



# Analysis of Critical Infrastructures with the Pyomo Modeling Software

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Sandia National Laboratories

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*Exceptional  
service  
in the  
national  
interest*



Sandia National Laboratories is a multi-program laboratory managed and operated by Sandia Corporation, a wholly owned subsidiary of Lockheed Martin Corporation, for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-AC04-94AL85000.

# Overview

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- [About Sandia National Laboratories](#)
- Optimization modeling for critical infrastructures
  - Water security
  - Electrical energy planning and management
- Optimization modeling with Pyomo

# DOE's National Laboratories

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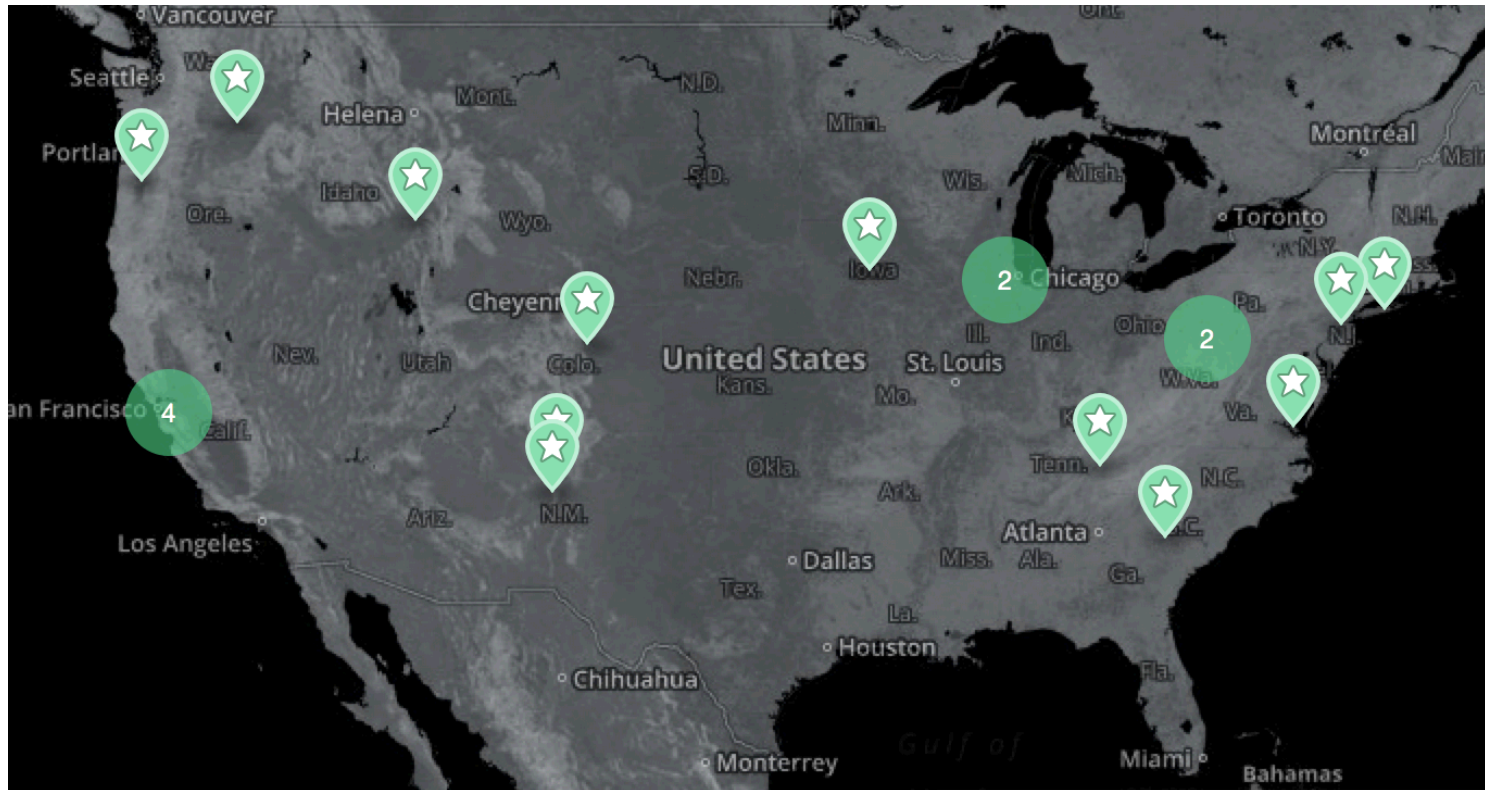
DOE National Labs address ...

- large scale, complex research and development challenges ...
- with a multidisciplinary approach ...
- that places an emphasis on translating basic science to innovation.

The Energy Department's National Labs tackle critical scientific challenges:

- Conduct research of the highest caliber
- Advance U.S. energy independence and leadership
- Enhance global, national, and homeland security
- Design, build, and operate distinctive scientific instrumentation and facilities

# DOE National Laboratories

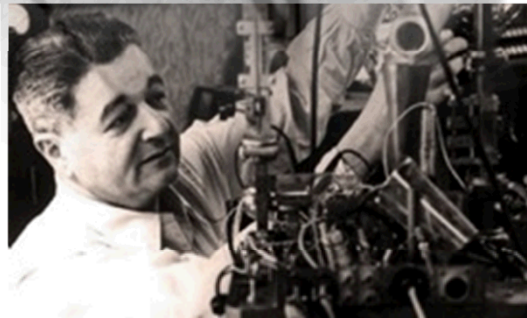
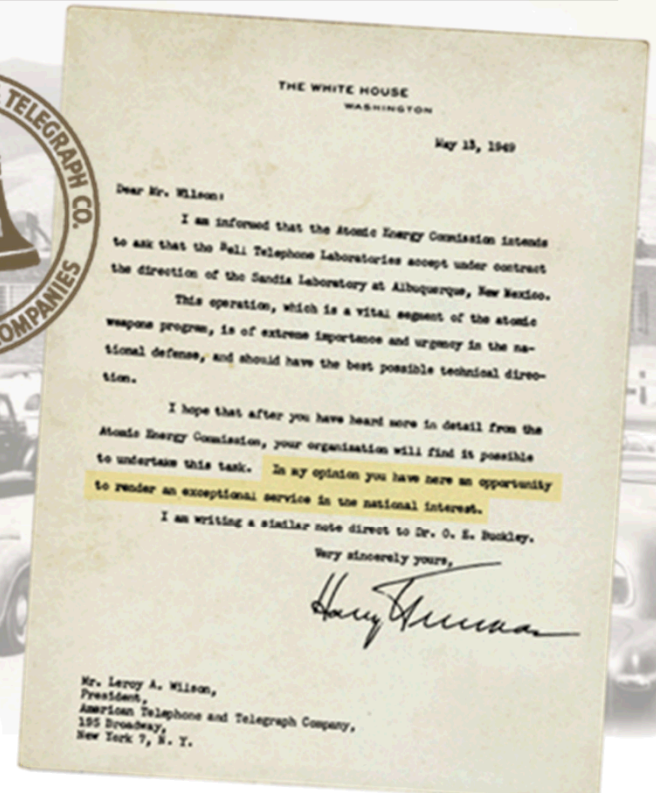


# Sandia's History

*Exceptional service in the national interest*

- July 1945: Los Alamos creates Z Division
- Nonnuclear component engineering
- November 1, 1949: Sandia Laboratory established

to undertake this task. In my opinion you have here an opportunity to render an exceptional service in the national interest.





