep-1,len(mSDUC.sc*mSDUC.nn),pTimeStep)]]
    pVariableMinStorage = pVariableMinStorage.loc[pVariableMinStorage.index[range(pTimeStep-1,len(mSDUC.sc*mSDUC.nn),pTimeStep)]]
    pVariableMaxStorage = pVariableMaxStorage.loc[pVariableMaxStorage.index[range(pTimeStep-1,len(mSDUC.sc*mSDUC.nn),pTimeStep)]]
    pEnergyInflows     = pEnergyInflows.loc     [pEnergyInflows.index     [range(pTimeStep-1,len(mSDUC.sc*mSDUC.nn),pTimeStep)]]

#%% generation parameters
pGenToTechnology  = dfGeneration['Technology'     ]                                                        # generator association to technology
pGenToCompany     = dfGeneration['Company'        ]                                                        # generator association to company
pRatedMinPower    = dfGeneration['MinimumPower'   ] * 1e-3                                                 # rated minimum power             [GW]
pRatedMaxPower    = dfGeneration['MaximumPower'   ] * 1e-3                                                 # rated maximum power             [GW]
pLinearVarCost    = dfGeneration['LinearTerm'     ] * 1e-3 * dfGeneration['FuelCost'] + dfGeneration['OMVariableCost'] * 1e-3  # linear   term variable cost
[MEUR/GWh]
pConstantVarCost  = dfGeneration['ConstantTerm'   ] * 1e-6 * dfGeneration['FuelCost']                      # constant term variable cost     [MEUR/h]
pStartUpCost      = dfGeneration['StartUpCost'    ]                                                        # startup  cost                   [MEUR]
pShutDownCost     = dfGeneration['ShutDownCost'   ]                                                        # shutdown cost                   [MEUR]
pRampUp           = dfGeneration['RampUp'         ] * 1e-3                                                 # ramp up   rate                  [GW/h]
pRampDw           = dfGeneration['RampDown'       ] * 1e-3                                                 # ramp down rate                  [GW/h]
pCO2EmissionRate  = dfGeneration['CO2EmissionRate'] * 1e-3                                                 # emission  rate                  [t
CO2/MWh]
pUpTime           = dfGeneration['UpTime'         ]                                                        # minimum up   time               [h]
pDwTime           = dfGeneration['DownTime'       ]                                                        # minimum down time               [h]
pMaxCharge        = dfGeneration['MaximumCharge'  ] * 1e-3                                                 # maximum ESS charge              [GW]
pInitialInventory = dfGeneration['InitialStorage' ]                                                        # initial ESS storage             [GWh]
pRatedMinStorage  = dfGeneration['MinimumStorage' ]                                                        # minimum ESS storage             [GWh]
pRatedMaxStorage  = dfGeneration['MaximumStorage' ]                                                        # maximum ESS storage             [GWh]
pEfficiency       = dfGeneration['Efficiency'     ]                                                        #         ESS efficiency          [p.u.]
pStorageType      = dfGeneration['StorageType'    ]                                                        #         ESS type

ReadingDataTime = time.time() - StartTime
StartTime       = time.time()
print('Reading    input data                 ... ', round(ReadingDataTime), 's')
```

SDUC (v)

```
#%% defining subsets: active load levels (n), thermal units (t), ESS units (es), all the lines (la), candidate lines (lc) and lines with losses (ll)
mSDUC.n  = Set(initialize=mSDUC.nn, ordered=True , doc='load levels'      , filter=lambda mSDUC,nn: nn in mSDUC.nn and pDuration     [nn] >  0  )
mSDUC.n2 = Set(initialize=mSDUC.nn, ordered=True , doc='load levels'      , filter=lambda mSDUC,nn: nn in mSDUC.nn and pDuration     [nn] >  0  )
mSDUC.g  = Set(initialize=mSDUC.gg, ordered=False, doc='generating units', filter=lambda mSDUC,gg: gg in mSDUC.gg and pRatedMaxPower[gg] >  0.0)
mSDUC.t  = Set(initialize=mSDUC.g , ordered=False, doc='thermal    units', filter=lambda mSDUC,g : g  in mSDUC.g  and pLinearVarCost [g] >  0.0)
mSDUC.r  = Set(initialize=mSDUC.g , ordered=False, doc='RES        units', filter=lambda mSDUC,g : g  in mSDUC.g  and pLinearVarCost [g] == 0.0 and pRatedMaxStorage[g] == 0.0)
mSDUC.es = Set(initialize=mSDUC.g , ordered=False, doc='ESS        units', filter=lambda mSDUC,g : g  in mSDUC.g  and                                pRatedMaxStorage[g] >  0.0)

# non-RES units
mSDUC.nr = mSDUC.g - mSDUC.r

# variable minimum and maximum power
pVariableMaxPower = pVariableMaxPower.replace(0.0, float('nan'))[mSDUC.g]
pMinPower         = pd.DataFrame([pRatedMinPower]*len(pVariableMaxPower.index), index=pd.MultiIndex.from_tuples(pVariableMaxPower.index), columns=pRatedMinPower.index)[mSDUC.g]
pMaxPower         = pd.DataFrame([pRatedMaxPower]*len(pVariableMaxPower.index), index=pd.MultiIndex.from_tuples(pVariableMaxPower.index), columns=pRatedMaxPower.index)[mSDUC.g]
pMaxPower         = pVariableMaxPower.where(pVariableMaxPower < pMaxPower, other=pMaxPower)
pMaxPower2ndBlock = pMaxPower - pMinPower

