Decomposition of uncertainty propagation through networks of heterogeneous energy systems

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Focus Period on Dynamics, Control and Pricing in Power Systems
Lund, Sweden: May 2 - May 27, 2011

Motivation – On Average

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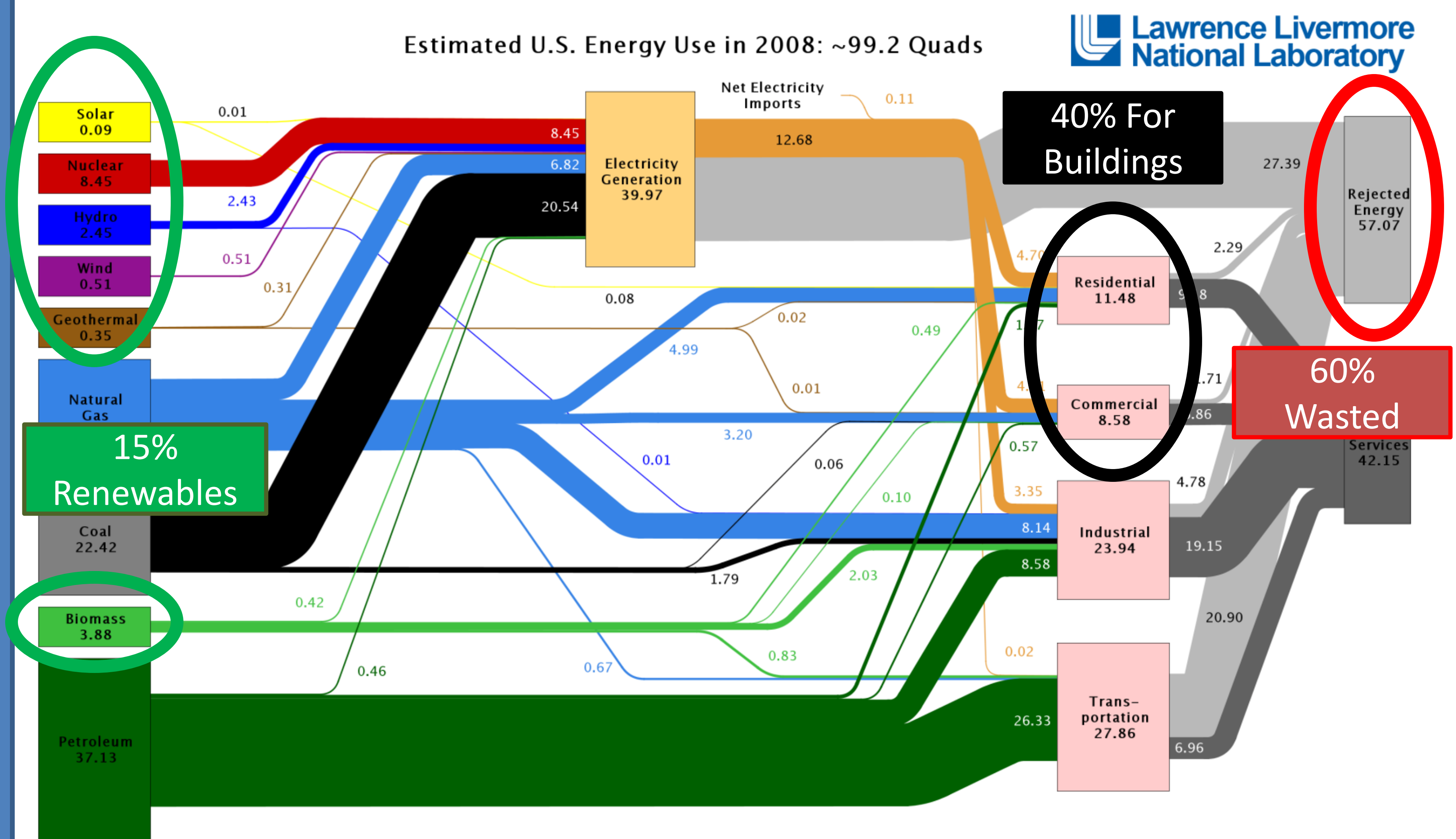

Source: LLNL 2009. Data is based on DOE/EIA-0384(2008), June 2009. If this information or a reproduction of it is used, credit must be given to the Lawrence Livermore National Laboratory and the Department of Energy, under whose auspices the work was performed. Distributed electricity represents only retail electricity sales and does not include self-generation. EIA reports flows for non-thermal resources (i.e., hydro, wind and solar) in BTU-equivalent values by assuming a typical fossil fuel plant "heat rate." The efficiency of electricity production is calculated as the total retail electricity delivered divided by the primary energy input into electricity generation. End use efficiency is estimated as 80% for the residential, commercial and industrial sectors, and as 25% for the transportation sector. Totals may not equal sum of components due to independent rounding. LLNL-MI-410527

Motivation – On Average

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End Use	2008 Annual Energy Use (QBTU)
Residential & Commercial Buildings	18.75
Lighting	2.01
Transportation	21.63
Cars	8.83

- ❑ ~30% reduction can be achieved by occupancy based lighting control (0.8 QBTU) ← DoD Spends ~3.4Billion Annual on ~1 QBTU
- ❑ A 47% reduction in buildings energy use will take ALL cars off the road!

Source: Buildings Energy Data Book & US EIA

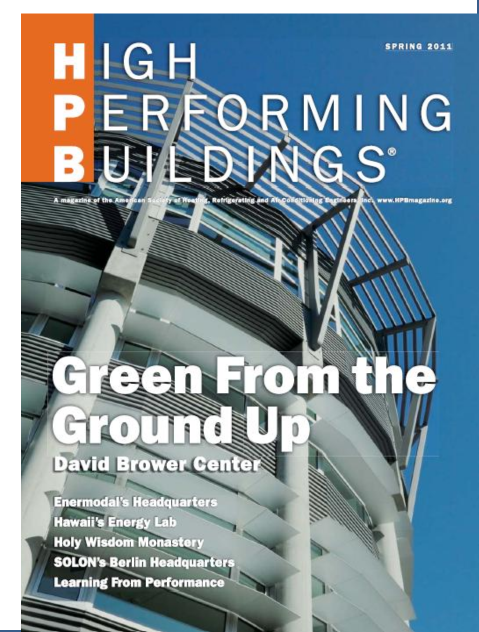
Motivation – On Average

- It can be done (1st three examples from recent HPB)!

A Grander View, Ontario Canada
- 22Kft^2 office
- **80% Energy savings** as recorded in first year
- Most energy efficient office in CA

David Brower Center, Ontario Canada
- 45Kft^2 office / group meetings
- **42.4 % Energy savings** as recorded in 11 months.

The Energy Lab, Kamuela Hawaii
- 5.9Kft^2 Educational
- **75% Energy savings** compared to CBECS
- 1st year generated 2x electricity that it used



Motivation – On Average

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❑ It will be done…

➢ DoD is the single largest energy user in U.S.

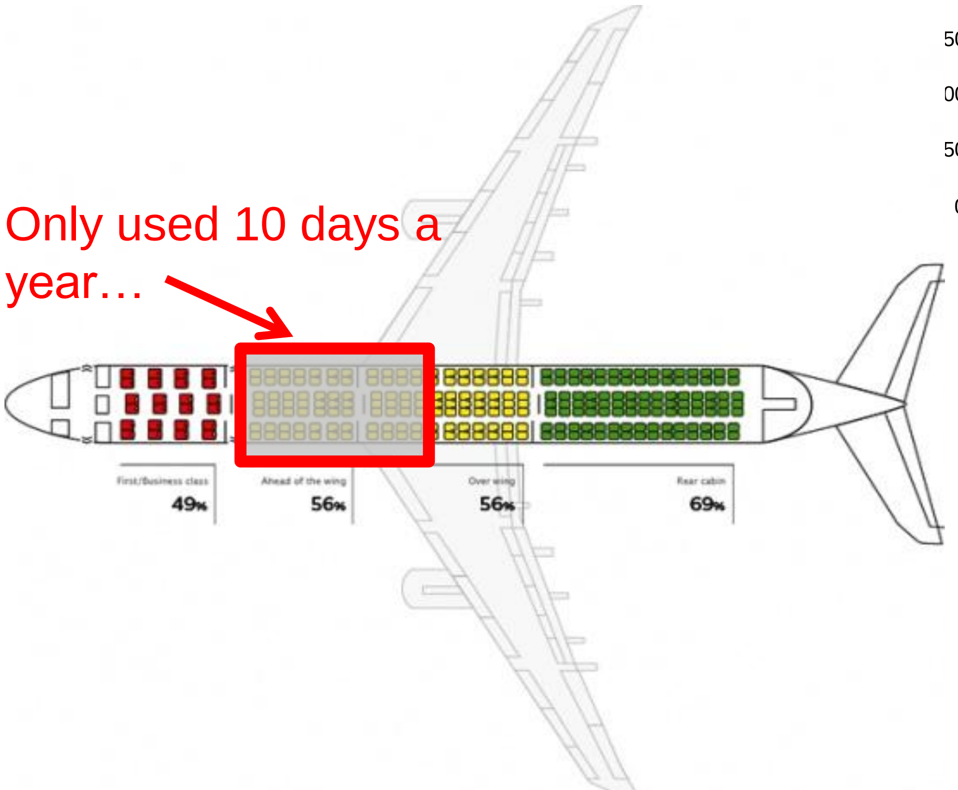
Legislation:
EPA2005:Section 109. *Federal Building Performance Standards amended the Energy* Conservation and Production Act11 by adopting the 2004 International Energy Conservation Code, and requiring revised energy efficiency standards and a 30% reduction in energy consumption of new federal buildings over the previous standards.
EISA2007: Section 431. *Energy Reduction Goals for Federal Buildings amends the National* Energy Conservation Policy Act (NECPA)13 by mandating a 30% energy reduction in federal buildings by 2015 relative to a 2005 baseline.
EISA2007: Section 433. *Federal Building Energy Efficiency Performance Standards requires* 55% reduced fossil energy use in new federal buildings and major renovations by 2010 relative to a 2003 baseline, and 100% by 2030.

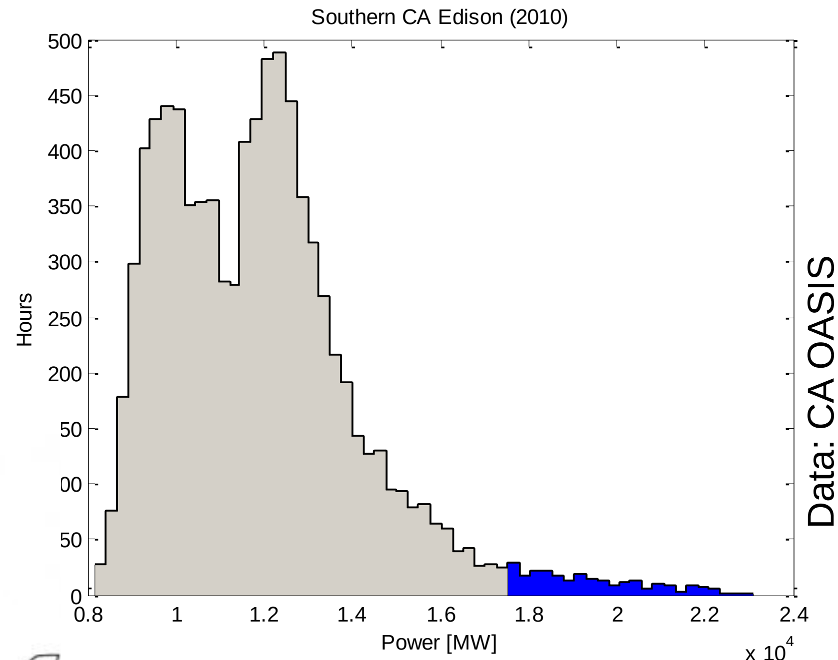
Net Zero will require ~70% reduction in energy use

Motivation – On Variance

- Some aspects of the design of the power grid are based on long tail demand concerns.