# Sandia Sites

*Albuquerque, New Mexico*



*Livermore, California*



*Kauai, Hawaii*



*Waste Isolation Pilot Plant,  
Carlsbad, New Mexico*



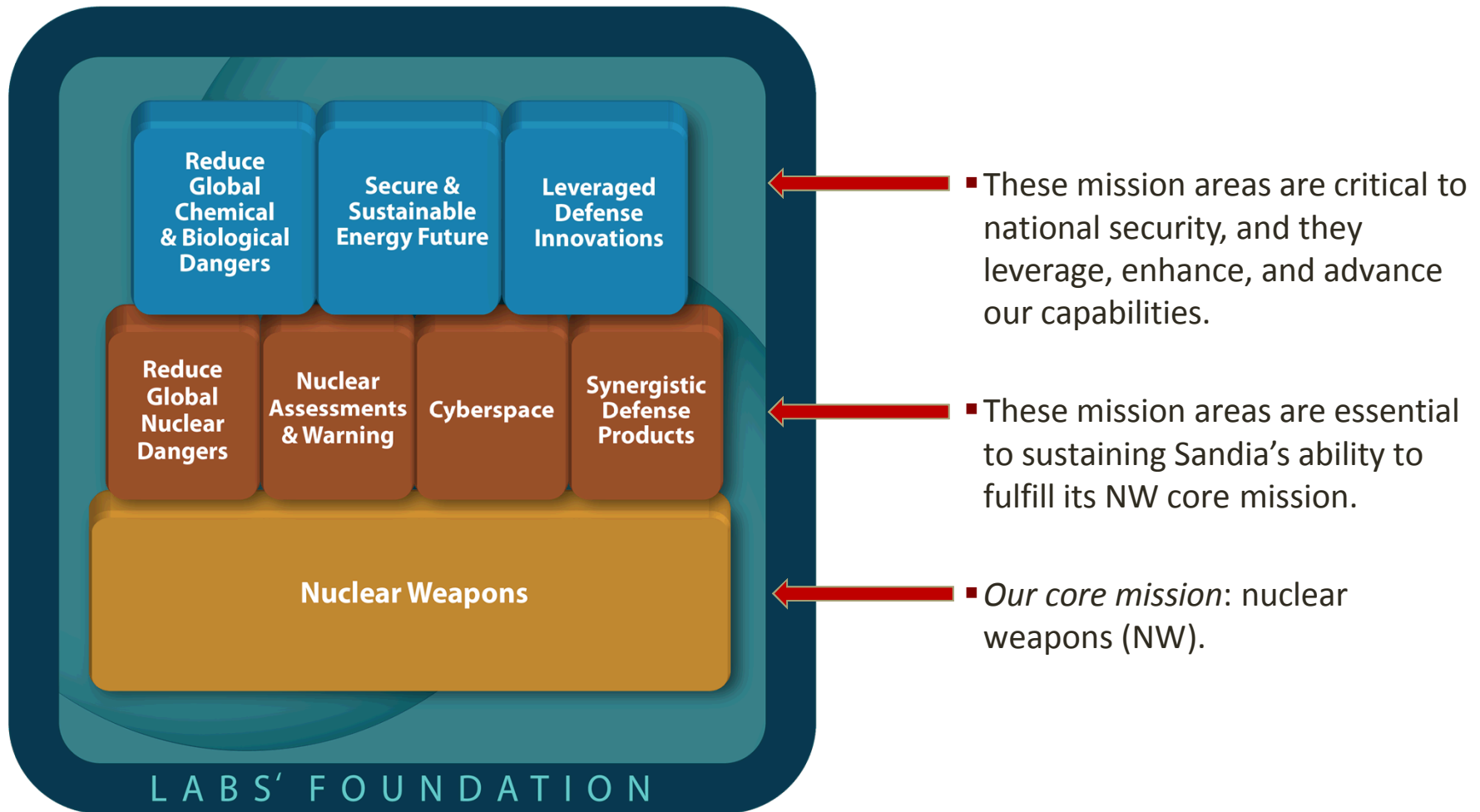
*Pantex Plant,  
Amarillo, Texas*



*Tonopah,  
Nevada*



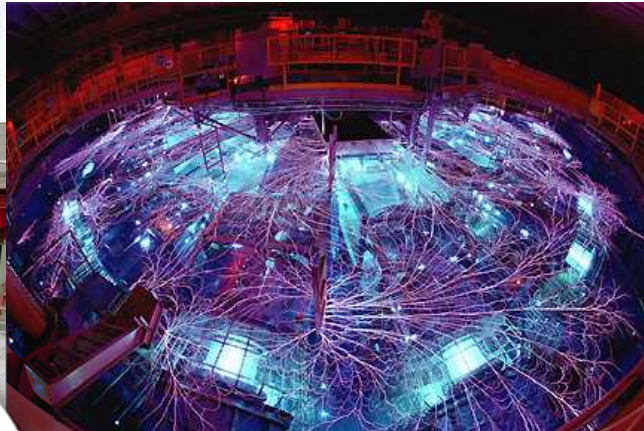
# National Security Mission Areas





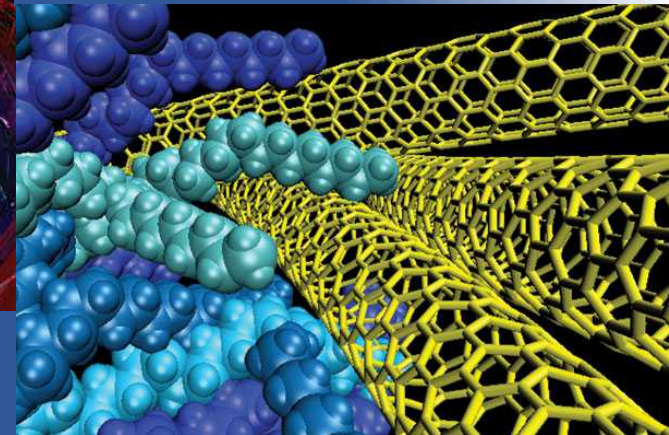
# Research Foundations

Computing &  
Information Sciences

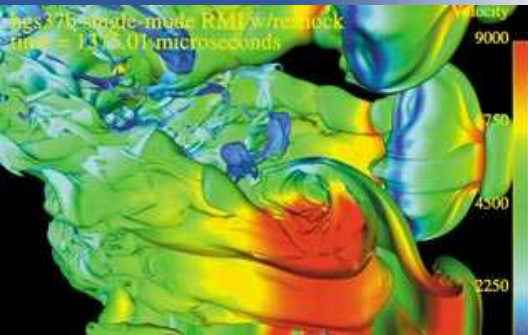


Radiation Effects &  
High Energy Density Science

Materials Sciences

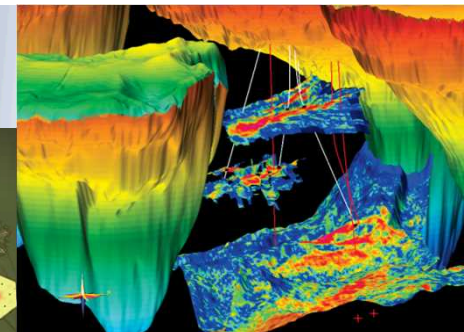
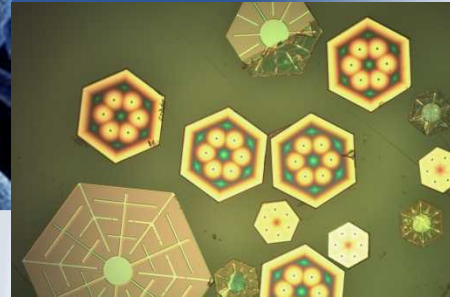


Engineering Sciences



Bioscience

Nanodevices &  
Microsystems



Geoscience



# Computing and Information Sciences

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## Computing Sciences

*“...the scientific approach to computation and application and specifically to the design of computing machines and processes”*

*Computational simulation is now considered a third fundamental tool of science, complementing theory and experiment.*

## Information Sciences

*“... the analysis, collection, classification, manipulation, storage, retrieval and dissemination of information ... e.g. mathematics, cognition”*

*We live in the “information age” and increasingly substitute information for materials and energy to increase societal efficiency*