# variable minimum and maximum storage capacity
pVariableMinStorage = pVariableMinStorage.replace(0.0, float('nan'))[mSDUC.g]
pVariableMaxStorage = pVariableMaxStorage.replace(0.0, float('nan'))[mSDUC.g]
pMinStorage         = pd.DataFrame([pRatedMinStorage]*len(pVariableMinStorage.index), index=pd.MultiIndex.from_tuples(pVariableMinStorage.index), columns=pRatedMinStorage.index)[mSDUC.g]
pMaxStorage         = pd.DataFrame([pRatedMaxStorage]*len(pVariableMaxStorage.index), index=pd.MultiIndex.from_tuples(pVariableMaxStorage.index), columns=pRatedMaxStorage.index)[mSDUC.g]
pMinStorage         = pVariableMinStorage.where(pVariableMinStorage > pMinStorage, other=pMinStorage)
pMaxStorage         = pVariableMaxStorage.where(pVariableMaxStorage < pMaxStorage, other=pMaxStorage)
```

SDUC (vi)

```
# values < 1e-6 times the maximum system demand are converted to 0
pEpsilon = pDemand.max()*1e-6
# these parameters are in GW
pDemand           [pDemand           < pEpsilon] = 0.0
pOperReserveUp    [pOperReserveUp    < pEpsilon] = 0.0
pOperReserveDw    [pOperReserveDw    < pEpsilon] = 0.0
pMinPower         [pMinPower         < pEpsilon] = 0.0
pMaxPower         [pMaxPower         < pEpsilon] = 0.0
pMaxPower2ndBlock[pMaxPower2ndBlock < pEpsilon] = 0.0
pMaxCharge        [pMaxCharge        < pEpsilon] = 0.0
pEnergyInflows    [pEnergyInflows    < pEpsilon/pTimeStep] = 0.0
# these parameters are in GWh
pMinStorage       [pMinStorage       < pEpsilon] = 0.0
pMaxStorage       [pMaxStorage       < pEpsilon] = 0.0
# this option avoids a warning in the following assignments
pd.options.mode.chained_assignment = None

# minimum up and down time converted to an integer number of time steps
pUpTime = round(pUpTime/pTimeStep).astype('int')
pDwTime = round(pDwTime/pTimeStep).astype('int')

# thermal and variable units ordered by increasing variable cost
mSDUC.go = pLinearVarCost.sort_values().index

# determine the initial committed units and their output
pInitialOutput = pd.Series([0.0]*len(mSDUC.g), dfGeneration.index)
pInitialUC     = pd.Series([0.0]*len(mSDUC.g), dfGeneration.index)
pSystemOutput  = 0.0
for go in mSDUC.go:
    n1 = next(iter(mSDUC.sc*mSDUC.n))
    if pSystemOutput < pDemand[n1]:
        if go in mSDUC.r:
            pInitialOutput[go] = pMaxPower[go][n1]
        else:
            pInitialOutput[go] = pMinPower[go][n1]
        pInitialUC     [go] = 1
        pSystemOutput      += pInitialOutput[go]
```

SDUC (vii)

```
#%% variables
mSDUC.vTotalVCost     = Var(                             within=NonNegativeReals,                                                                              doc='total system variable cost [MEUR]')
mSDUC.vTotalECost     = Var(                             within=NonNegativeReals,                                                                              doc='total system emission cost [MEUR]')
mSDUC.vTotalOutput    = Var(mSDUC.sc, mSDUC.n, mSDUC.g , within=NonNegativeReals, bounds=lambda mSDUC,sc,n,g :(0.0,pMaxPower         [g ][sc,n]),       doc='total output of the unit     [GW]')
mSDUC.vOutput2ndBlock = Var(mSDUC.sc, mSDUC.n, mSDUC.nr, within=NonNegativeReals, bounds=lambda mSDUC,sc,n,nr:(0.0,pMaxPower2ndBlock  [nr][sc,n]),       doc='second block of the unit     [GW]')
mSDUC.vReserveUp      = Var(mSDUC.sc, mSDUC.n, mSDUC.nr, within=NonNegativeReals, bounds=lambda mSDUC,sc,n,nr:(0.0,pMaxPower2ndBlock  [nr][sc,n]),       doc='operating reserve up         [GW]')
mSDUC.vReserveDown    = Var(mSDUC.sc, mSDUC.n, mSDUC.nr, within=NonNegativeReals, bounds=lambda mSDUC,sc,n,nr:(0.0,pMaxPower2ndBlock  [nr][sc,n]),       doc='operating reserve down       [GW]')
mSDUC.vESSInventory   = Var(mSDUC.sc, mSDUC.n, mSDUC.es, within=NonNegativeReals, bounds=lambda mSDUC,sc,n,es:(pMinStorage[es][sc,n],pMaxStorage[es][sc,n]), doc='ESS inventory               [GWh]')
mSDUC.vESSSpillage    = Var(mSDUC.sc, mSDUC.n, mSDUC.es, within=NonNegativeReals,                                                                        doc='ESS spillage                [GWh]')
mSDUC.vESSCharge      = Var(mSDUC.sc, mSDUC.n, mSDUC.es, within=NonNegativeReals, bounds=lambda mSDUC,sc,n,es:(0.0,pMaxCharge         [es]      ),       doc='ESS     charge power         [GW]')
mSDUC.vENS            = Var(mSDUC.sc, mSDUC.n,           within=NonNegativeReals, bounds=lambda mSDUC,sc,n   :(0.0,pDemand                [sc,n]),       doc='energy not served in node    [GW]')

mSDUC.vCommitment     = Var(          mSDUC.n, mSDUC.nr, within=Binary,                                                                                doc='commitment of the unit      {0,1}')
mSDUC.vStartUp        = Var(          mSDUC.n, mSDUC.nr, within=Binary,                                                                                doc='StartUp    of the unit      {0,1}')
mSDUC.vShutDown       = Var(          mSDUC.n, mSDUC.nr, within=Binary,                                                                                doc='ShutDown   of the unit      {0,1}')

# fixing the ESS inventory at the last load level at the end of the time scope
for sc,es in mSDUC.sc*mSDUC.es:
    mSDUC.vESSInventory[sc,mSDUC.n.last(),es].fix(pInitialInventory[es])