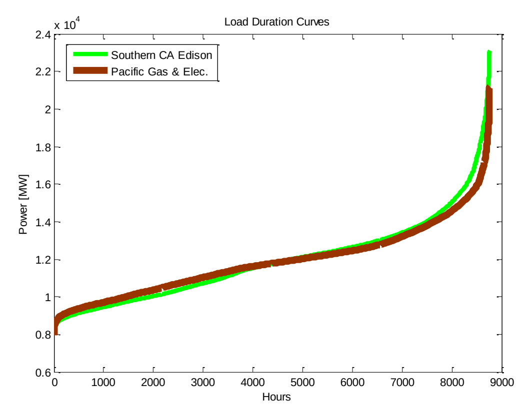
Only used 10 days a year…





Top 25% of power only 2.74% of year.

Load Duration Curve



Motivation – On Variance

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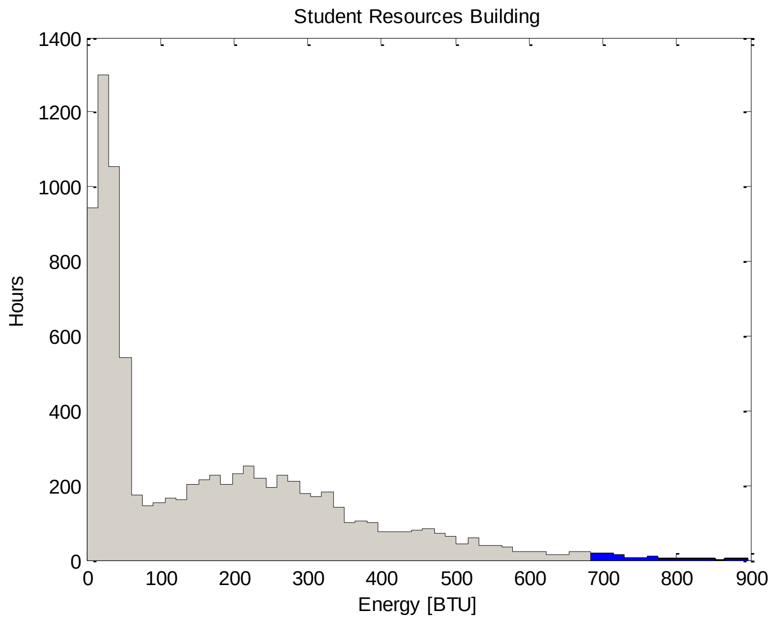
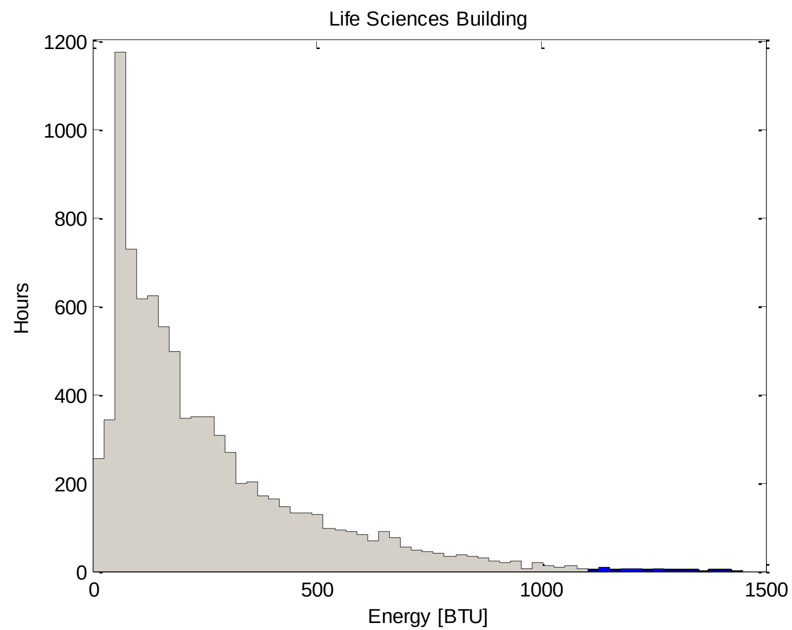
❑ Similar long tail distributions are seen at the building level (no surprise)



Top 25% of power only 0.41% of year.



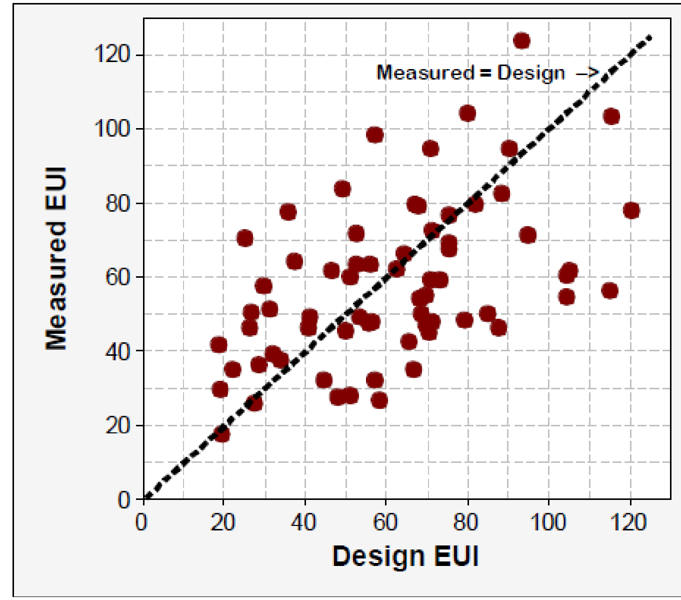
Top 25% of power only 0.99% of year.

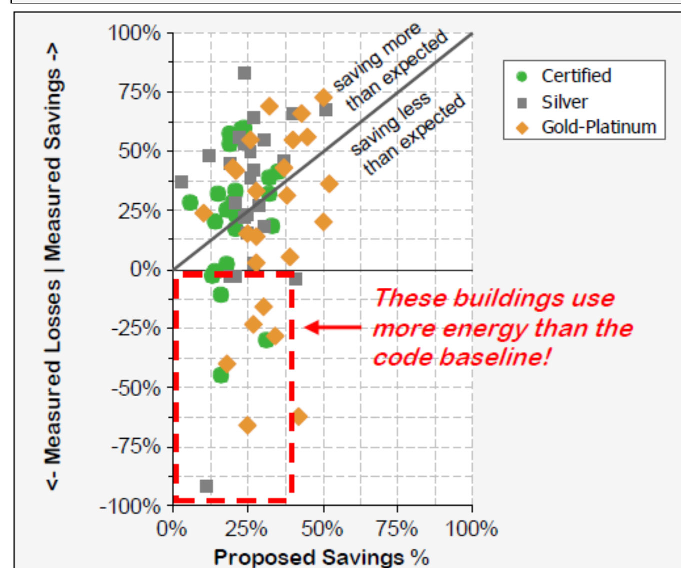
Data: Cooling energy for two buildings @ UCSB

Motivation

❑ Pitfalls

- “….these strategies must be applied together and properly integrated in the design and operation to realize energy savings. There is no single efficiency measure or checklist of measures to achieve low-energy buildings. “ ← Modeling
- “… dramatic improvement in performance with monitoring and correcting some problem areas identified by the metering “ ← Monitoring
- “There was often a lack of control software or appropriate control logic to allow the technologies to work well together “ ← Control





[Frankel 2008]

[Lessons Learned from Case Studies of Six High-Performance Buildings, P. Torcellini, S. Pless, M. Deru, B. Griffith, N. Long, R. Judkoff, 2006, NREL Technical Report.]

Summary

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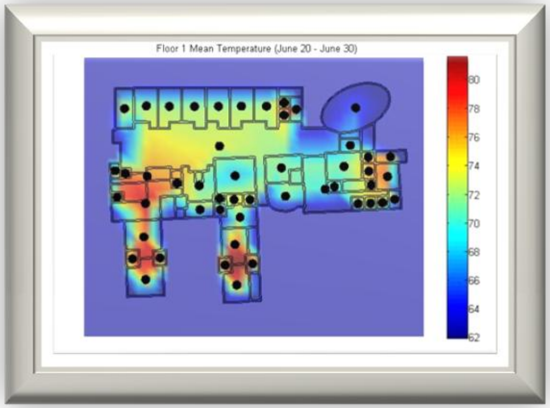
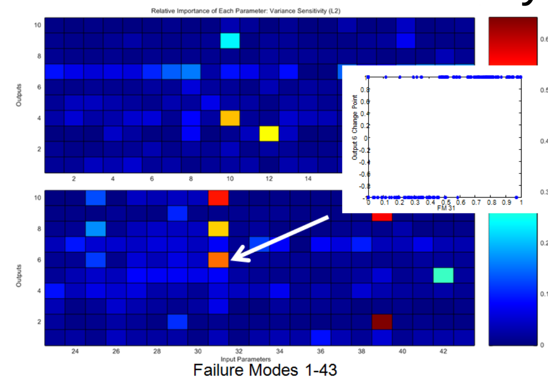
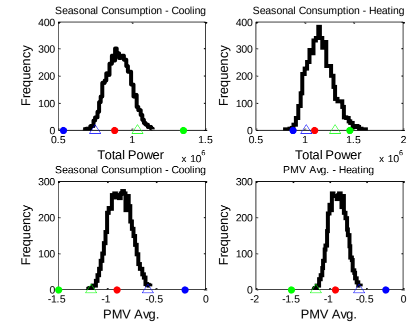
Energy Visualization