### Focus Areas

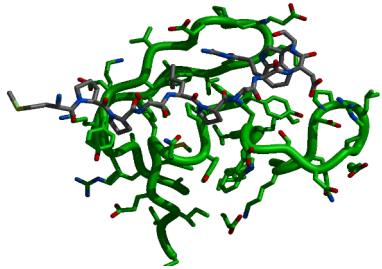
- Computational Engineering
- Scalable supercomputing
- Trusted information systems

# Optimization Research at Sandia

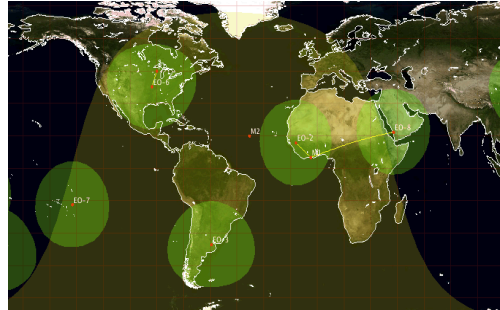
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- Parallel optimization algorithms
  - Branch-and-bound, simulation-based optimization, etc
- PDE-constrained optimization
- Stochastic programming
- Parameter estimation
- Direct search
- Surrogate-based optimization
- Optimization under uncertainty
- *and more ...*
- Optimization software frameworks
  - Engineering design and uncertainty quantification
  - Modeling frameworks
  - Solver libraries

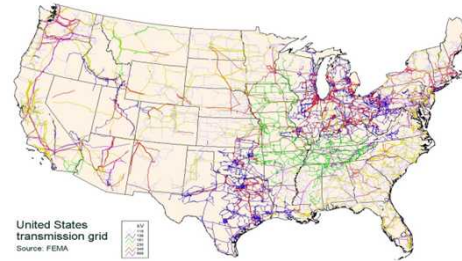
# Optimization Application Examples



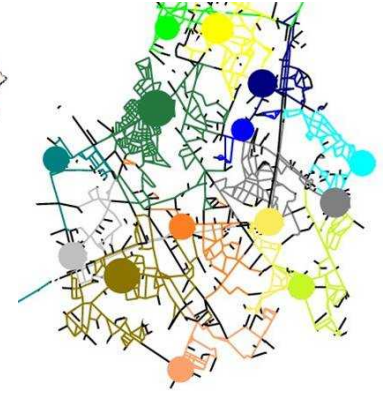
Molecular Docking



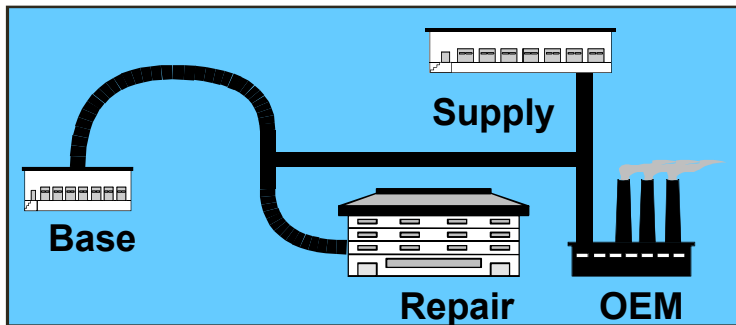
Satellite Scheduling



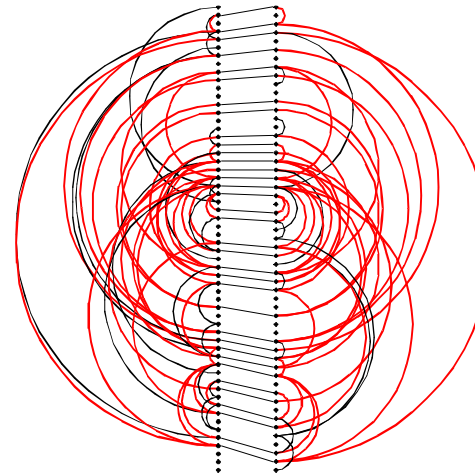
Power Grid Planning



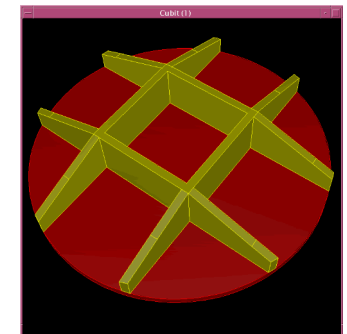
Water Security



Inventory Logistics



Protein Comparison



Topology Design



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# Resilient Critical Infrastructures

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Presidential Policy Directive 21 (PPD-21): Critical Infrastructure Security and Resilience advances a national policy to strengthen and maintain secure, functioning, and resilient critical infrastructure.