#%% definition of the time-steps leap to observe the stored energy at ESS
pCycleTimeStep = pUpTime*0
for es in mSDUC.es:
    if  pStorageType[es] == 'Daily'  :
        pCycleTimeStep[es] = int(  24/pTimeStep)
    if  pStorageType[es] == 'Weekly' :
        pCycleTimeStep[es] = int( 168/pTimeStep)
    if  pStorageType[es] == 'Monthly':
        pCycleTimeStep[es] = int( 672/pTimeStep)
    if  pStorageType[es] == 'Yearly' :
        pCycleTimeStep[es] = int(8736/pTimeStep)
```

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SDUC (viii)

```
# fixing the ESS inventory at the end of the following pCycleTimeStep (weekly, yearly), i.e., for daily ESS is fixed at the end of the week, for weekly/monthly ESS is fixed at the end of the year
for sc,n,es in mSDUC.sc*mSDUC.n*mSDUC.es:
     if pStorageType[es] == 'Daily'   and mSDUC.n.ord(n) % ( 168/pTimeStep) == 0:
         mSDUC.vESSInventory[sc,n,es].fix(pInitialInventory[es])
     if pStorageType[es] == 'Weekly'  and mSDUC.n.ord(n) % (8736/pTimeStep) == 0:
         mSDUC.vESSInventory[sc,n,es].fix(pInitialInventory[es])
     if pStorageType[es] == 'Monthly' and mSDUC.n.ord(n) % (8736/pTimeStep) == 0:
         mSDUC.vESSInventory[sc,n,es].fix(pInitialInventory[es])

SettingUpDataTime = time.time() - StartTime
StartTime         = time.time()
print('Setting up input data                 ... ', round(SettingUpDataTime), 's')

def eTotalVCost(mSDUC):
    return mSDUC.vTotalVCost == (sum(pScenProb[sc] * pDuration[n] * pENSCost             * mSDUC.vENS        [sc,n   ] for sc,n    in mSDUC.sc*mSDUC.n         ) +
                                 sum(pScenProb[sc] * pDuration[n] * pLinearVarCost  [nr] * mSDUC.vTotalOutput[sc,n,nr] for sc,n,nr in mSDUC.sc*mSDUC.n*mSDUC.nr) +
                                 sum(                pDuration[n] * pConstantVarCost[nr] * mSDUC.vCommitment [   n,nr]                                           +
                                                                    pStartUpCost    [nr] * mSDUC.vStartUp    [   n,nr]                                           +
                                                                    pShutDownCost   [nr] * mSDUC.vShutDown   [   n,nr] for    n,nr in          mSDUC.n*mSDUC.nr) )
mSDUC.eTotalVCost = Constraint(rule=eTotalVCost, doc='total system variable cost [MEUR]')

def eTotalECost(mSDUC):
    return mSDUC.vTotalECost == sum(pScenProb[sc] * pCO2Cost * pCO2EmissionRate[nr] * mSDUC.vTotalOutput[sc,n,nr] for sc,n,nr in mSDUC.sc*mSDUC.n*mSDUC.nr)
mSDUC.eTotalECost = Constraint(rule=eTotalECost, doc='total system emission cost [MEUR]')

def eTotalTCost(mSDUC):
    return mSDUC.vTotalVCost + mSDUC.vTotalECost
mSDUC.eTotalTCost = Objective(rule=eTotalTCost, sense=minimize, doc='total system cost [MEUR]')

GeneratingOFTime = time.time() - StartTime
StartTime        = time.time()
print('Generating objective function         ... ', round(GeneratingOFTime), 's')
```

SDUC (ix)

```
#%% constraints
def eOperReserveUp(mSDUC,sc,n):
    if pOperReserveUp[sc,n]:
        return sum(mSDUC.vReserveUp  [sc,n,nr] for nr in mSDUC.nr) >= pOperReserveUp[sc,n]
    else:
        return Constraint.Skip
mSDUC.eOperReserveUp = Constraint(mSDUC.sc, mSDUC.n, rule=eOperReserveUp, doc='up   operating reserve [GW]')

def eOperReserveDw(mSDUC,sc,n):
    if pOperReserveDw[sc,n]:
        return sum(mSDUC.vReserveDown[sc,n,nr] for nr in mSDUC.nr) >= pOperReserveDw[sc,n]
    else:
        return Constraint.Skip
mSDUC.eOperReserveDw = Constraint(mSDUC.sc, mSDUC.n, rule=eOperReserveDw, doc='down operating reserve [GW]')

def eBalance(mSDUC,sc,n):
    return sum(mSDUC.vTotalOutput[sc,n,g] for g in mSDUC.g) - sum(mSDUC.vESSCharge[sc,n,es] for es in mSDUC.es) + mSDUC.vENS[sc,n] == pDemand[sc,n]
mSDUC.eBalance = Constraint(mSDUC.sc, mSDUC.n, rule=eBalance, doc='load generation balance [GW]')

def eESSInventory(mSDUC,sc,n,es):
    if   mSDUC.n.ord(n) == pCycleTimeStep[es]:
        return pInitialInventory[es]                                        + sum(pDuration[n2]*(pEnergyInflows[es][sc,n2] - mSDUC.vTotalOutput[sc,n2,es] + pEfficiency[es]*mSDUC.vESSCharge[sc,n2,es]) for n2 in list(mSDUC.n2)[mSDUC.n.ord(n)-
pCycleTimeStep[es]:mSDUC.n.ord(n)]) == mSDUC.vESSInventory[sc,n,es] + mSDUC.vESSSpillage[sc,n,es]
    elif mSDUC.n.ord(n) >  pCycleTimeStep[es] and mSDUC.n.ord(n) % pCycleTimeStep[es] == 0:
        return mSDUC.vESSInventory[sc,mSDUC.n.prev(n,pCycleTimeStep[es]),es] + sum(pDuration[n2]*(pEnergyInflows[es][sc,n2] - mSDUC.vTotalOutput[sc,n2,es] + pEfficiency[es]*mSDUC.vESSCharge[sc,n2,es]) for n2 in list(mSDUC.n2)[mSDUC.n.ord(n)-
pCycleTimeStep[es]:mSDUC.n.ord(n)]) == mSDUC.vESSInventory[sc,n,es] + mSDUC.vESSSpillage[sc,n,es]
    else:
        return Constraint.Skip
mSDUC.eESSInventory = Constraint(mSDUC.sc, mSDUC.n, mSDUC.es, rule=eESSInventory, doc='ESS inventory balance [GWh]')