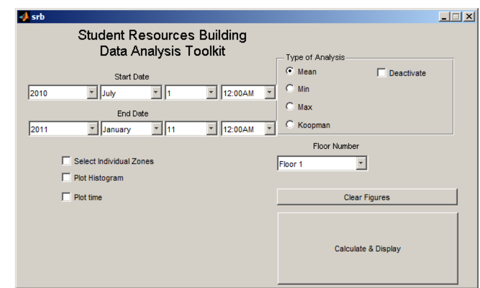
Failure Mode Effect Analysis



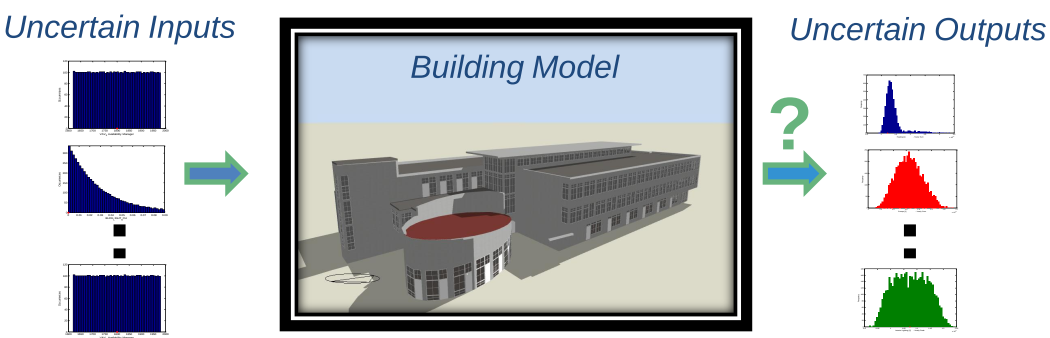
Energy/Comfort Optimization



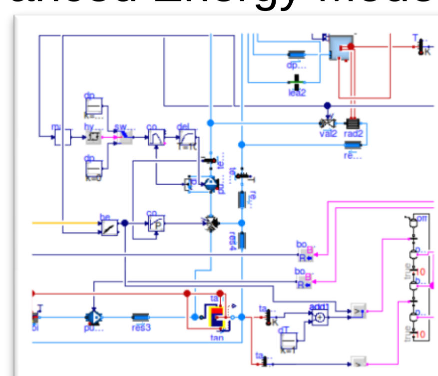
Data analysis toolkits

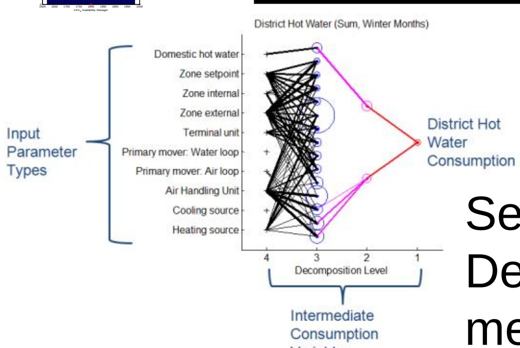


Uncertainty Analysis



Advanced Energy Modeling





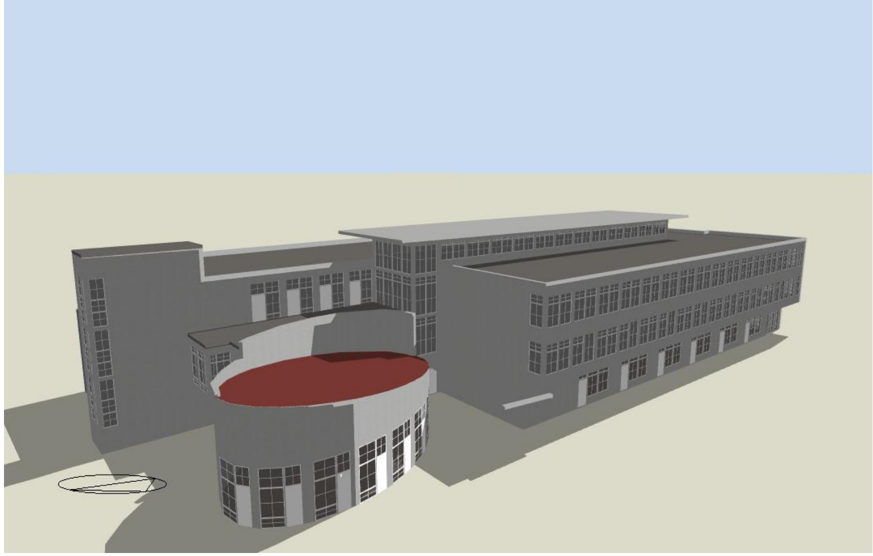
Sensitivity Decomposition methods

Modelling / Analysis

Energy Modeling

- ❑ Energy models capture both the architectural components of the building as well as its thermal physics
- ❑ Typical software contains front-end for drawing purposes, with mathematical engine for computation

Models are built with highschool / undergrad help



Ryan

Casey

Erika

TRNSYS

EnergyPlus

DOE-2

eQUEST

Building design ⟷ Equations / Physics / etc.

Energy Modeling – Uses

Reasons for modeling (entire building)

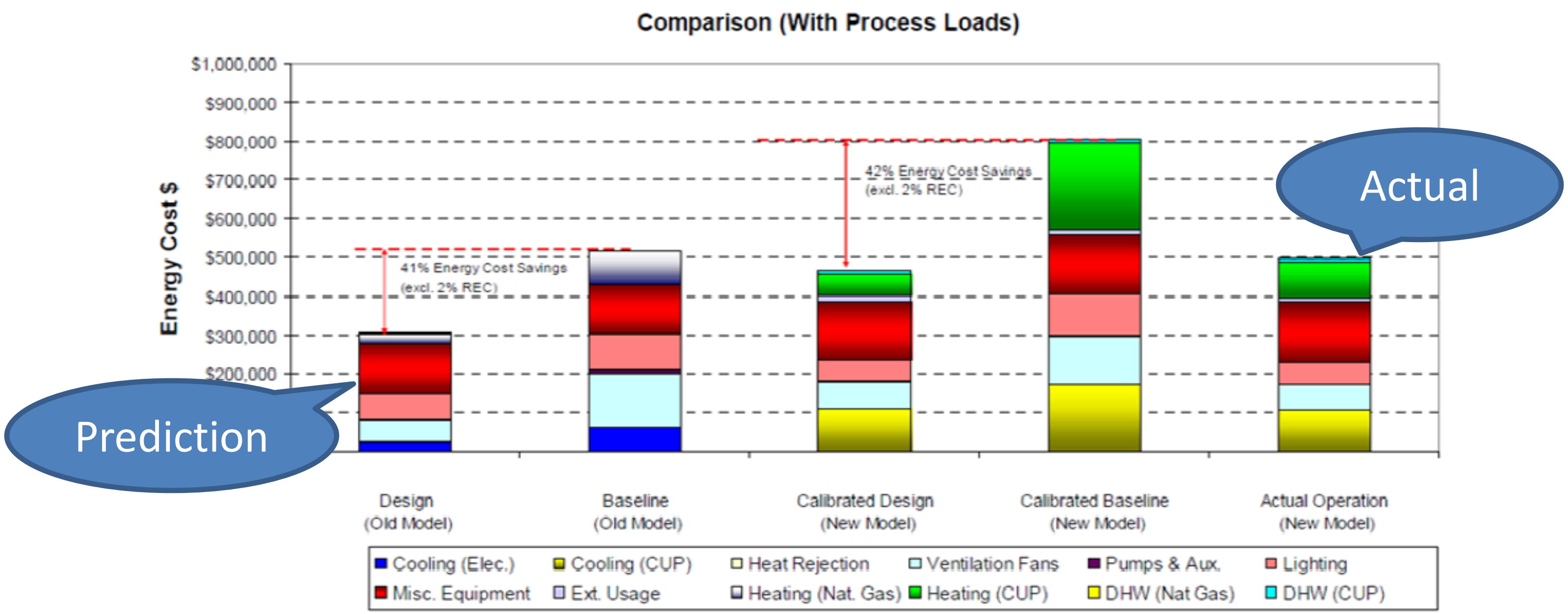
- ❑ Compliance
  - Leadership in Energy and Environmental Design (LEED)
  - ASHRAE
  - Rebates for efficient design
- ❑ Design trades
  - Usually very few performed in design firm
- ❑ Academic Studies
  - Prediction of un-sensed data
  - Uncertainty / Sensitivity Analysis
  - Optimization (design / operation)
  - ….

➢ Very little control design is performed with these models at the building level (some work at the component level).

➢ Whole-building energy models not connected to grid.

Energy Modeling & Uncertainty

- ❑ Decades spent on developing energy models
  - ➢ Most are validated on a component basis
- ❑ At the systems level, the most advanced energy models, are still do not predict consumption accurately during the design stage



* Stanford Y2E2 Building

Energy Modeling & Uncertainty

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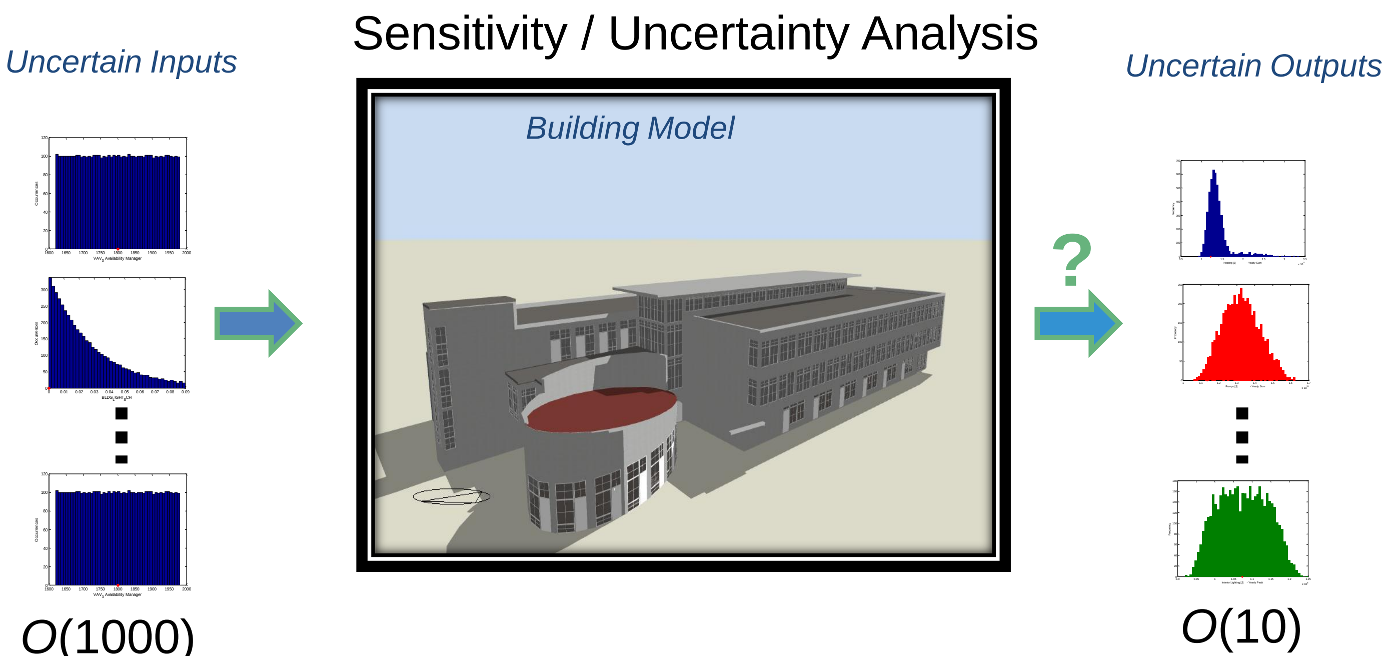
- ❑ Discrepancy is often introduced because of uncertainty
  - ➢ Commissioning / Operation
  - ➢ Material selection
  - ➢ Usage
  - ➢ … Other unknowns
- ❑ Sensitivity / Uncertainty Analysis helps manage these concerns



Energy Modeling & Uncertainty

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Sampling

- O.A.T.
- Monte Carlo
- Latin Hypercube
- Quasi-Monte Carlo (deterministic)

Uncertainty Analysis

- STD(), VAR()
- COV
- Amplification factors

Sensitivity Analysis

- Elementary Effects / screening & local methods
- Morris Method
- ANOVA
- Derivative-based
- Propagation analysis through decomposition

Red: In this talk

UA / SA – Historically (Building Sys.)