- PPD-21 identifies 16 critical infrastructure sectors
- <http://www.dhs.gov/critical-infrastructure-sectors>

DHS provides broad guidance for supporting decisions and investments in infrastructure that will enhance the resilience of critical infrastructure systems, including:

- Leveraging science and predictive tools on future trends and risks
- Utilizing available risk assessment and scenario planning tools to make risk-informed decisions
- Mapping potential cascading effects from potential infrastructure disruptions

# Some Practical Challenges

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- The resiliency “problem” is poorly defined
  - *Need to explore alternative formulations*
  - *Need generic modeling/optimization strategies (e.g. MIP)*
- We may not have the data we need to solve “the problem”
  - *Some “good” formulations may not be practical*
  - *Inform stakeholders about the value of additional information*
- There are competing objectives for infrastructure resiliency
  - *Need multi-objective or goal-constrained techniques*
- Decision makers may need to make rapid decisions
  - *Need parallel techniques*
  - *Need good, fast heuristics*



# Example: Electric Power Management

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Unit commitment: a planning problem for scheduling electric power generation

Challenge: There is increased uncertainty in power generation

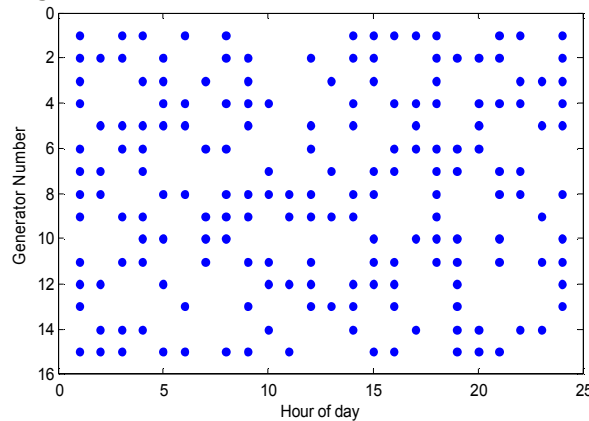
- Uncertainty and variability in alternative sources (e.g. wind, solar)
- Potential uncertainties in charging/discharging patterns for electric vehicles

Idea: use stochastic unit commitment

- A scenario based uncertainty representation in the unit commitment formulation
- The objective is to minimize the expected cost

# The General Structure of a Stochastic Unit Commitment Optimization Model

Objective: Minimize expected cost



First stage variables:

- Unit On / Off



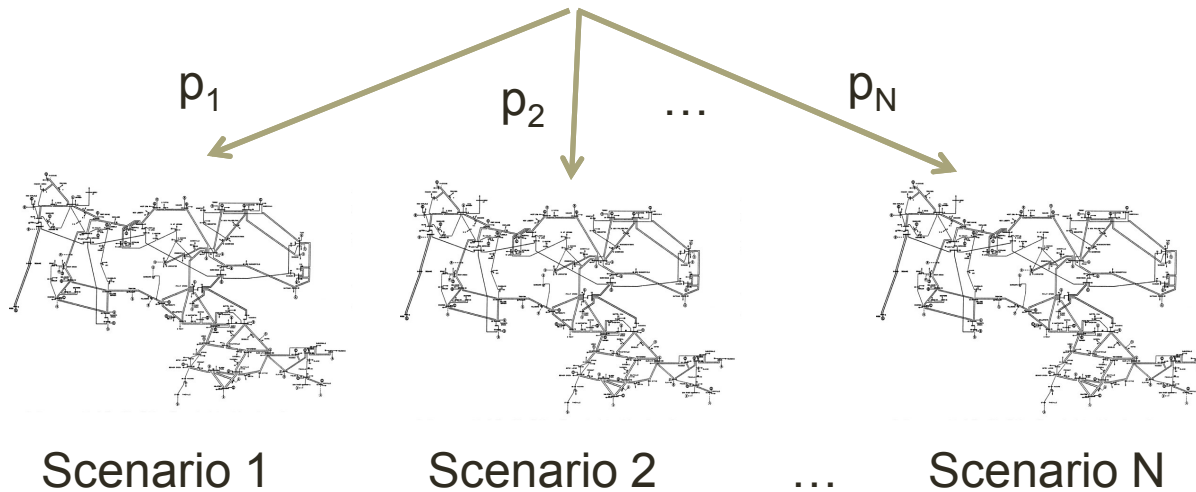
Nature resolves uncertainty

- Load
- Renewables output
- Forced outages



Second stage variables  
(*per time period*):

- Generation levels
- Power flows
- Voltage angles
- ...



# (Some) Historical Barriers to Adoption of Stochastic Unit Commitment

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- We can't create sufficiently accurate sets of scenarios to capture load and renewables uncertainty
- Even if we could create accurate sets of scenarios, the resulting models are too difficult to solve
- Even if we could solve the resulting models, it would require significant HPC resources - which is a major impediment to industrial adoption