GeneratingRBITime = time.time() - StartTime
StartTime         = time.time()
print('Generating reserves/balance/inventory ... ', round(GeneratingRBITime), 's')
```

SDUC (x)

```python
#%%
def eMaxOutput2ndBlock(mSDUC,sc,n,nr):
    if   pOperReserveUp[sc,n] and pMaxPower2ndBlock[nr][sc,n]:
        return (mSDUC.vOutput2ndBlock[sc,n,nr] + mSDUC.vReserveUp  [sc,n,nr]) / pMaxPower2ndBlock[nr][sc,n] <= mSDUC.vCommitment[n,nr]
    else:
        return Constraint.Skip
mSDUC.eMaxOutput2ndBlock = Constraint(mSDUC.sc, mSDUC.n, mSDUC.nr, rule=eMaxOutput2ndBlock, doc='max output of the second block of a committed unit [p.u.]')

def eMinOutput2ndBlock(mSDUC,sc,n,nr):
    if   pOperReserveDw[sc,n] and pMaxPower2ndBlock[nr][sc,n]:
        return (mSDUC.vOutput2ndBlock[sc,n,nr] + mSDUC.vReserveDown[sc,n,nr]) / pMaxPower2ndBlock[nr][sc,n] >= 0.0
    else:
        return Constraint.Skip
mSDUC.eMinOutput2ndBlock = Constraint(mSDUC.sc, mSDUC.n, mSDUC.nr, rule=eMinOutput2ndBlock, doc='min output of the second block of a committed unit [p.u.]')

def eTotalOutput(mSDUC,sc,n,nr):
    if pMinPower[nr][sc,n] == 0.0:
        return mSDUC.vTotalOutput[sc,n,nr]                        ==                            mSDUC.vOutput2ndBlock[sc,n,nr]
    else:
        return mSDUC.vTotalOutput[sc,n,nr] / pMinPower[nr][sc,n] == mSDUC.vCommitment[n,nr] + mSDUC.vOutput2ndBlock[sc,n,nr] / pMinPower[nr][sc,n]

mSDUC.eTotalOutput = Constraint(mSDUC.sc, mSDUC.n, mSDUC.nr, rule=eTotalOutput, doc='total output of a unit [GW]')

def eUCStrShut(mSDUC,n,nr):
    if n == mSDUC.n.first():
        return mSDUC.vCommitment[n,nr] - pInitialUC[nr]                        == mSDUC.vStartUp[n,nr] - mSDUC.vShutDown[n,nr]
    else:
        return mSDUC.vCommitment[n,nr] - mSDUC.vCommitment[mSDUC.n.prev(n),nr] == mSDUC.vStartUp[n,nr] - mSDUC.vShutDown[n,nr]
mSDUC.eUCStrShut = Constraint(mSDUC.n, mSDUC.nr, rule=eUCStrShut, doc='relation among commitment startup and shutdown')

GeneratingGenConsTime = time.time() - StartTime
StartTime             = time.time()
print('Generating generation constraints     ... ', round(GeneratingGenConsTime), 's')

#%%
def eRampUp(mSDUC,sc,n,t):
    if   pRampUp[t] and pRampUp[t] < pMaxPower2ndBlock[t][sc,n] and n == mSDUC.n.first():
        return (mSDUC.vOutput2ndBlock[sc,n,t] - max(pInitialOutput[t]-pMinPower[t][sc,n],0.0) + mSDUC.vReserveUp  [sc,n,t]) / pDuration[n] / pRampUp[t] <= mSDUC.vCommitment[n,t] - mSDUC.vStartUp[n,t]
    elif pRampUp[t] and pRampUp[t] < pMaxPower2ndBlock[t][sc,n]:
        return (mSDUC.vOutput2ndBlock[sc,n,t] - mSDUC.vOutput2ndBlock[sc,mSDUC.n.prev(n),t]   + mSDUC.vReserveUp  [sc,n,t]) / pDuration[n] / pRampUp[t] <= mSDUC.vCommitment[n,t] - mSDUC.vStartUp[n,t]
    else:
        return Constraint.Skip
mSDUC.eRampUp = Constraint(mSDUC.sc, mSDUC.n, mSDUC.t, rule=eRampUp, doc='maximum ramp up   [p.u.]')

def eRampDw(mSDUC,sc,n,t):
    if   pRampDw[t] and pRampDw[t] < pMaxPower2ndBlock[t][sc,n] and n == mSDUC.n.first():
        return (mSDUC.vOutput2ndBlock[sc,n,t] - max(pInitialOutput[t]-pMinPower[t][sc,n],0.0) - mSDUC.vReserveDown[sc,n,t]) / pDuration[n] / pRampDw[t] >= - pInitialUC[t]                         + mSDUC.vShutDown[n,t]
    elif pRampDw[t] and pRampDw[t] < pMaxPower2ndBlock[t][sc,n]:
        return (mSDUC.vOutput2ndBlock[sc,n,t] - mSDUC.vOutput2ndBlock[sc,mSDUC.n.prev(n),t]   - mSDUC.vReserveDown[sc,n,t]) / pDuration[n] / pRampDw[t] >= - mSDUC.vCommitment[mSDUC.n.prev(n),t] + mSDUC.vShutDown[n,t]
    else:
        return Constraint.Skip
mSDUC.eRampDw = Constraint(mSDUC.sc, mSDUC.n, mSDUC.t, rule=eRampDw, doc='maximum ramp down [p.u.]')