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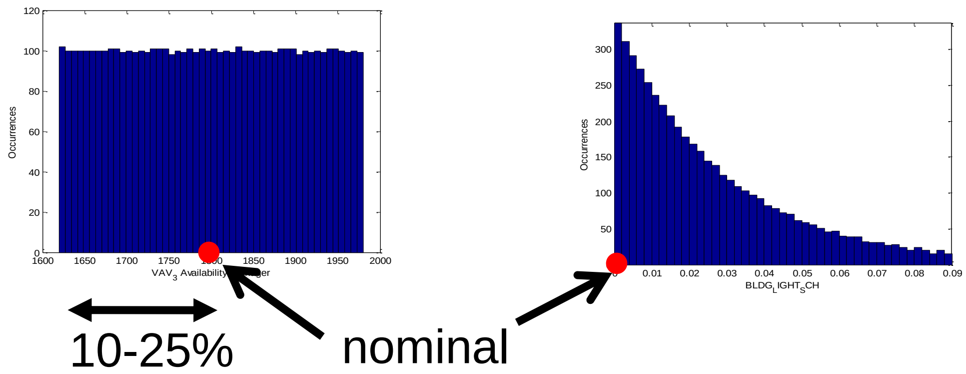
Author(s)	# Param.	Technique	Notes
Rahni [1997]	390->23	Pre-screening	
Brohus [2009]	57->10	Pre-screening / ANOVA	
Spitler [1989]	5	OAT / local	Residential housing
Struck [2009]	10		
Lomas [1992]	72	Local methods	
Lam [2008]	10	OAT	10 different building types
Firth [2010]	27	Local	Household models
de Wit [2009]	89	Morris	Room air distribution model
Corrado [2009]	129->10	LHS / Morris	
Heiselberg [2009]	21	Morris	Elementary effects of a building model
Mara [2008]	35	ANOVA	Identify important parameters for calibration also.
Capozzoli [2009]	6		Architectural parameters
Eisenhower [2011]	1009 (up to 2000)	Deterministic sampling, global derivative sensitivity	'All' available parameters in building

Parameter Variation

All numerical design & operation parameters in the model are varied concurrently (not arch. design)



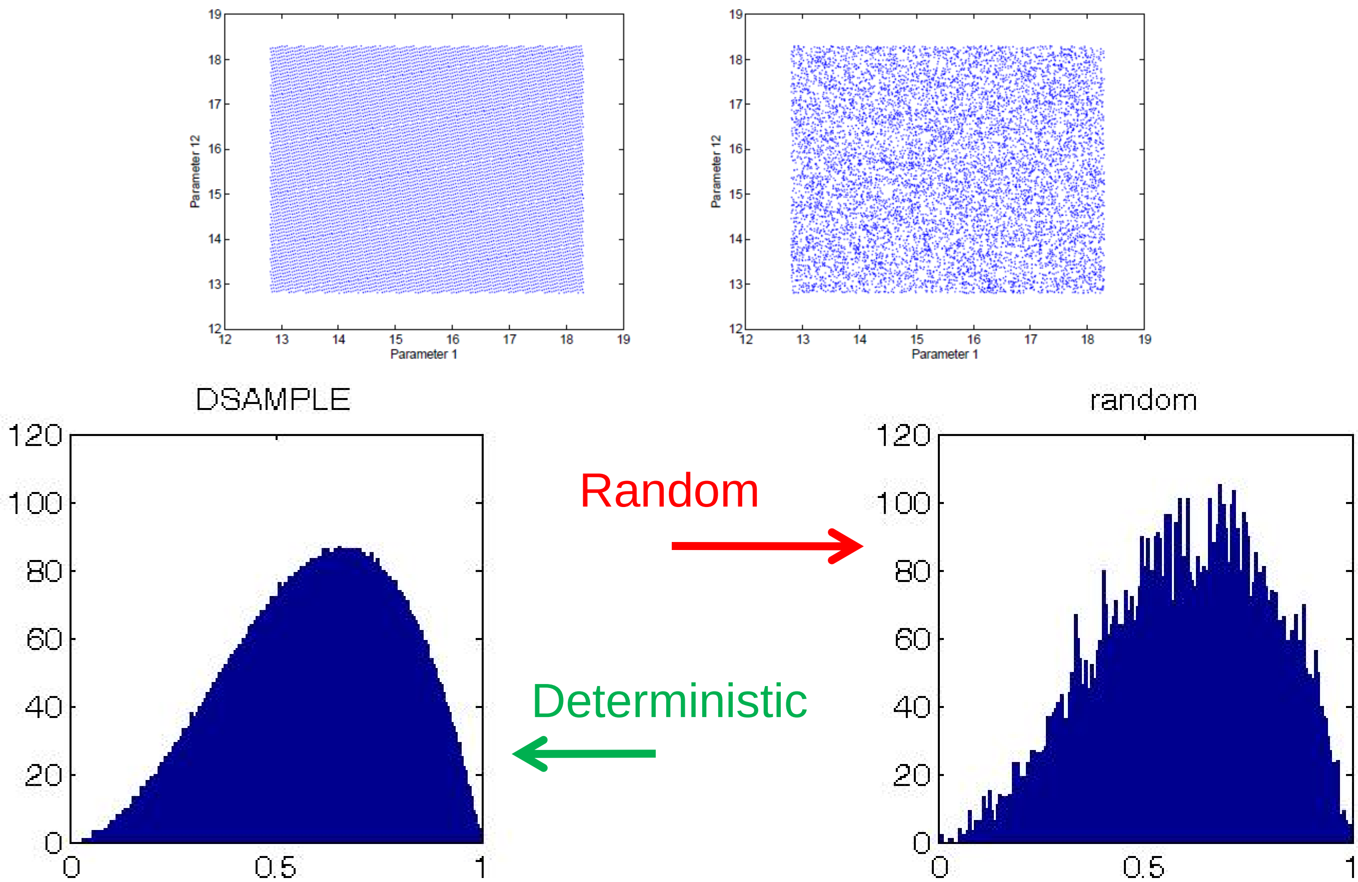
- Parameters varied 10-25% of their mean
- Some parameters are of the form a+b < 1

Parameters organized by type

Type	Examples
Heating source	**(Furnace, boiler, HWGSHP etc)**
Cooling source	**(chiller, CHWGSHP etc)**
AHU	**(AHU SAT setpoint, coil paramters etc)**
Air Loop	**(Fans)**
Water Loop	**(Pumps)**
Terminal unit	**(VAV box, chilled beam, radiant heating floor)**
Zone external	**(Envelope, outdoor conditions)**
Zone internal	**(Usage, internal heat gains schedule,)**
Zone setpoint	**(Zone temp setpoint)**
Sizing parameter	**(Design parameters for zone, system, plant)**

Parameter Variation

- Large number of parameters and lengthy simulation time require efficient parameter selection (for parameter *sweeps*)
- Deterministic sampling avoids the 'clumping' that occurs in Monte Carlo based sampling



Convergence Properties

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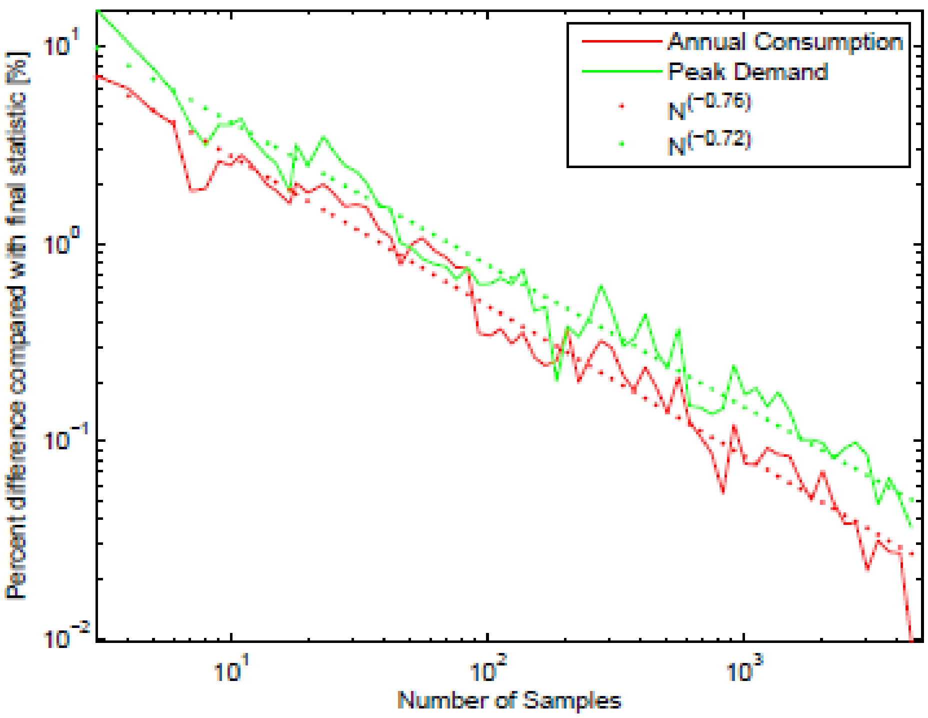
- Monte Carlo bound ~ 1/sqrt(N)
- Deterministic bound ~ 1/N

Faster convergence means more parameters can be studied in the same amount of time!

Example Convergence from Building Simulation



Typical Output Distributions

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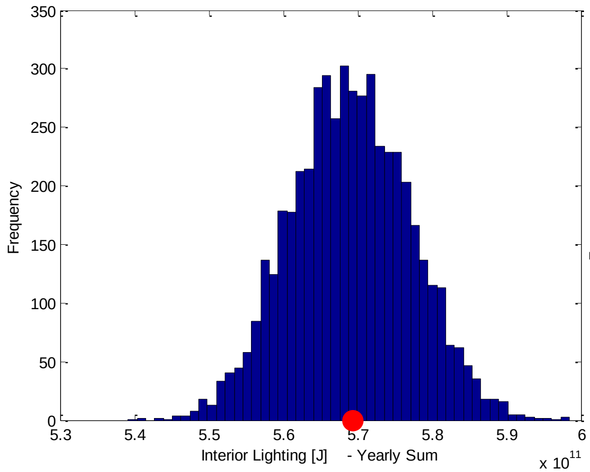
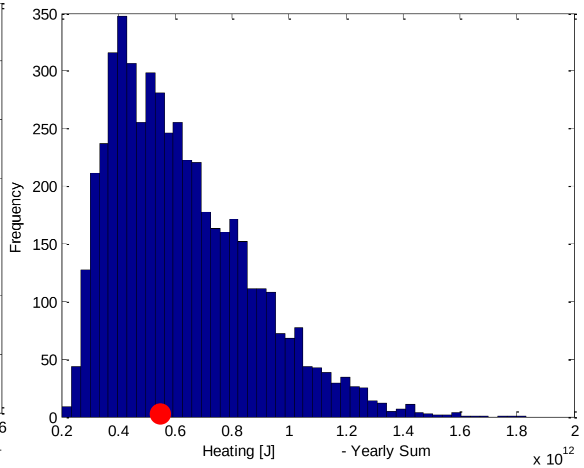
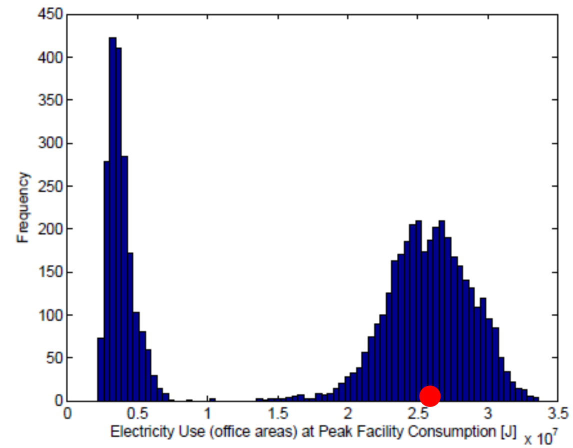
Key Outputs

+ Gas Facility
+ Electricity Facility
Heating
Cooling
Pump
Fan
Interior Lighting
Interior Equipment

- 5000 realizations performed to obtain convergence
- The ‘control’ mechanisms in the model drive distributions towards Gaussian although others exist as well







* TRNSYS results

Case Studies

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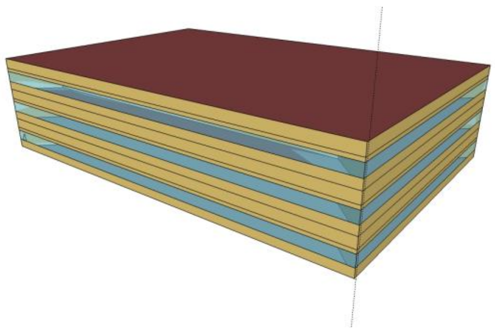
DOE benchmark models

- Medium office model in Las Vegas
  3 floors, ~50K ft^2, 15 zones



Building 1225 in Ft. Carson with TRNSYS

- An administration and training facility built in 70’s.
- One floor with an area of ~24000 ft^2.
- Major HVAC systems: 2 constant-air-volume multi-zone-units, chilled water from a central plant (May-October), hot water by a gas boiler (November-April).
- Domestic hot water generated by a gas water heater.