# Solving with the Stochastic Extensive Form

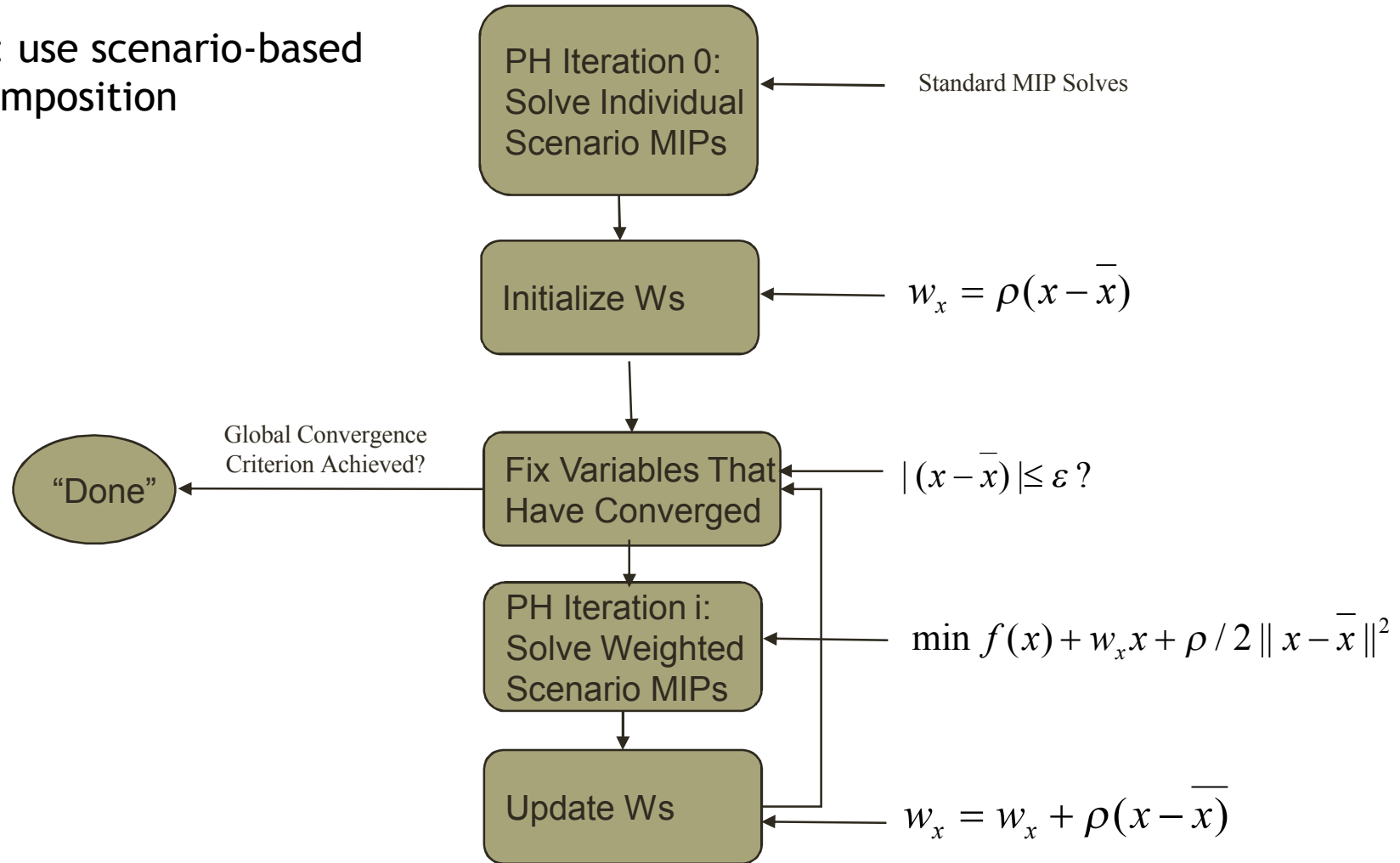
- Reliability Unit Commitment (RUC) Test Instance: WECC-240++
- J.E. Price, Reduced Network Modeling of WECC as a Market Design Prototype, 2011 IEEE PES General Meeting
- Changes necessary to create viable RUC test case
  - Addition of realistic ramping rates and min up/down time constraints
- Results

**Table 3** Solution quality statistics for the extensive form of the *WECC-240-r1* instance, given 4 hours of run time.

| # Scenarios | Objective Value | MIP Lower Bound | Gap % | Run Time (s) |
|-------------|-----------------|-----------------|-------|--------------|
| 3           | 64278.20        | 63797.72        | 0.75  | 14491        |
| 5           | 62740.67        | 62180.86        | 0.89  | 14723        |
| 10          | 61563.10        | 60835.45        | 1.18  | 14630        |
| 25          | 61455.55        | 59963.78        | 2.36  | 14960        |
| 50          | 61911.74        | 59540.87        | 3.83  | 15480        |
| 100         | 62388.85        | 59548.23        | 4.51  | 16562        |

# Solving with Progressive Hedging

Idea: use scenario-based decomposition



# Parallelization and Bundling

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- Progressive Hedging is, at least conceptually, easily parallelized
  - Scenario sub-problem solves are clearly independent
  - Advantage over Benders, in that “bloat” is distributed
    - Critical in low-memory-per-node cluster environments
  - Parallel efficiency drops rapidly as the number of processors increases
    - But: Relaxing barrier synchronization does not impact PH convergence
  - Bundling scenarios might help with parallel scaling
    - May increase number of iterations required
- PH can provide bounds!
  - Now comes with (rather tight) lower bounds
  - See “Obtaining Lower Bounds from the Progressive Hedging Algorithm for Stochastic Mixed-Integer Programs” (Under review)



# PH Results: Workstation and RedSky (HPC)

**Table 4** Solve time (in seconds) and solution quality statistics for PH executing on the *WECC-240-r1* instance, with  $\alpha = 1.0$ ,  $\mu = 3$ , and  $\gamma = 0.03$

| # Scenarios                 | Convergence Metric | Obj. Value | PH L.B.   | # Vars Fx. | Time |
|-----------------------------|--------------------|------------|-----------|------------|------|
| 64-Core Workstation Results |                    |            |           |            |      |
| 3                           | 0.0 (in 23 iters)  | 64727.714  | 63188.709 | 4080       | 155  |
| 5                           | 0.0 (in 26 iters)  | 62911.104  | 61609.576 | 4080       | 163  |
| 10                          | 0.0 (in 26 iters)  | 61493.375  | 60347.220 | 4080       | 227  |
| 25                          | 0.0 (in 27 iters)  | 60990.111  | 59875.661 | 4080       | 364  |
| 50                          | 0.0 (in 17 iters)  | 60721.319  | 59527.252 | 4076       | 584  |
| 100                         | 0.0 (in 23 iters)  | 61156.832  | 59880.559 | 4080       | 1218 |
| Red Sky Results             |                    |            |           |            |      |
| 50                          | 0.0 (in 29 iters)  | 60676.383  | 59670.142 | 4062       | 514  |
| 100                         | 0.0 (in 33 iters)  | 61122.781  | 60148.285 | 4073       | 672  |

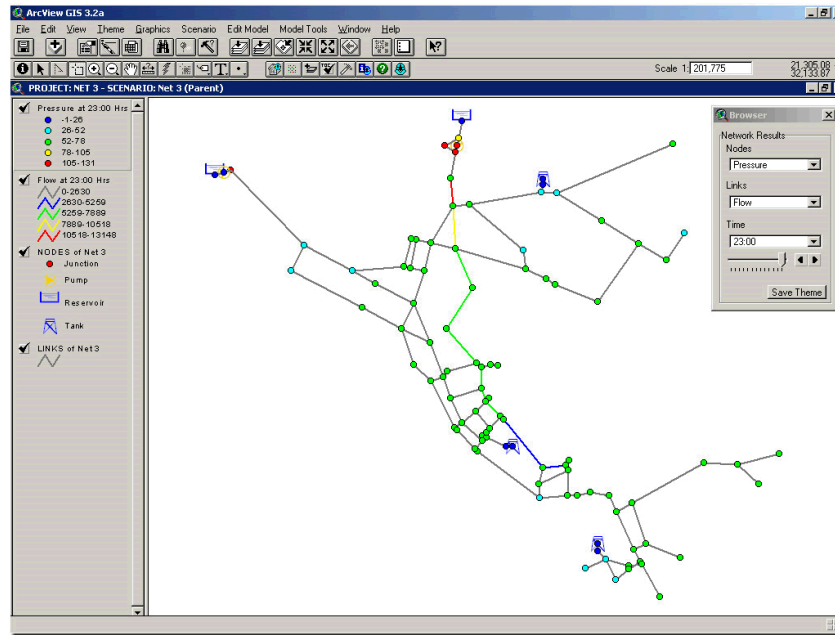
# Example: Water Security

## Drinking Water

- Water source
- Treatment facilities
- Transmission systems
- Distribution systems