GeneratingRampsTime = time.time() - StartTime
StartTime           = time.time()
print('Generating ramps   up/down            ... ', round(GeneratingRampsTime), 's')
```

SDUC (xi)

```
#%%
def eMinUpTime(mSDUC,n,t):
    if pUpTime[t] > 1 and mSDUC.n.ord(n) >= pUpTime[t]:
        return sum(mSDUC.vStartUp [n2,t] for n2 in list(mSDUC.n2)[mSDUC.n.ord(n)-pUpTime[t]:mSDUC.n.ord(n)]) <=     mSDUC.vCommitment[n,t]
    else:
        return Constraint.Skip
mSDUC.eMinUpTime   = Constraint(mSDUC.n, mSDUC.t, rule=eMinUpTime  , doc='minimum up   time [h]')

def eMinDownTime(mSDUC,n,t):
    if pDwTime[t] > 1 and mSDUC.n.ord(n) >= pDwTime[t]:
        return sum(mSDUC.vShutDown[n2,t] for n2 in list(mSDUC.n2)[mSDUC.n.ord(n)-pDwTime[t]:mSDUC.n.ord(n)]) <= 1 - mSDUC.vCommitment[n,t]
    else:
        return Constraint.Skip
mSDUC.eMinDownTime = Constraint(mSDUC.n, mSDUC.t, rule=eMinDownTime, doc='minimum down time [h]')

GeneratingMinUDTime = time.time() - StartTime
StartTime           = time.time()
print('Generating minimum up/down time       ... ', round(GeneratingMinUDTime), 's')

#%% solving the problem
mSDUC.write('openSDUC_'+CaseName+'.lp', io_options={'symbolic_solver_labels': True}) # create lp-format file
Solver = SolverFactory(SolverName)                                                   # select solver
if SolverName == 'gurobi':
    Solver.options['LogFile'       ] = 'openSDUC_'+CaseName+'.log'
    #Solver.options['IISFile'      ] = 'openSDUC_'+CaseName+'.ilp'                   # should be uncommented to show results of IIS
    #Solver.options['Method'       ] = 2                                             # barrier method
    Solver.options['MIPGap'        ] = 0.02
    Solver.options['Threads'       ] = int((psutil.cpu_count(logical=True) + psutil.cpu_count(logical=False))/2)
    #Solver.options['TimeLimit'     ] = 7200
    #Solver.options['IterationLimit'] = 7200000
SolverResults = Solver.solve(mSDUC, tee=True)                                        # tee=True displays the output of the solver
SolverResults.write()                                                                # summary of the solver results

#%% fix values of binary variables to get dual variables and solve it again
for n,t in mSDUC.n*mSDUC.t:
    mSDUC.vCommitment[n,t].fix(mSDUC.vCommitment[n,t]())
    mSDUC.vStartUp   [n,t].fix(mSDUC.vStartUp   [n,t]())
    mSDUC.vShutDown  [n,t].fix(mSDUC.vShutDown  [n,t]())

if SolverName == 'gurobi':
    Solver.options['relax_integrality'] = 1                                          # introduced to show results of the dual variables
mSDUC.dual    = Suffix(direction=Suffix.IMPORT)
SolverResults = Solver.solve(mSDUC, tee=True)                                        # tee=True displays the output of the solver
SolverResults.write()                                                                # summary of the solver results

SolvingTime = time.time() - StartTime
StartTime   = time.time()
print('Solving                               ... ', round(SolvingTime), 's')

print('Objective function value                  ', mSDUC.eTotalTCost.expr())
```

comillas.edu

SDUC (xii)

```
#%% inverse index generator to technology and to company
pTechnologyToGen = pGenToTechnology.reset_index().set_index('Technology').set_axis(['Generator'], axis=1, inplace=False)['Generator']
pCompanyToGen    = pGenToCompany.reset_index().set_index   ('Company'   ).set_axis(['Generator'], axis=1, inplace=False)['Generator']

#%% outputting the generation operation

OutputResults = pd.Series(data=[mSDUC.vCommitment[n,nr]() for n,nr in mSDUC.n*mSDUC.t], index=pd.MultiIndex.from_tuples(list(mSDUC.n*mSDUC.t)))
OutputResults.to_frame(name='p.u.').reset_index().pivot_table(index=['level_0'], columns='level_1', values='p.u.').rename_axis(['LoadLevel'], axis=0).rename_axis([None],
axis=1).to_csv('oUC_Result_GenerationCommitment_'+CaseName+'.csv', sep=',')
OutputResults = pd.Series(data=[mSDUC.vStartUp   [n,nr]() for n,nr in mSDUC.n*mSDUC.t], index=pd.MultiIndex.from_tuples(list(mSDUC.n*mSDUC.t)))
OutputResults.to_frame(name='p.u.').reset_index().pivot_table(index=['level_0'], columns='level_1', values='p.u.').rename_axis(['LoadLevel'], axis=0).rename_axis([None],
axis=1).to_csv('oUC_Result_GenerationStartUp_'    +CaseName+'.csv', sep=',')
OutputResults = pd.Series(data=[mSDUC.vShutDown  [n,nr]() for n,nr in mSDUC.n*mSDUC.t], index=pd.MultiIndex.from_tuples(list(mSDUC.n*mSDUC.t)))
OutputResults.to_frame(name='p.u.').reset_index().pivot_table(index=['level_0'], columns='level_1', values='p.u.').rename_axis(['LoadLevel'], axis=0).rename_axis([None],
axis=1).to_csv('oUC_Result_GenerationShutDown_'   +CaseName+'.csv', sep=',')

if sum(pOperReserveUp[sc,n] for sc,n in mSDUC.sc*mSDUC.n):
    OutputResults = pd.Series(data=[mSDUC.vReserveUp  [sc,n,nr]()*1e3 for sc,n,nr in mSDUC.sc*mSDUC.n*mSDUC.nr], index=pd.MultiIndex.from_tuples(list(mSDUC.sc*mSDUC.n*mSDUC.nr)))
    OutputResults.to_frame(name='MW').reset_index().pivot_table(index=['level_0','level_1'], columns='level_2', values='MW').rename_axis(['Scenario','LoadLevel'], axis=0).rename_axis([None],
axis=1).to_csv('oUC_Result_GenerationReserveUp_'+CaseName+'.csv', sep=',')

if sum(pOperReserveDw[sc,n] for sc,n in mSDUC.sc*mSDUC.n):
    OutputResults = pd.Series(data=[mSDUC.vReserveDown[sc,n,nr]()*1e3 for sc,n,nr in mSDUC.sc*mSDUC.n*mSDUC.nr], index=pd.MultiIndex.from_tuples(list(mSDUC.sc*mSDUC.n*mSDUC.nr)))
    OutputResults.to_frame(name='MW').reset_index().pivot_table(index=['level_0','level_1'], columns='level_2', values='MW').rename_axis(['Scenario','LoadLevel'], axis=0).rename_axis([None],
axis=1).to_csv('oUC_Result_GenerationReserveDown_'+CaseName+'.csv', sep=',')