Case Studies

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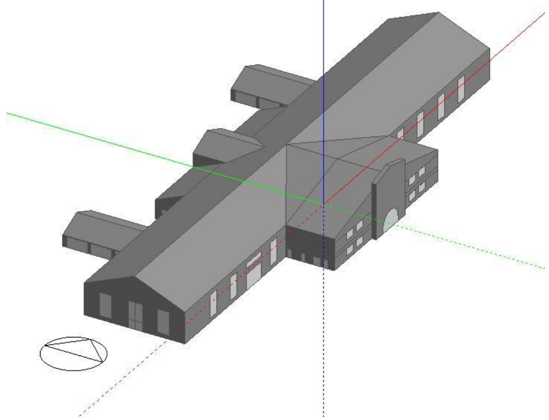
DOD: Atlantic Fleet Drill Hall

- 6430 m2 (69 K ft^2)
- Model developed in EnergyPlus
- 30 Conditioned zones
- 1009 uncertain parameters



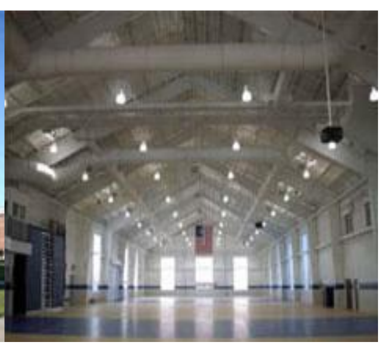


Table 3. Parameter Types.

Number	Type	Note: examples in this Drill Hall system 1
1	Heating source	District heating system (normal capacity, maximum hot water system temperature, loop flow rate, etc.)
2	Cooling source	Air cooled chiller (chiller reference capacity, reference COP, reference leaving chilled water temperature, etc.)
3	AHU	AHU (supply air temperature setpoint, cooling coil design flow rate, design inlet water temperature, design inlet air temperature, etc.)
4	Primary Mover: Air loop	Fans (efficiency, pressure rise, etc.)
5	Primary Mover: Water loop	Pumps (rated flow rate, rated head, rated power consumption, etc.)
6	Terminal unit	VAV boxes (maximum air flow rate, minimum air flow fraction, etc.), maximum zonal flow rates
7	Zone external	Building envelope(material thermal properties such as conductivity, density, and specific heat, window thermal and optic properties, etc.), outdoor conditions (ground temperature, ground reflectance, etc.)
8	Zone internal	Internal heat gains design level (lighting load, number of people, people activity level, etc.), schedules
9	Zone setpoint	Zone temperature setpoint (space cooling and heating setpoints)
10	Domestic hot water	Domestic hot water usage (peak flow rate, target temperature, etc.)

Table 2. Consumption outputs chosen for the analysis.

Number	Name
1	DistrictHeating:Domestic Hot Water Energy [J]
2	DistrictHeating:HVAC [J]
3	Electricity:Facility [J]
4	DistrictHeating:Facility [J]
5	InteriorEquipment:Electricity [J]
6	InteriorLights:Electricity [J]
7	Cooling:Electricity [J]
8	Pumps:Electricity [J]
9	Fans:Electricity [J]
10	Chillers:EnergyTransfer [J]

Model Results - UA

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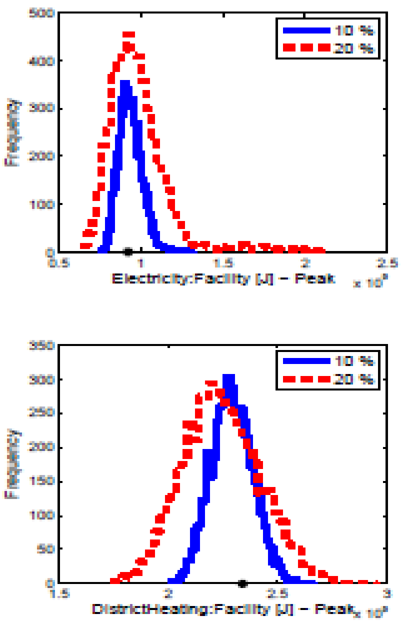
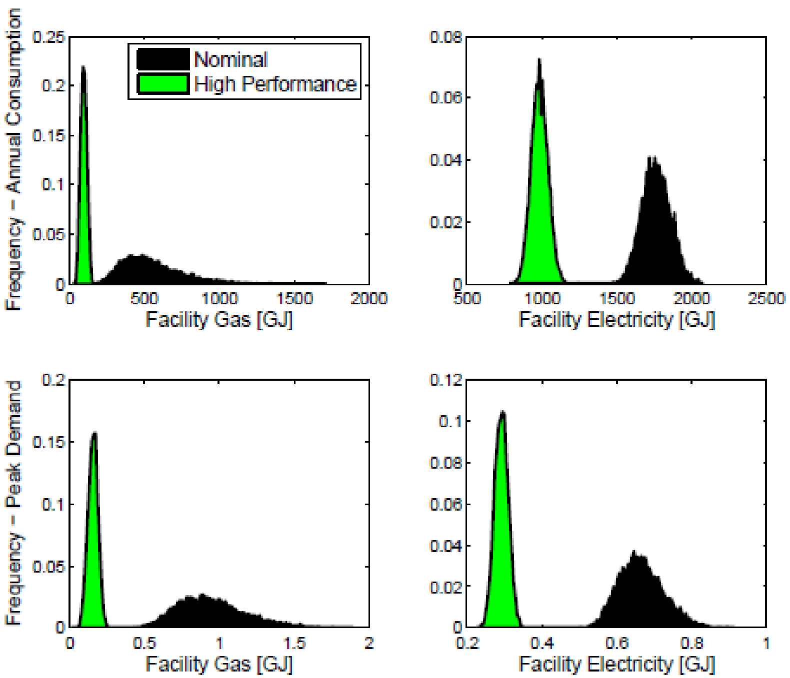
Characteristics of the output are considered based on different inputs, or different models

Influence of Different Parameter Variation (size)



[E+ Drill Hall]

Nominal vs. High Efficiency Design



[E+ DOE Models]

B. Eisenhower, et al. The Impact of Uncertainty in High Performance Building Design *Prepared for: International Building Performance Simulation Association, BuildSim 2011*

Model Results - UA

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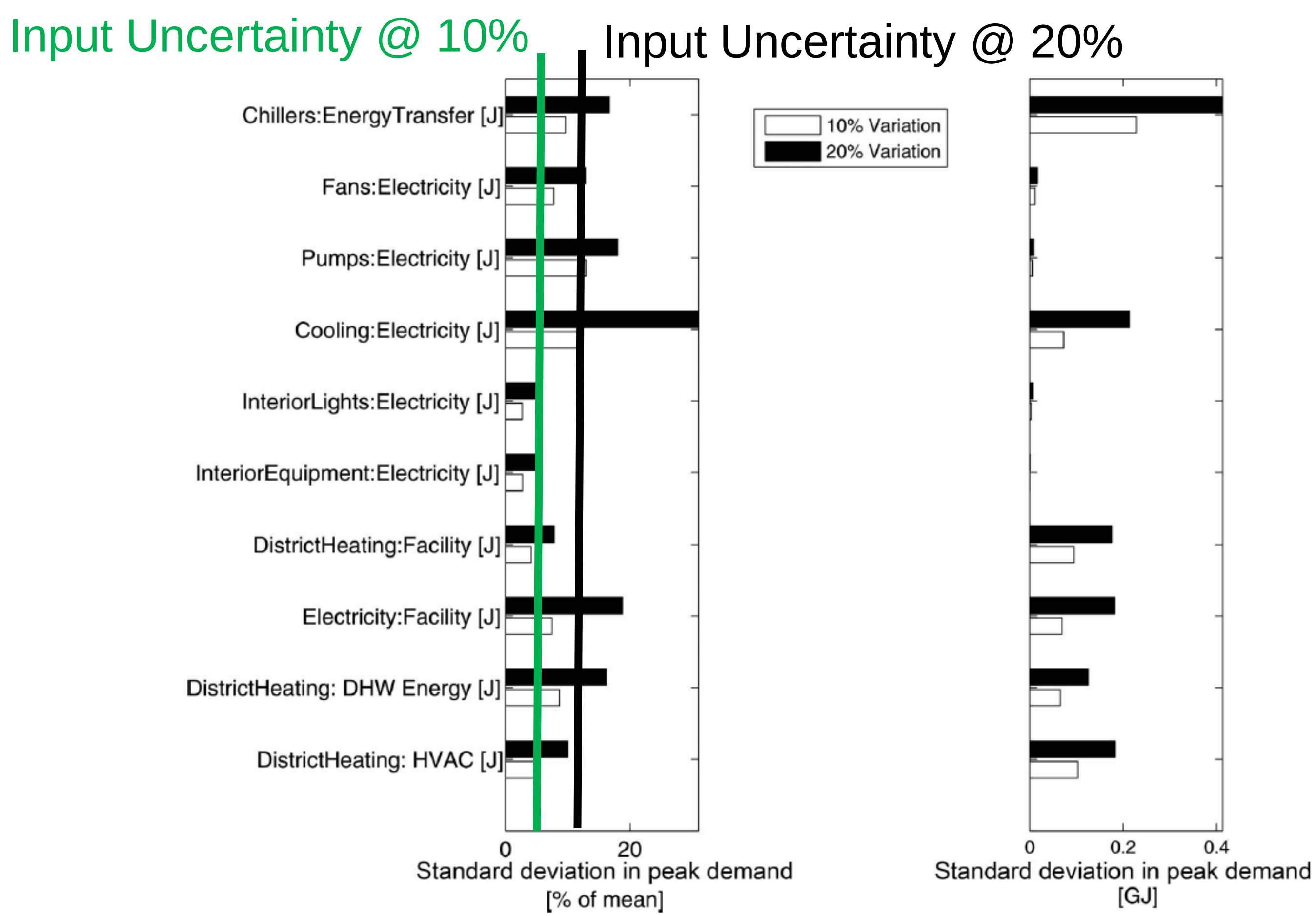
Amplification & Attenuation of uncertainty is quantified on a subsystem and facility basis



[E+ Drill Hall]

Meta-Modelling

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For analysis, a meta-model is derived to analytically characterize the building energy model