## Wastewater

- Wastewater source
- Collection system
- Treatment facility
- Receiving water body



# Designing a Contamination Warning System

Technical Goal: placement of sensors in a water distribution system within a budget

Possible objectives:

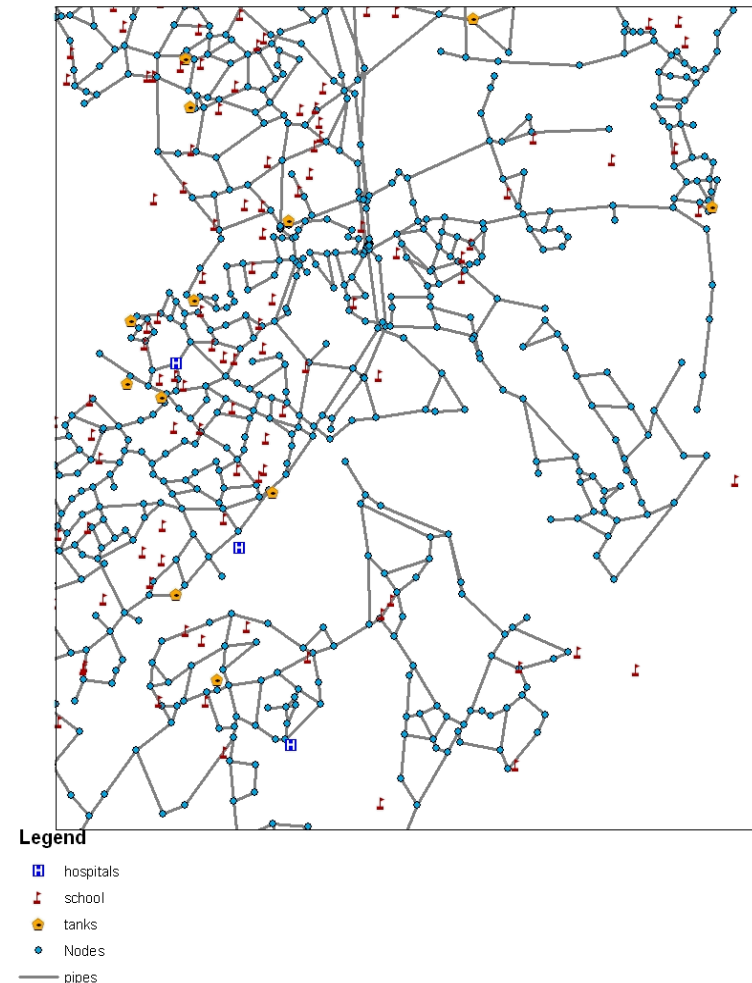
- Minimize response time
- Minimize health impacts
- Minimize contamination extent

Place sensors at networks junctions

- Public buildings, hospitals, etc

Sensors are expensive

- Cost of sensors
- Cost of installation



# Contamination Scenarios

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Water movement (direction, velocity in each pipe) determined by

- Demand (consumption), pumps, gravity, valves, sources/tanks, etc.

Current (most trusted) simulator

- EPANET code computes hydraulic equations to determine flows
- Discrete-event simulation for contaminant movement

Contamination impact

- Scenarios defined by start time, location and contaminant characteristics
- For each scenario, determine when/where the contaminant can be observed
- Compute cumulative impact statistics
  - Population exposed, # deaths, time of detection, mass consumed, etc

# A Canonical Sensor Placement Problem

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- Classic p-median facility location problem:
  - Open  $p$  facilities
  - Each of a set of customers served by closest facility
  - Minimize total distance
- Sensor placement is structurally equivalent
  - Assume: perfect sensors, a general alarm is raised that stops water consumption
  - Sensors = Facilities
  - Events = Customers to be “served” (witnessed)
  - “Distance” from an event  $a$  to a node  $n$  = impact if a sensor at node  $n$  witnesses event  $a$ .
  - If no sensors witness an event, the impact for that event is the maximum possible over the simulation time-horizon



# Solving p-Median Sensor Placement

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- Integer programming
  - IP model can capture different objectives/networks
  - Can be solved with COTS software on 64-bit computers
- GRASP heuristic
  - Runs quickly on real-world distribution networks (2000-20000 junctions)
  - In practice, often finds optimal sensor placements (!?!)
- Stochastic programming
  - The IP model can be viewed as the extensive form of a stochastic model
  - Can apply Progressive Hedging heuristic to solve in parallel and/or with limited memory
  - Can compute confidence interval for a sensor placement

# Other Formulations

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- Imperfect sensors
  - Allow sensors to fail with a fixed probability (perhaps dependent on location)
  - Is well-approximated by p-Median model
  - Need more data!
- Minimize number of sensors
  - Given a performance goal, minimize # of sensors
  - Requires a target goal ...
- Multi-stage sensor placement
  - Place some sensors now and others later
  - Requires a model for the value of life today vs. tomorrow
- Multi-objective sensor placement
  - Goal-constrained sensor placement is harder for GRASP and IP solvers
  - Robust objectives (e.g. CVaR) are computationally challenging (\*)

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# Optimization Modeling

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## Goal:

- Provide a natural syntax to describe mathematical models
- Formulate large models with a concise syntax
- Separate modeling and data declarations
- Enable data import and export in commonly used formats

## Impact:

- Robustly model large constraint matrices (e.g. for MILPs)
- Integrated support of automatic differentiation for complex nonlinear models

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

# Pyomo Overview

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**Idea:** a Pythonic framework for formulating optimization models

- Provide a natural syntax to describe mathematical models
- Formulate large models with a concise syntax
- Separate modeling and data declarations
- Enable data import and export in commonly used formats

## Highlights:

- Python provides a clean, intuitive syntax
- Python scripts provide a flexible context for exploring the structure of Pyomo models

```
# simple.py
from pyomo.environ import *

M = ConcreteModel()
M.x1 = Var()
M.x2 = Var(bounds=(-1,1))
M.x3 = Var(bounds=(1,2))
M.o = Objective(
    expr=M.x1**2 + (M.x2*M.x3)**4 + \
        M.x1*M.x3 + \
        M.x2*sin(M.x1+M.x3) + M.x2)

model = M
```