OutputResults = pd.Series(data=[mSDUC.vTotalOutput[sc,n,g]()*1e3 for sc,n,g in mSDUC.sc*mSDUC.n*mSDUC.g], index=pd.MultiIndex.from_tuples(list(mSDUC.sc*mSDUC.n*mSDUC.g)))
OutputResults.to_frame(name='MW').reset_index().pivot_table(index=['level_0','level_1'], columns='level_2', values='MW').rename_axis(['Scenario','LoadLevel'], axis=0).rename_axis([None],
axis=1).to_csv('oUC_Result_GenerationOutput_'+CaseName+'.csv', sep=',')

OutputResults = pd.Series(data=[mSDUC.vENS[sc,n]()*1e3 for sc,n in mSDUC.sc*mSDUC.n], index=pd.MultiIndex.from_tuples(list(mSDUC.sc*mSDUC.n)))
OutputResults.to_frame(name='MW').reset_index().pivot_table(index=['level_0','level_1'], values='MW').rename_axis(['Scenario','LoadLevel'], axis=0).rename_axis([None],
axis=1).to_csv('oUC_Result_PNS_'+CaseName+'.csv', sep=',')

OutputResults = pd.Series(data=[mSDUC.vENS[sc,n]()*pDuration[n] for sc,n in mSDUC.sc*mSDUC.n], index=pd.MultiIndex.from_tuples(list(mSDUC.sc*mSDUC.n)))
OutputResults.to_frame(name='GWh').reset_index().pivot_table(index=['level_0','level_1'], values='GWh').rename_axis(['Scenario','LoadLevel'], axis=0).rename_axis([None],
axis=1).to_csv('oUC_Result_ENS_'+CaseName+'.csv', sep=',')

OutputResults = pd.Series(data=[(pMaxPower[g][sc,n]-mSDUC.vTotalOutput[sc,n,g]())*1e3 for sc,n,g in mSDUC.sc*mSDUC.n*mSDUC.r], index=pd.MultiIndex.from_tuples(list(mSDUC.sc*mSDUC.n*mSDUC.r)))
OutputResults.to_frame(name='MW').reset_index().pivot_table(index=['level_0','level_1'], columns='level_2', values='MW').rename_axis(['Scenario','LoadLevel'], axis=0).rename_axis([None],
axis=1).to_csv('oUC_Result_RESCurtailment_'+CaseName+'.csv', sep=',')
```

SDUC (xiii)

```
OutputResults = pd.Series(data=[mSDUC.vTotalOutput[sc,n,g]()*pDuration[n]             for sc,n,g in mSDUC.sc*mSDUC.n*mSDUC.g], index=pd.MultiIndex.from_tuples(list(mSDUC.sc*mSDUC.n*mSDUC.g)))
OutputResults.to_frame(name='GWh' ).reset_index().pivot_table(index=['level_0','level_1'], columns='level_2', values='GWh' ).rename_axis(['Scenario','LoadLevel'], axis=0).rename_axis([None],
axis=1).to_csv('oUC_Result_GenerationEnergy_'+CaseName+'.csv', sep=',')

OutputResults = pd.Series(data=[mSDUC.vTotalOutput[sc,n,nr]()*pCO2EmissionRate[nr]*1e3 for sc,n,nr in mSDUC.sc*mSDUC.n*mSDUC.t], index=pd.MultiIndex.from_tuples(list(mSDUC.sc*mSDUC.n*mSDUC.t)))
OutputResults.to_frame(name='tCO2').reset_index().pivot_table(index=['level_0','level_1'], columns='level_2', values='tCO2').rename_axis(['Scenario','LoadLevel'], axis=0).rename_axis([None],
axis=1).to_csv('oUC_Result_GenerationEmission_'+CaseName+'.csv', sep=',')

#%% outputting the ESS operation
if len(mSDUC.es):
    OutputResults = pd.Series(data=[mSDUC.vESSCharge   [sc,n,es]()*1e3           for sc,n,es in mSDUC.sc*mSDUC.n*mSDUC.es], index=pd.MultiIndex.from_tuples(list(mSDUC.sc*mSDUC.n*mSDUC.es)))
    OutputResults.to_frame(name='MW' ).reset_index().pivot_table(index=['level_0','level_1'], columns='level_2', values='MW' ).rename_axis(['Scenario','LoadLevel'], axis=0).rename_axis([None],
axis=1).to_csv('oUC_Result_ESSChargeOutput_'+CaseName+'.csv', sep=',')

    OutputResults = pd.Series(data=[mSDUC.vESSCharge[sc,n,es]()*pDuration[n]     for sc,n,es in mSDUC.sc*mSDUC.n*mSDUC.es], index=pd.MultiIndex.from_tuples(list(mSDUC.sc*mSDUC.n*mSDUC.es)))
    OutputResults.to_frame(name='GWh').reset_index().pivot_table(index=['level_0','level_1'], columns='level_2', values='GWh').rename_axis(['Scenario','LoadLevel'], axis=0).rename_axis([None],
axis=1).to_csv('oUC_Result_ESSChargeEnergy_'+CaseName+'.csv', sep=',')