Sobol' decomposition into 2^n summands

$$f(\mathbf{x}) = f_0 + \sum_{i=1}^{n} f_i(x_i) + \sum_{1 \le i < j \le n} f_{ij}(x_i, x_j) + \cdots$$

$$+ \sum_{1 \le i_1 < \cdots < i_l \le n} f_{i_1 i_2 \ldots i_l}(x_{i_1}, x_{i_2}, \ldots, x_{i_l}) + \cdots$$

$$+ f_{12\ldots n}(x_1, x_2, \ldots, x_n),$$

Building energy model

x: uncertain parameters
f: zeroth, first, second, … order component functions

If f(x) is square integrable, $f_{i\ldots n}()$ are square integrable as well

$$f_i(x_i) \approx \sum_{r=1}^{k} \alpha_r^i \varphi_r^i(x_i),$$

$$f_{ij}(x_i, x_j) \approx \sum_{p=1}^{l} \sum_{q=1}^{l'} \beta_{pq}^{ij} \varphi_p^i(x_i) \varphi_q^j(x_j),$$

$$f_{ijk}(x_i, x_j, x_k) \approx \sum_{p=1}^{m} \sum_{q=1}^{m'} \sum_{r=1}^{m''} \gamma_{pqr}^{ijk} \varphi_p^i(x_i) \varphi_q^j(x_j) \varphi_r^k(x_k),$$

$$\ldots,$$

Component functions are parameterized by unknown weights on orthonormal basis functions

Model created using Gaussian Kernels

Sobol', I., 2001

Sensitivity Calculation

Three approaches to calculating global sensitivity:

- L2-norm derivative sensitivity indices can be calculated as

$$N_i^{tot} = \frac{\alpha_i \sigma_i^2}{D} \int \left[\frac{\partial f(\mathbf{x})}{\partial x_i} \right]^2 \rho(\mathbf{x}) d\mathbf{x},$$

where $\sigma_i^2 = \frac{1}{2} \int \left(x_i - x_i' \right)^2 \rho(x_i) dx_i \, \rho(x_i') dx_i'$

and α_i is a constant for each distribution $\rho(x_i)$

- L1-norm derivative sensitivity indices can be calculated as

$$L_i^{tot} = \sqrt{\frac{\alpha_i \sigma_i^2}{D}} \int \left| \frac{\partial f(\mathbf{x})}{\partial x_i} \right| \rho(\mathbf{x}) d\mathbf{x}$$

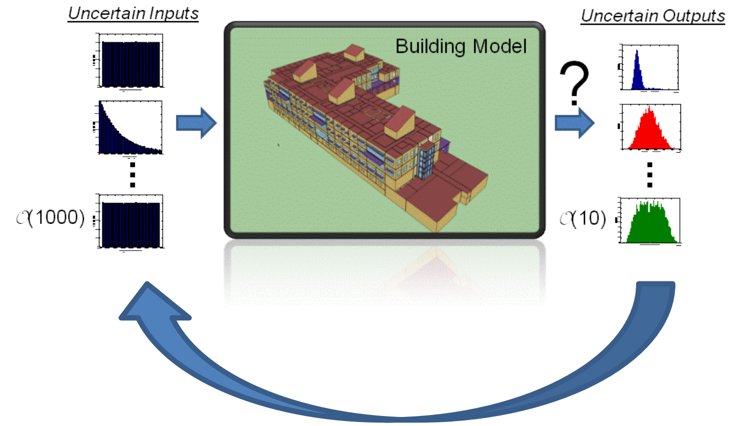
- Average derivatives can be calculated as

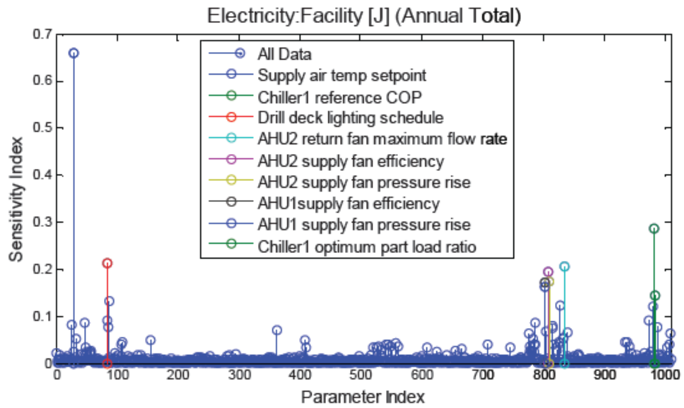
$$M_i^{tot} = \sqrt{\frac{\alpha_i \sigma_i^2}{D}} \int \frac{\partial f(\mathbf{x})}{\partial x_i} \rho(\mathbf{x}) d\mathbf{x}$$

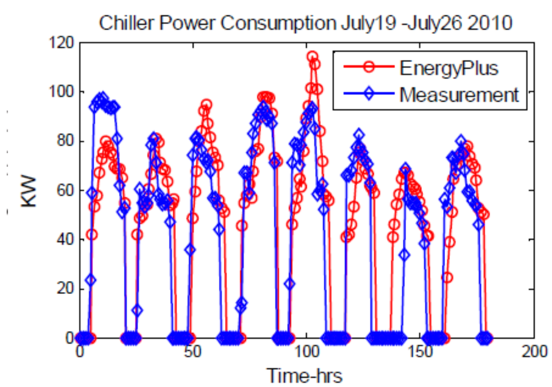
Sobol', I. and Kucherenko, S., 2009

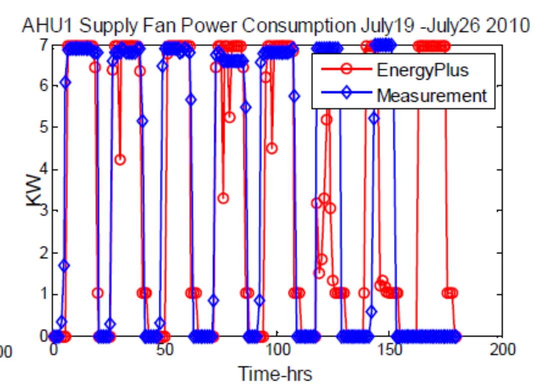
Sensitivity Analysis

- ❑ Uncertainty Analysis considers the forward progress of how uncertainty influences the output.
- ❑ Sensitivity Analysis identifies which parameters are causing the most influence







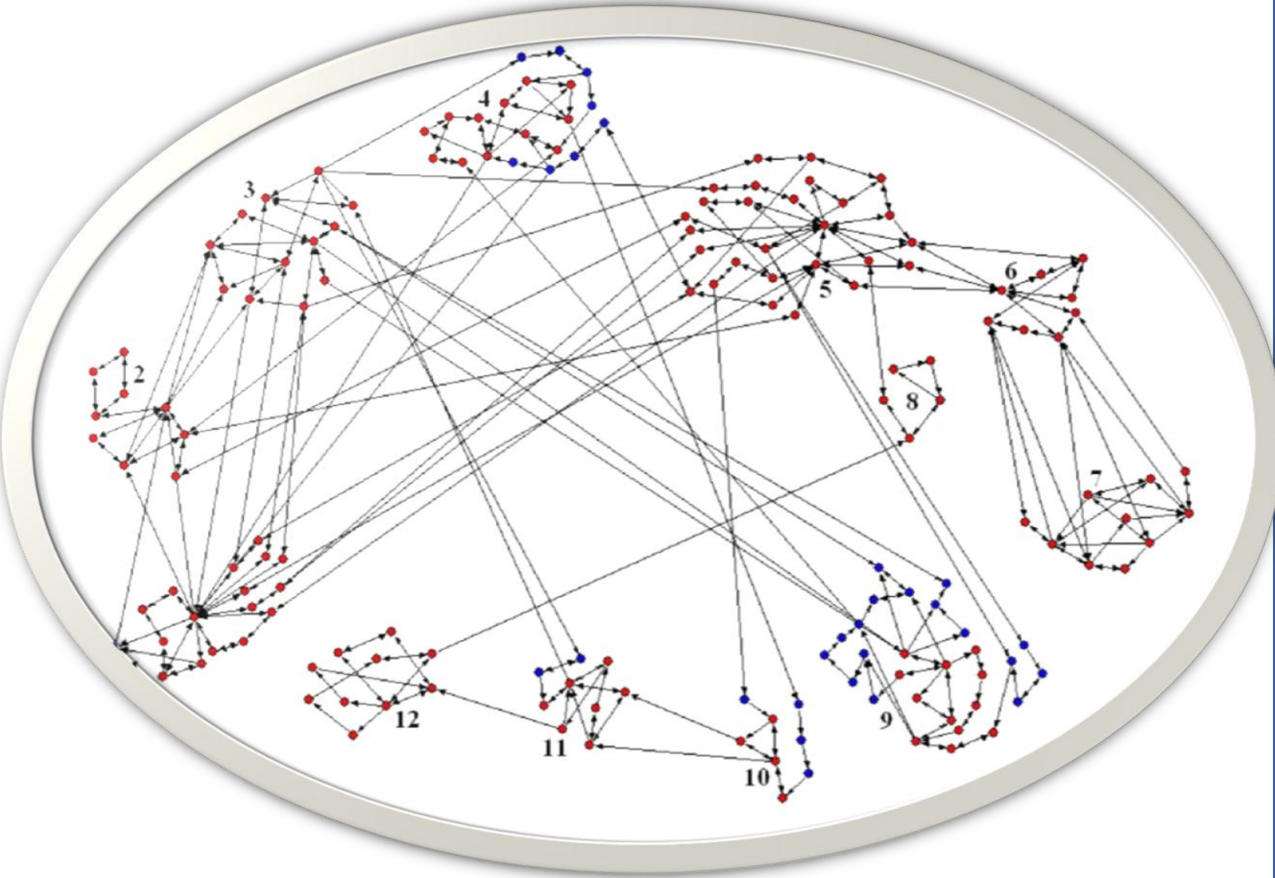


[E+ Drill Hall]

Identifying key parameters in a building helps in design optimization, continuous commissioning, model calibration, …

Zheng O'Neill, Bryan Eisenhower, et al <u>Modeling and Calibration of Energy Models for a DoD Building</u> ASHRAE Annual Conference, Montreal 2011