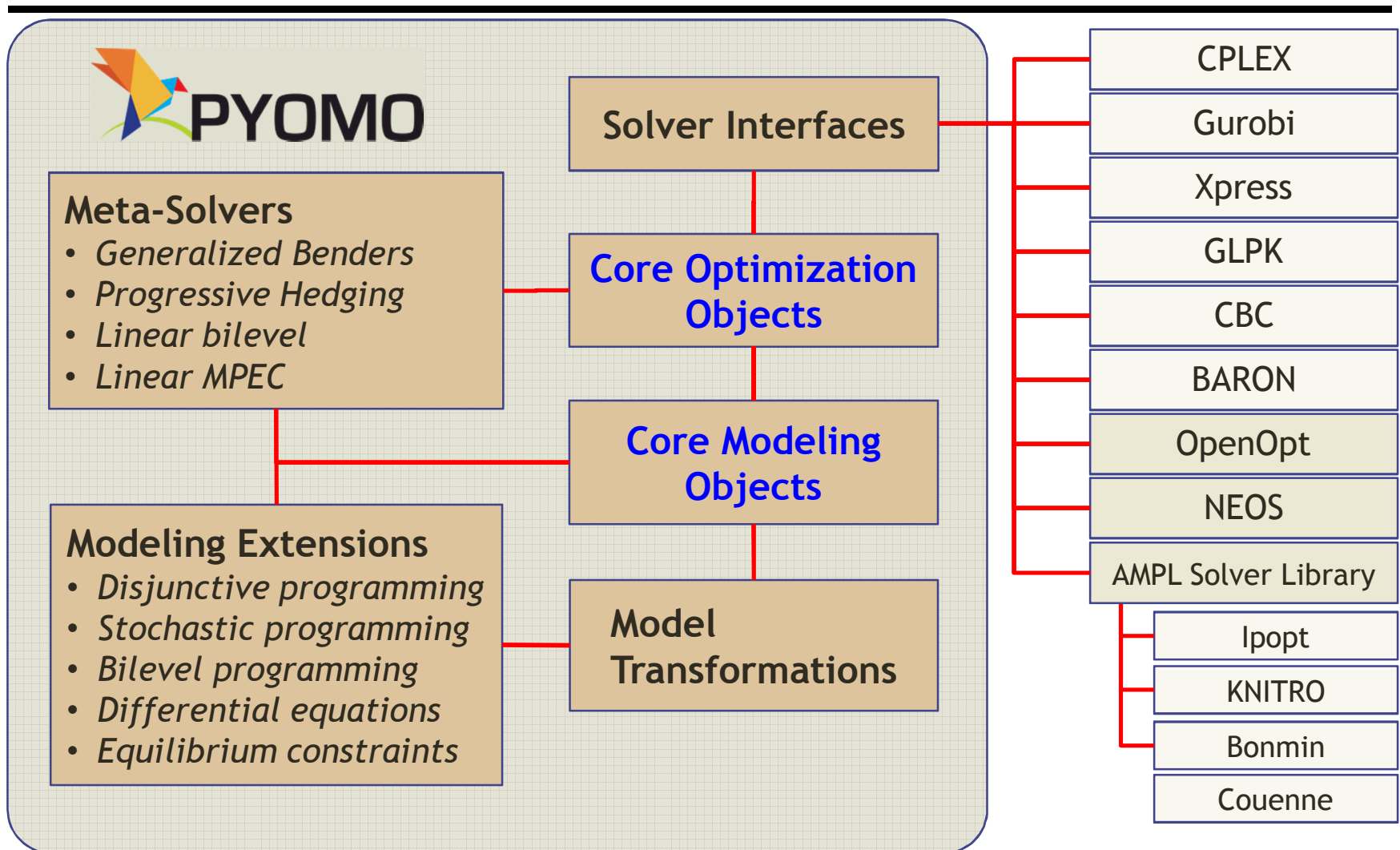


# Comparison with Other Python Modeling Tools

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- **Pyomo**
  - Supports concrete/abstract modeling for LP/MILP/NLP models
  - Modeling extensions for stochastic programming, bilevel, MPEC, etc
  - Separate model objects
- **PuLP**
  - Supports concrete modeling for LP/MILP models
  - Separate model objects
  - Simple object model
- **APLEpy**
  - Supports concrete modeling for LP/MILP models
  - Single global model object
- **PyMathProg, pyglpk, cplex, gurobi**
  - Python interfaces for specific solver tools

# Pyomo at a Glance



# Why Model within a Programming Language?

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## Open Source License

- No licensing issues w.r.t. the language itself
- Can extend/refine the language in some cases

## Extensibility and Robustness

- Highly stable and well-supported
- Simple model for integrating code developed by a user

## Support and Documentation

- Extensive online documentation and several excellent books
- Long-term support for the language is not a factor

## Standard Library

- Includes a large number of useful modules.

## Scripting

- Language features includes functions, classes, looping, procedural constructs, etc.

## Portability

- Widely available on many platforms

# More than just mathematical modeling ...

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## Scripting

- Construct models using native Python data
- Iterative analysis of models leveraging Python functionality
- Data analysis and visualization of optimization results

## Model transformations (a.k.a. reformulations)

- Automate generation of one model from another
- Leverage Pyomo's object model to apply transformations sequentially
- E.g.: relax integrality, GDP -> Big M

## Meta-solvers

- Integrate scripting and/or transformations into optimization solver
- Leverage Python's introspective nature to build “generic” capabilities
- E.g.: progressive hedging, SP extensive form -> MIP

# Impact on Critical Infrastructure Analysis

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- Agility
  - Optimization models were able to express a wide range of sensor placement formulations
    - Used both AMPL and Pyomo models
  - Pyomo facilitated the transition between IP and SP models
    - The SP representation supported by Pyomo requires a single-scenario model
    - Can easily transition between IP solvers optimizing the extensive form and PH
  - Transformations can be used to tailor analysis to available solvers
    - Commercial IP solvers are not available in some environments
    - Meta-solvers like PH can leverage weaker open-source IP solvers when analyzing subproblems



# Impact on Critical Infrastructure Analysis

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- Leveraging generic capabilities
  - Pyomo is developing generic SP analysis capabilities
    - The SP analysis is separate from the model specification
  - Consequently, extensions to these capabilities can be immediately leveraged by any/all SP applications
- Fast analysis
  - Leverage Python's capabilities to support scalable parallelism
  - We leverage portable parallel libraries in Pyomo, so no customization is required between workstation, cluster or HPC environments

# Acknowledgements

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- Sensor placement
  - Cindy Phillips, Jon Berry, Jean-Paul Watson, John Sirola, Regan Murray, Jim Uber, and more ...
- Stochastic unit commitment
  - Jean-Paul Watson, Dave Woodruff, Roger Wets
- Pyomo
  - Jean-Paul Watson, John Sirola, Dave Woodruff, Carl Laird

# The End

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Questions?