    OutputResults = pd.Series(data=[OutputResults[sc,n].filter(pTechnologyToGen[gt]).sum() for sc,n,gt in mSDUC.sc*mSDUC.n*mSDUC.gt], index=pd.MultiIndex.from_tuples(list(mSDUC.sc*mSDUC.n*mSDUC.gt)))
    OutputResults.to_frame(name='GWh').reset_index().pivot_table(index=['level_0','level_1'], columns='level_2', values='GWh').rename_axis(['Scenario','LoadLevel'], axis=0).rename_axis([None],
axis=1).to_csv('oUC_Result_ESSTechnologyEnergy_'+CaseName+'.csv', sep=',')

    OutputResults = pd.Series(data=[mSDUC.vESSInventory[sc,n,es]()              for sc,n,es in mSDUC.sc*mSDUC.n*mSDUC.es], index=pd.MultiIndex.from_tuples(list(mSDUC.sc*mSDUC.n*mSDUC.es)))
    OutputResults *= 1e3
    OutputResults.to_frame(name='GWh').reset_index().pivot_table(index=['level_0','level_1'], columns='level_2', values='GWh', dropna=False).rename_axis(['Scenario','LoadLevel'], axis=0).rename_axis([None],
axis=1).to_csv('oUC_Result_ESSInventory_'+CaseName+'.csv', sep=',')

    OutputResults = pd.Series(data=[mSDUC.vESSSpillage [sc,n,es]()              for sc,n,es in mSDUC.sc*mSDUC.n*mSDUC.es], index=pd.MultiIndex.from_tuples(list(mSDUC.sc*mSDUC.n*mSDUC.es)))
    OutputResults *= 1e3
    OutputResults.to_frame(name='GWh').reset_index().pivot_table(index=['level_0','level_1'], columns='level_2', values='GWh', dropna=False).rename_axis(['Scenario','LoadLevel'], axis=0).rename_axis([None],
axis=1).to_csv('oUC_Result_ESSSpillage_'+CaseName+'.csv', sep=',')

    OutputResults = pd.Series({Key:OptimalSolution.value*1e3 for Key,OptimalSolution in mSDUC.vESSCharge.items()})
    OutputResults = pd.Series(data=[OutputResults[sc,n].filter(pTechnologyToGen[gt]).sum() for sc,n,gt in mSDUC.sc*mSDUC.n*mSDUC.gt], index=pd.MultiIndex.from_tuples(list(mSDUC.sc*mSDUC.n*mSDUC.gt)))
    OutputResults.to_frame(name='MW' ).reset_index().pivot_table(index=['level_0','level_1'], columns='level_2', values='MW' ).rename_axis(['Scenario','LoadLevel'], axis=0).rename_axis([None],
axis=1).to_csv('oUC_Result_TechnologyCharge_'+CaseName+'.csv', sep=',')

    TechnologyCharge = OutputResults.loc[:,:,:]

#%% plot SRMC for all the scenarios
RESCurtailment = OutputResults.loc[:,:,:]

fig, fg = plt.subplots()
for r in mSDUC.r:
    fg.plot(range(len(mSDUC.sc*mSDUC.n)), RESCurtailment[:,:,r], label=r)
fg.set(xlabel='Hours', ylabel='MW')
fg.set_ybound(lower=0)
plt.title('RES Curtailment')
fg.tick_params(axis='x', rotation=90)
fg.legend()
plt.tight_layout()
#plt.show()
plt.savefig('oUC_Plot_RESCurtailment_'+CaseName+'.png', bbox_inches=None)
```

SDUC (xiv)

```python
OutputResults = pd.Series({Key:OptimalSolution.value*1e3 for Key,OptimalSolution in mSDUC.vTotalOutput.items()})
OutputResults = pd.Series(data=[OutputResults[sc,n].filter(pTechnologyToGen[gt]).sum() for sc,n,gt in mSDUC.sc*mSDUC.n*mSDUC.gt], index=pd.MultiIndex.from_tuples(list(mSDUC.sc*mSDUC.n*mSDUC.gt)))
OutputResults.to_frame(name='MW').reset_index().pivot_table(index=['level_0','level_1'], columns='level_2', values='MW').rename_axis(['Scenario','LoadLevel'], axis=0).rename_axis([None], axis=1).to_csv('oUC_Result_TechnologyOutput_'+CaseName+'.csv',
sep=',')

TechnologyOutput = OutputResults.loc[:,:,:]

for sc in mSDUC.sc:
    fig, fg = plt.subplots()
    fg.stackplot(range(len(mSDUC.n)),  TechnologyOutput.loc[sc,:,:].values.reshape(len(mSDUC.n),len(mSDUC.gt)).transpose().tolist(), labels=list(mSDUC.gt))
    fg.plot     (range(len(mSDUC.n)), -TechnologyCharge.loc[sc,:,'ESS'], label='ESSCharge', linewidth=0.5, color='b')
    fg.plot     (range(len(mSDUC.n)),  pDemand[sc]*1e3,                  label='Demand'   , linewidth=0.5, color='k')
    fg.set(xlabel='Hours', ylabel='MW')
    plt.title(sc)
    fg.tick_params(axis='x', rotation=90)
    fg.legend()
    plt.tight_layout()
    #plt.show()
    plt.savefig('oUC_Plot_TechnologyOutput_'+sc+'_'+CaseName+'.png', bbox_inches=None)

OutputResults = pd.Series(data=[mSDUC.vTotalOutput[sc,n,g]()*pDuration[n] for sc,n,g in mSDUC.sc*mSDUC.n*mSDUC.g], index=pd.MultiIndex.from_tuples(list(mSDUC.sc*mSDUC.n*mSDUC.g)))
OutputResults = pd.Series(data=[OutputResults[sc,n].filter(pTechnologyToGen[gt]).sum() for sc,n,gt in mSDUC.sc*mSDUC.n*mSDUC.gt], index=pd.MultiIndex.from_tuples(list(mSDUC.sc*mSDUC.n*mSDUC.gt)))
OutputResults.to_frame(name='GWh').reset_index().pivot_table(index=['level_0','level_1'], columns='level_2', values='GWh').rename_axis(['Scenario','LoadLevel'], axis=0).rename_axis([None], axis=1).to_csv('oUC_Result_TechnologyEnergy_'+CaseName+'.csv',
sep=',')