System Decomposition



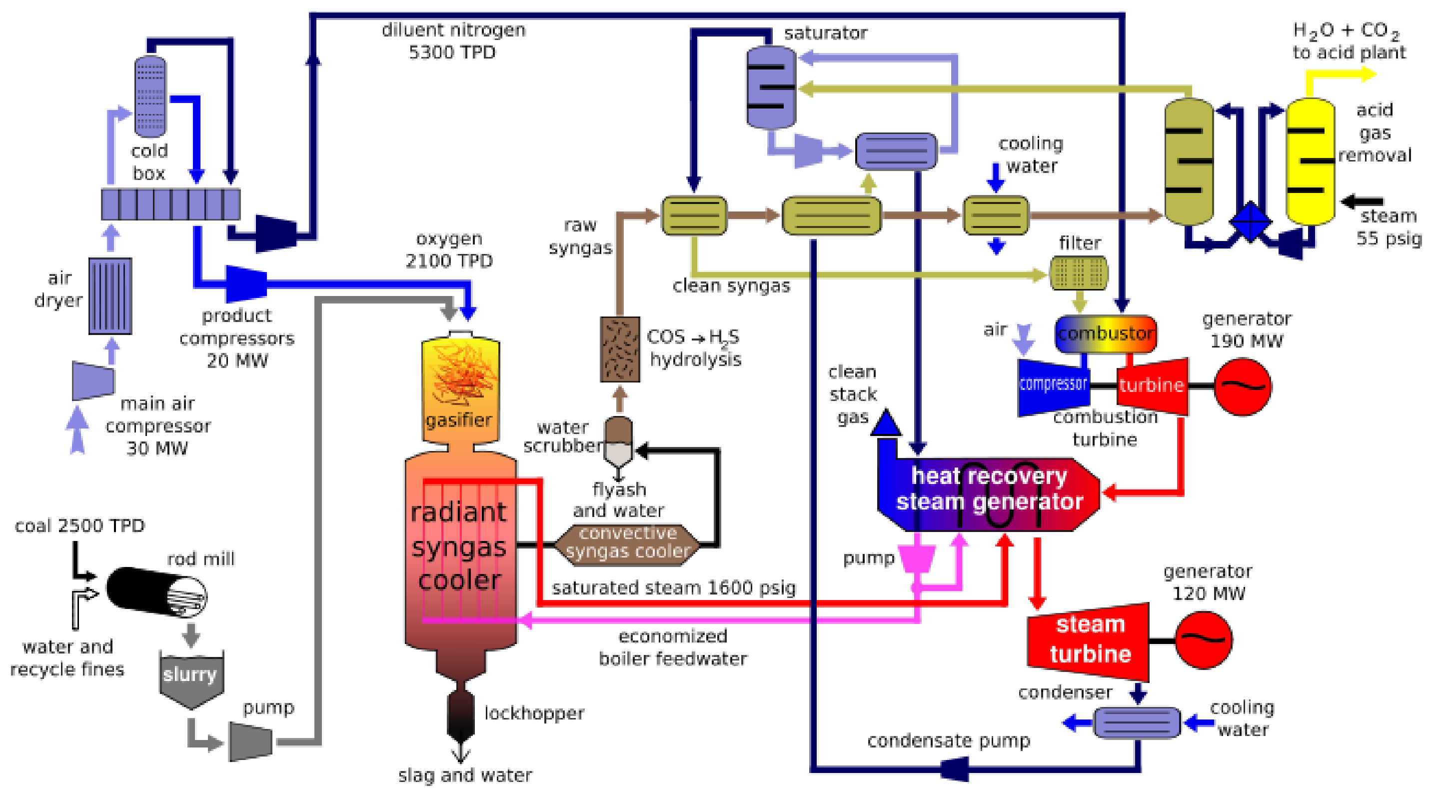
http://www.biomedcentral.com/14712105/7/386/figure/F2?highres=y

Decomposition Methods

What are the *essential components of a productive network?*

Decomposition provides an understanding of essential production units and the pathway energy/information/uncertainty flows through the dynamical system

Integrated Gasification Combined Cycle, or IGCC, is a technology that turns coal into gas into electricity



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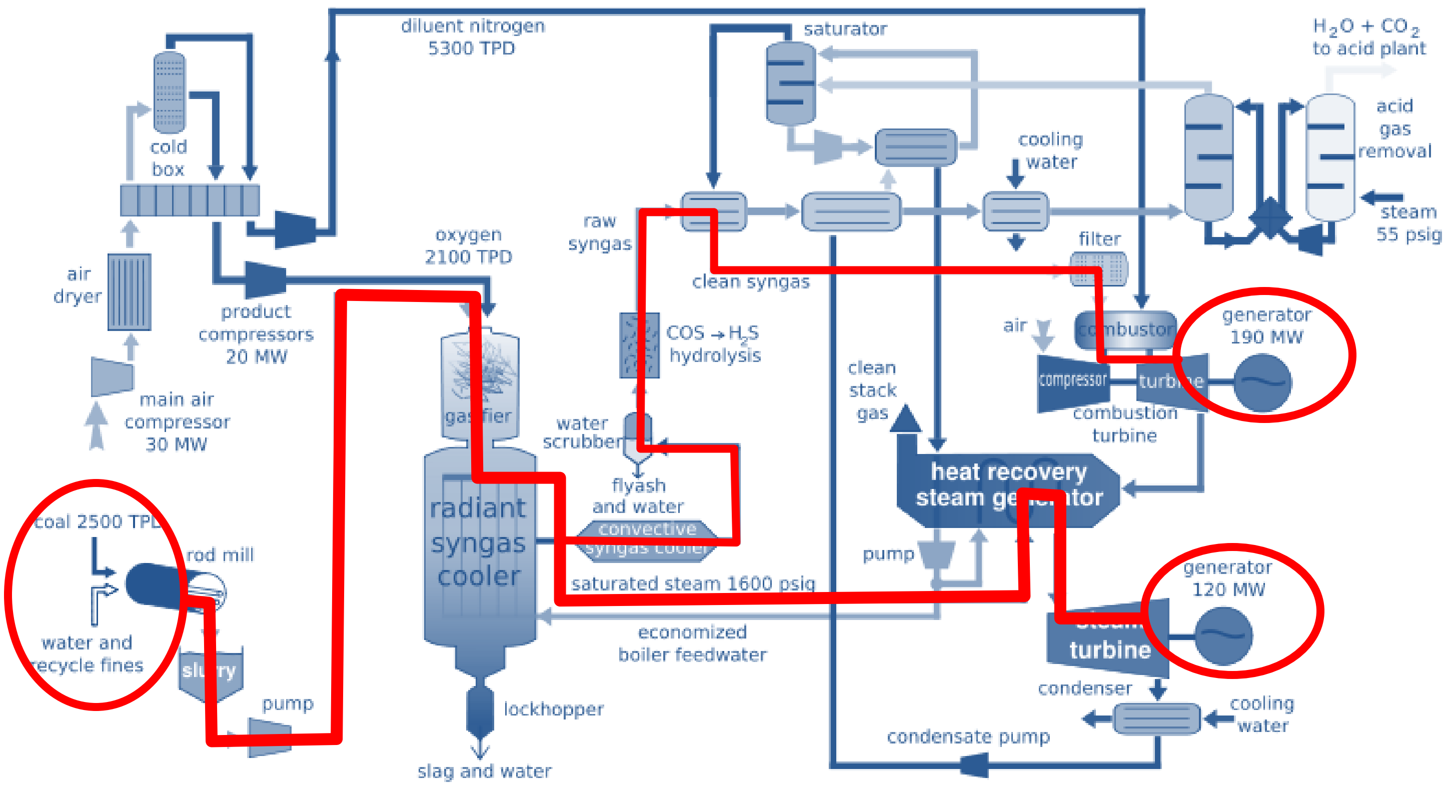
Decomposition provides an understanding of essential production units and the pathway energy/information/uncertainty flows through the dynamical system

Integrated Gasification Combined Cycle, or IGCC, is a technology that turns coal into gas into electricity



Decomposition Methods

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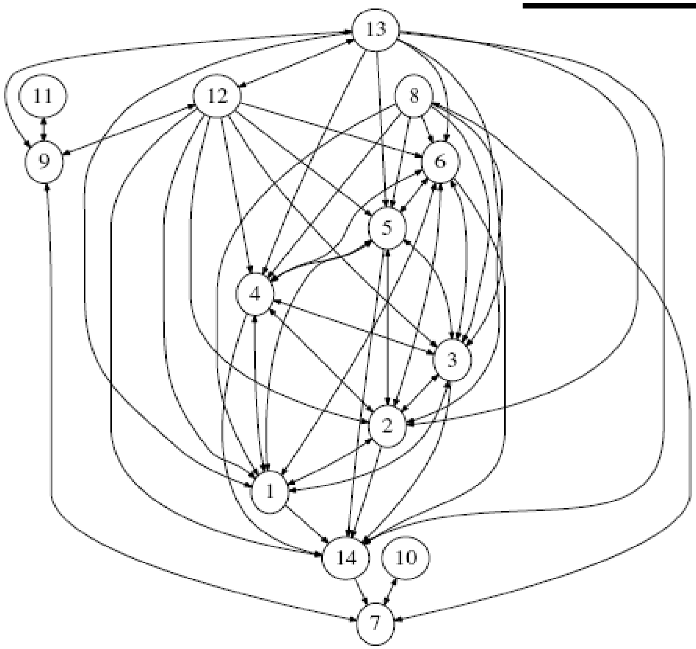
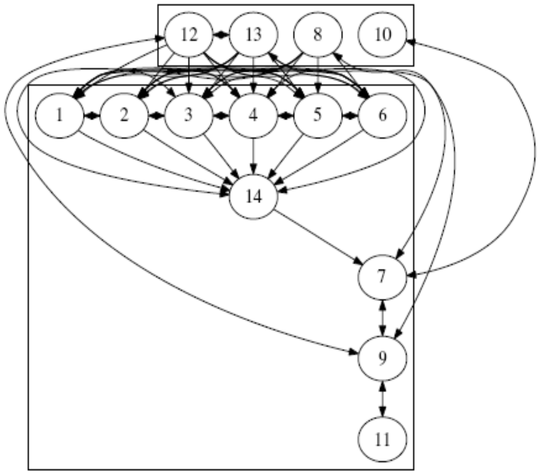
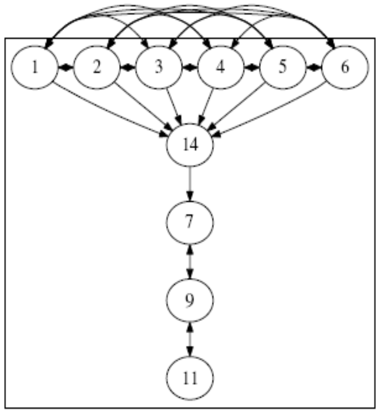
Dynamical systems on graphs highlights dominating function of network
Mean production units (MPU)

- What are the *essential components of a productive network*

B. Subtilis chemotaxis network





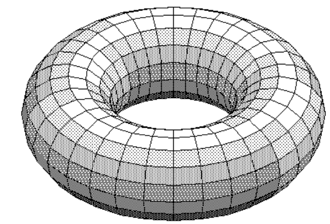


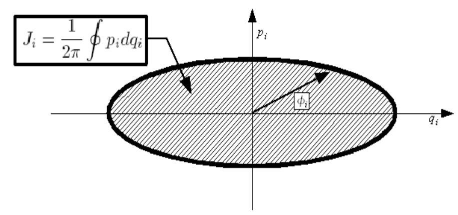
[Y. Lan and I. Mezic *On the Architecture of Cell Regulation Networks, BMC Systems Biology 2011]*

Decomposition Methods - Cascade

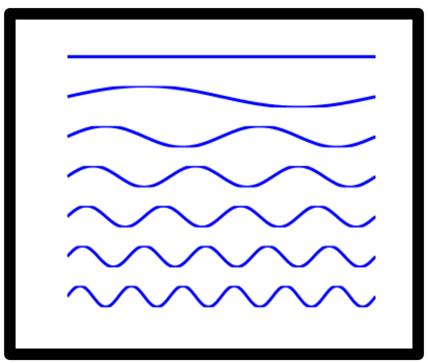
Action-Angle system describes energy behavior