# For More Information

See the new Pyomo homepage

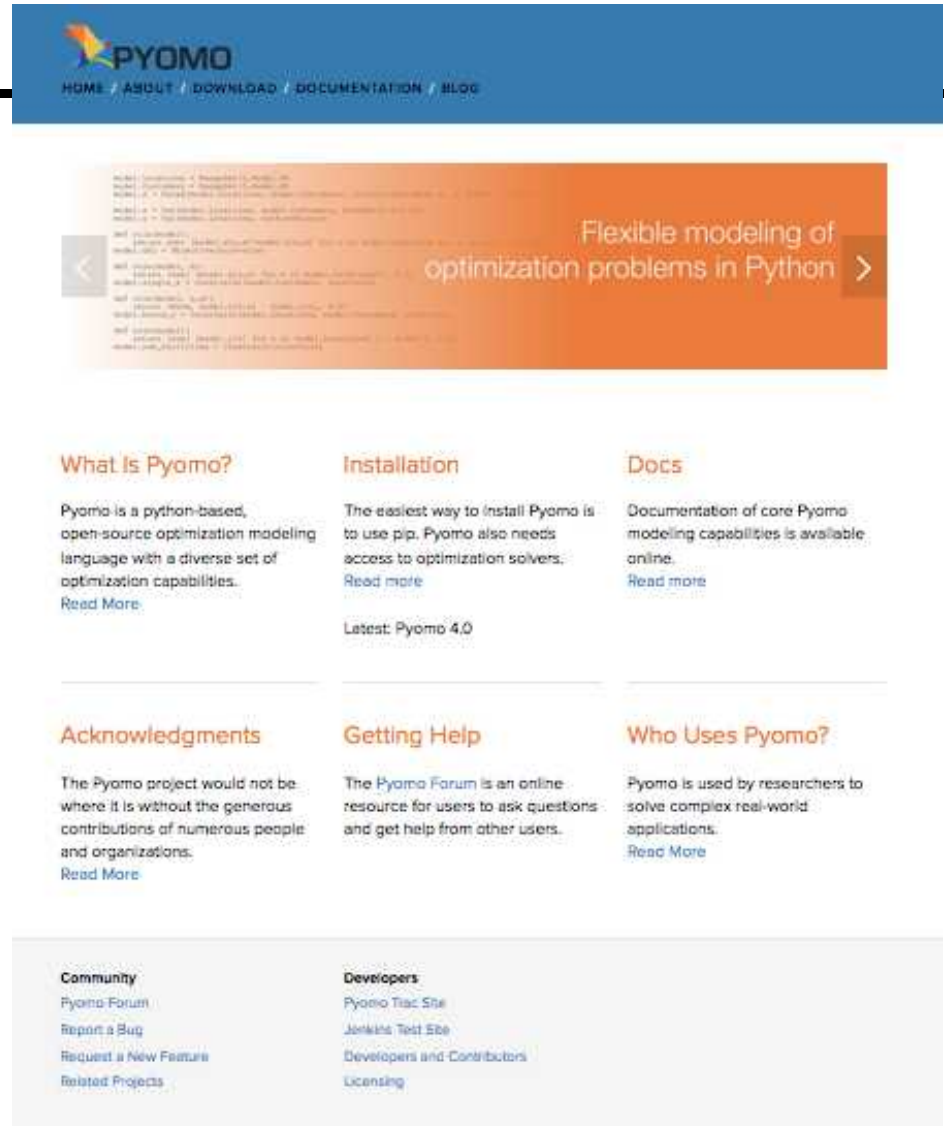
- [www.pyomo.org](http://www.pyomo.org)

The Pyomo homepage provides a portal for:

- Online documentation
- Installation instructions
- Help information
- Developer links

Coming soon:

- Blogging about Pyomo capabilities and features
- A gallery of simple examples



# Integer Programming Formulation

IPs can be used to model sensor placement for water security

- Berry et al (2003, 2006); Watson et al (2004)

Objective:

$$\sum_{a \in A} \sum_{i \in L} \alpha_a w_{ai} x_{ai}$$

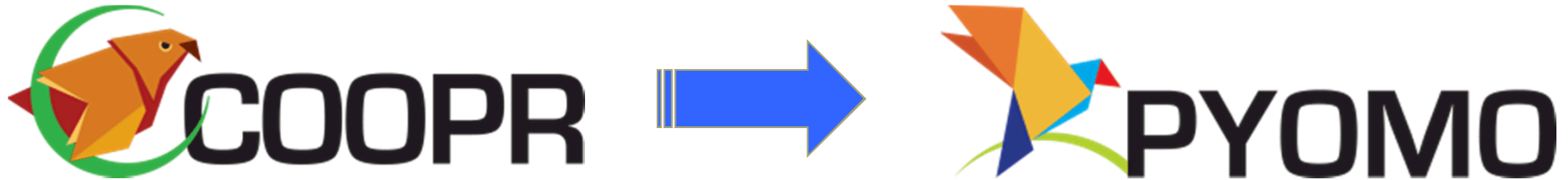
- $\alpha$  - contamination likelihood
- $w$  - contamination impact
- $x$  - witness variable
- $s$  - sensor placement variable

(\*)

$$\begin{aligned} &\text{minimize } \sum_{a \in A} \sum_{i \in L} \alpha_a w_{ai} x_{ai} \\ &s.t. \\ &\sum_{i \in L} x_{ai} = 1 \quad \forall a \in A \\ &x_{ai} \leq s_i \quad \forall a \in A, i \in L \\ &\sum_{i \in L} s_i \leq S_{\max} \\ &s_i \in \{0,1\} \\ &0 \leq x_{ai} \leq 1 \quad \forall a \in A, i \in L \end{aligned}$$

# What Happened to Coopr?

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- Users were installing Coopr but using Pyomo
  - Pyomo modeling extensions were not distinct enough
  - Researchers cited “Coopr/Pyomo”
- Users/Developers were confused by the `coopr` and `pyomo` commands
- Developers were coding in Coopr but talking about Pyomo

**We need to provide clear branding this project!**



# Who Uses Pyomo?

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- Students
  - Rose-Hulman, UC Davis, U Texas, Iowa State, NPS
- Researchers
  - Sandia National Labs, Lawrence Livermore National Lab, Los Alamos National Lab, UC Davis, TAMU, Rose-Hulman, UT, USC, GMU, Iowa State, NCSU, U Washington, NPS, U de Santiago de Chile, U Pisa, Federal Energy Regulatory Agency, ...
- Software Projects
  - TEMOA - Energy economy optimization models
  - Minpower - Power systems toolkit
  - Water Security Toolkit - Planning/Response for water contamination
  - SolverStudio - Excel plugin for optimization modeling