#%% outputting the SRMC
if SolverName == 'gurobi':
    OutputResults = pd.Series(data=[mSDUC.dual[mSDUC.eBalance[sc,n]]*1e3/pScenProb[sc]/pDuration[n] for sc,n in mSDUC.sc*mSDUC.n], index=pd.MultiIndex.from_tuples(list(mSDUC.sc*mSDUC.n)))
    OutputResults.to_frame(name='SRMC').reset_index().pivot_table(index=['level_0','level_1'], values='SRMC').rename_axis(['Scenario','LoadLevel'], axis=0).rename_axis([None], axis=1).to_csv('oUC_Result_SRMC_'+CaseName+'.csv', sep=',')

    #%% plot SRMC for all the scenarios
    SRMC = OutputResults.loc[:,:]

    fig, fg = plt.subplots()
    for sc in mSDUC.sc:
        fg.plot(range(len(mSDUC.n)), SRMC[sc], label=sc)
        fg.set(xlabel='Hours', ylabel='EUR/MWh')
        fg.set_ybound(lower=0, upper=100)
        plt.title('SRMC')
        fg.tick_params(axis='x', rotation=90)
        fg.legend()
        plt.tight_layout()
        #plt.show()
        plt.savefig('oUC_Plot_SRMC_'+CaseName+'.png', bbox_inches=None)

WritingResultsTime = time.time() - StartTime
StartTime          = time.time()
print('Writing output results                ... ', round(WritingResultsTime), 's')
print('Total time                            ... ', round(ReadingDataTime + GeneratingOFTime + GeneratingRBITime + GeneratingGenConsTime + GeneratingRampsTime + GeneratingMinUDTime + SolvingTime + WritingResultsTime), 's')
```

JuanitoJaimitoJorgito

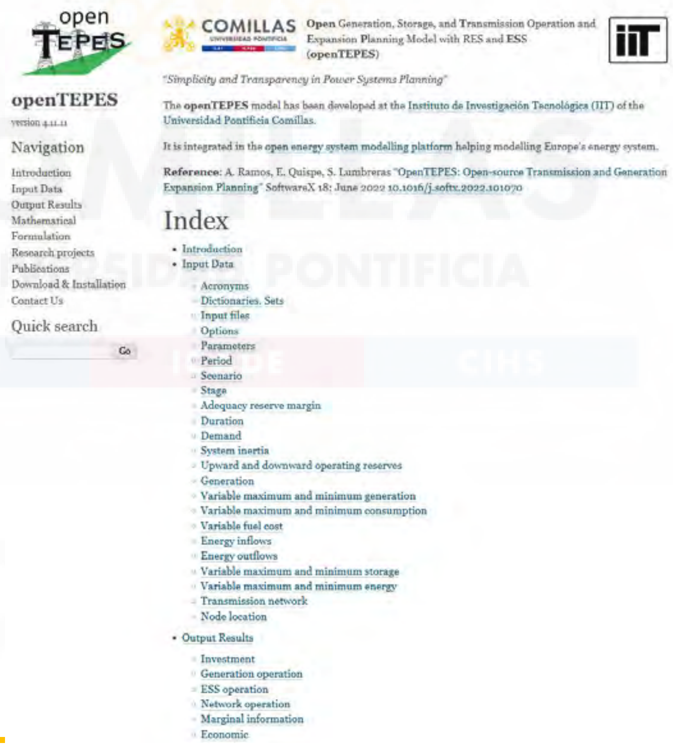
https://gitlab001.iit.comillas.edu/pdeotaola/Ejemplo_Optimizacion_Python-Pyomo

- Simple Unit Commitment with profit maximization against prices of the day-ahead market

openTEPES

https://opentepes.readthedocs.io/en/latest/index.html
https://github.com/IIT-EnergySystemModels/openTEPES

- Open Generation, Storage, and Transmission Operation and Expansion Planning Model with RES and ESS
  - Web page created with `sphinx`


open TEPES

COMILLAS UNIVERSIDAD PONTIFICIA

Open Generation, Storage, and Transmission Operation and Expansion Planning Model with RES and ESS (openTEPES)

"Simplicity and Transparency in Power Systems Planning"

openTEPES

version 4.11.11

Navigation

Introduction
Input Data
Output Results
Mathematical Formulation
Research projects
Publications
Download & Installation
Contact Us

Quick search

Go

The **openTEPES** model has been developed at the Instituto de Investigación Tecnológica (IIT) of the Universidad Pontificia Comillas.

It is integrated in the open energy system modelling platform helping modelling Europe's energy system.

Reference: A. Ramos, E. Quispe, S. Lumbreras "OpenTEPES: Open-source Transmission and Generation Expansion Planning" SoftwareX 18: June 2022 10.1016/j.softx.2022.101070

Index

- Introduction
- Input Data
  - Acronyms
  - Dictionaries. Sets
  - Input files
  - Options
  - Parameters
  - Period
  - Scenario
  - Stage
  - Adequacy reserve margin
  - Duration
  - Demand
  - System inertia
  - Upward and downward operating reserves
  - Generation
  - Variable maximum and minimum generation
  - Variable maximum and minimum consumption
  - Variable fuel cost
  - Energy inflows
  - Energy outflows
  - Variable maximum and minimum storage
  - Variable maximum and minimum energy
  - Transmission network
  - Node location
- Output Results
  - Investment
  - Generation operation
  - ESS operation
  - Network operation
  - Marginal information
  - Economic

The openTEPES code is provided under the GNU General Public License:
•the code can't become part of a closed-source commercial software product
•any future changes and improvements to the code remain free and open

Disclaimer:
This model is a work in progress and will be updated accordingly.

Enjoy Formulating, writing and solving optimization models

Thank you for your attention

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