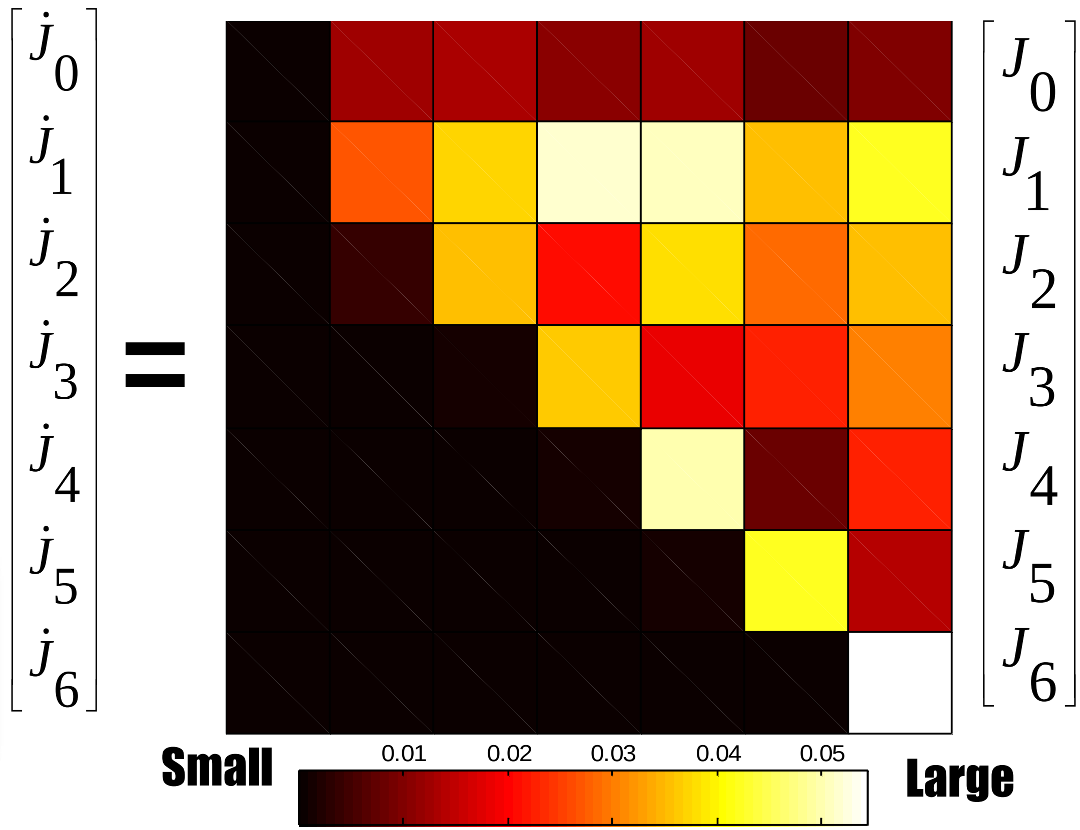
Jacobian describes energy transfer characteristics

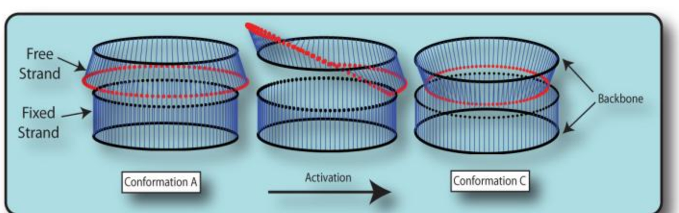




$$\begin{bmatrix}\dot{\phi}\\ \dot{\mathbf{j}}\end{bmatrix} = \left[\begin{array}{c|c} A_{11} & A_{12} \\ \hline A_{21} & A_{22}\end{array}\right]\begin{bmatrix}\phi \\ \mathbf{J}\end{bmatrix}$$



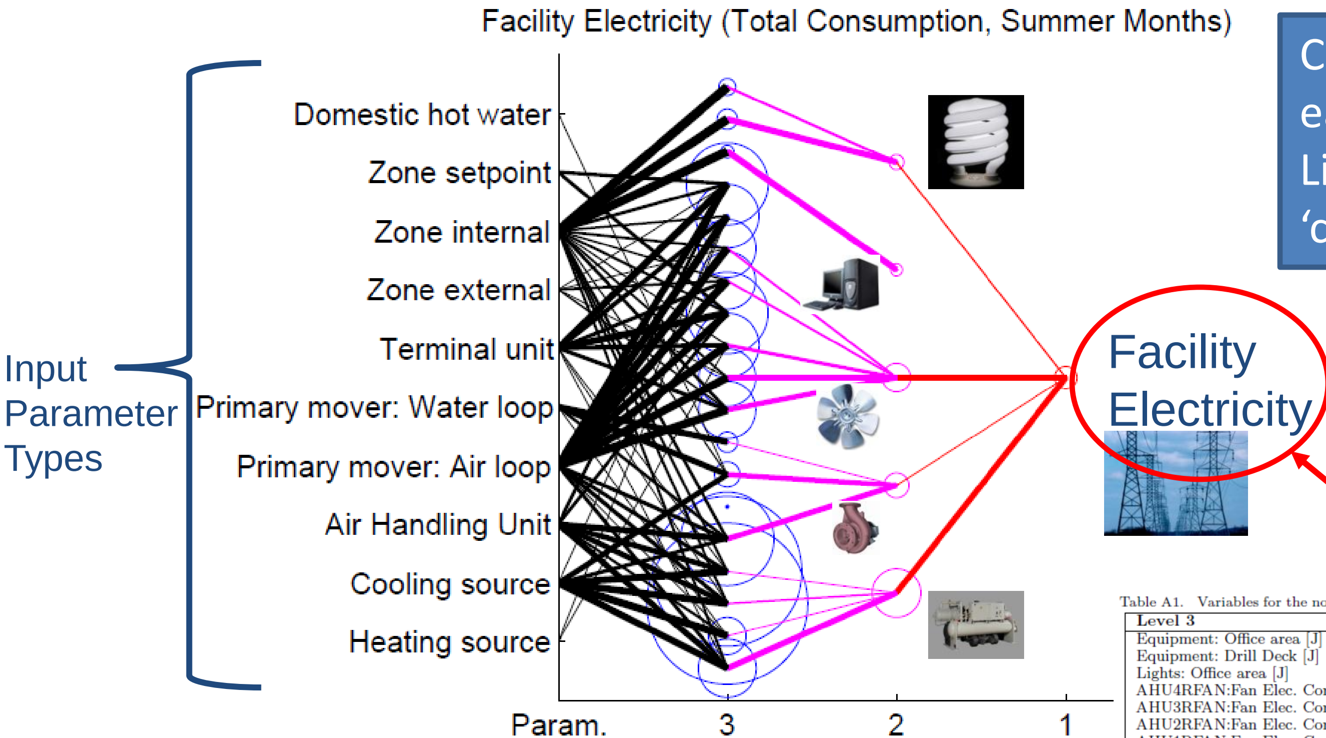




[Eisenhower and I. Mezic *Physical Review E, 2010*]

Uncertainty at each node and pathway flow identified for a heterogeneous building

Circles: Uncertainty at each node
Line Thickness: 'conductance'



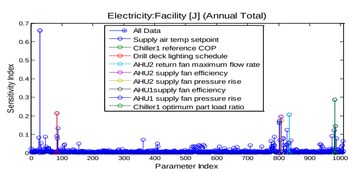
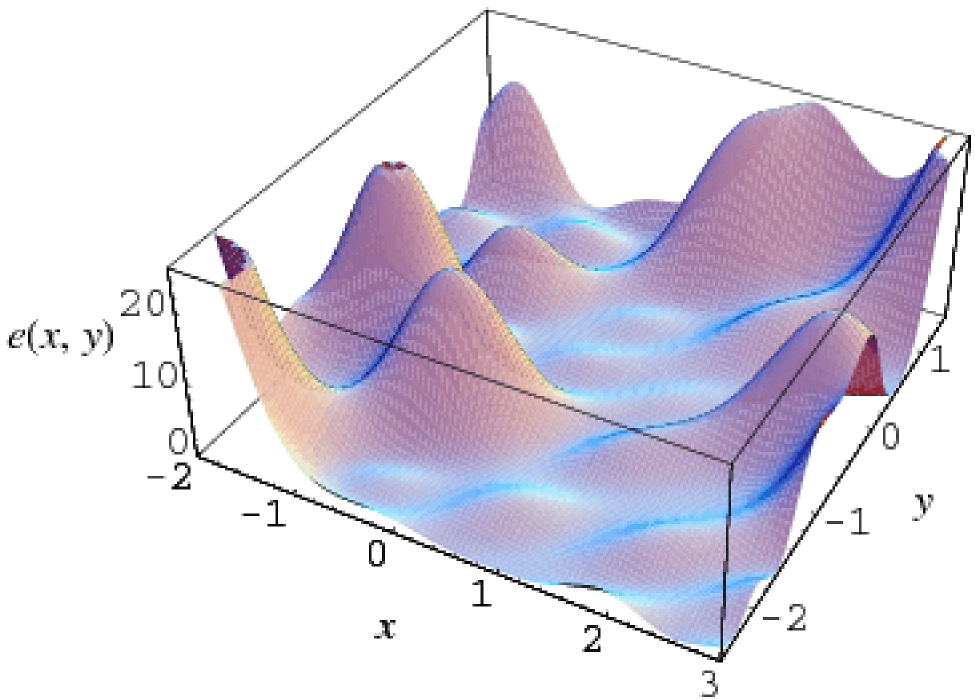


Table A1. Variables for the nodes of the sensitivity decomposition of Facility Electricity (Figure 7).

Level 3	Level 2	Level 1
Equipment: Office area [J]		
Equipment: Drill Deck [J]		
Lights: Office area [J]		
AHU4RFAN:Fan Elec. Cons. [J]		
AHU3RFAN:Fan Elec. Cons. [J]		
AHU2RFAN:Fan Elec. Cons. [J]	InteriorLights:Elec. [J]	
AHU1RFAN:Fan Elec. Cons. [J]		
AHU4SFAN:Fan Elec. Cons. [J]	Int.Equip.:Elec. [J]	
AHU3SFAN:Fan Elec. Cons. [J]		
AHU2SFAN:Fan Elec. Cons. [J]	Fans:Elec. [J]	Facility Elec. [J]
AHU1SFAN:Fan Elec. Cons. [J]		
DHWPUMP:Pump Elec. Cons. [J]	Pumps:Elec. [J]	
PRIMARYPUMP:Pump Elec. Cons. [J]		
HWPUMP:Pump Elec. Cons. [J]	Cooling:Elec. [J]	
SECONDARYPUMP:Pump Elec. Cons. [J]		
CHILLER2:Chiller Cond Fan Elec. Cons. [J]		
CHILLER2:Chiller Elec. Cons. [J]		
CHILLER1:Chiller Cond Fan Elec. Cons. [J]		
CHILLER1:Chiller Elec. Cons. [J]		

Eisenhower et al. Uncertainty and Sensitivity Decomposition of Building Energy Models *Journal of Building Performance Simulation, 2011*

Optimization



Meta-Model-based Optimization

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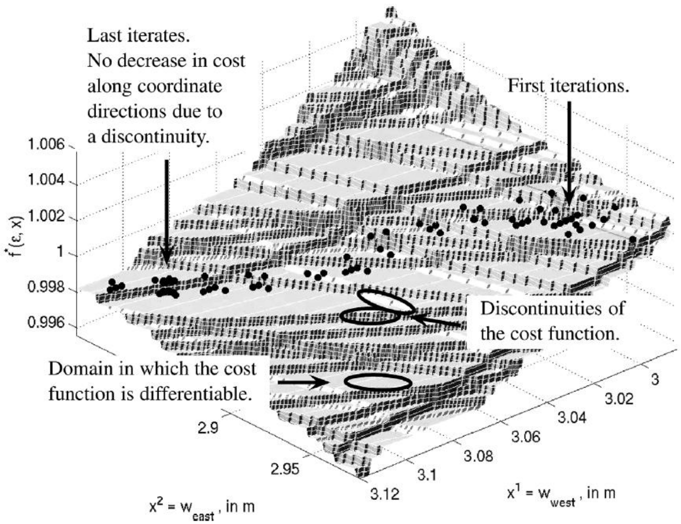
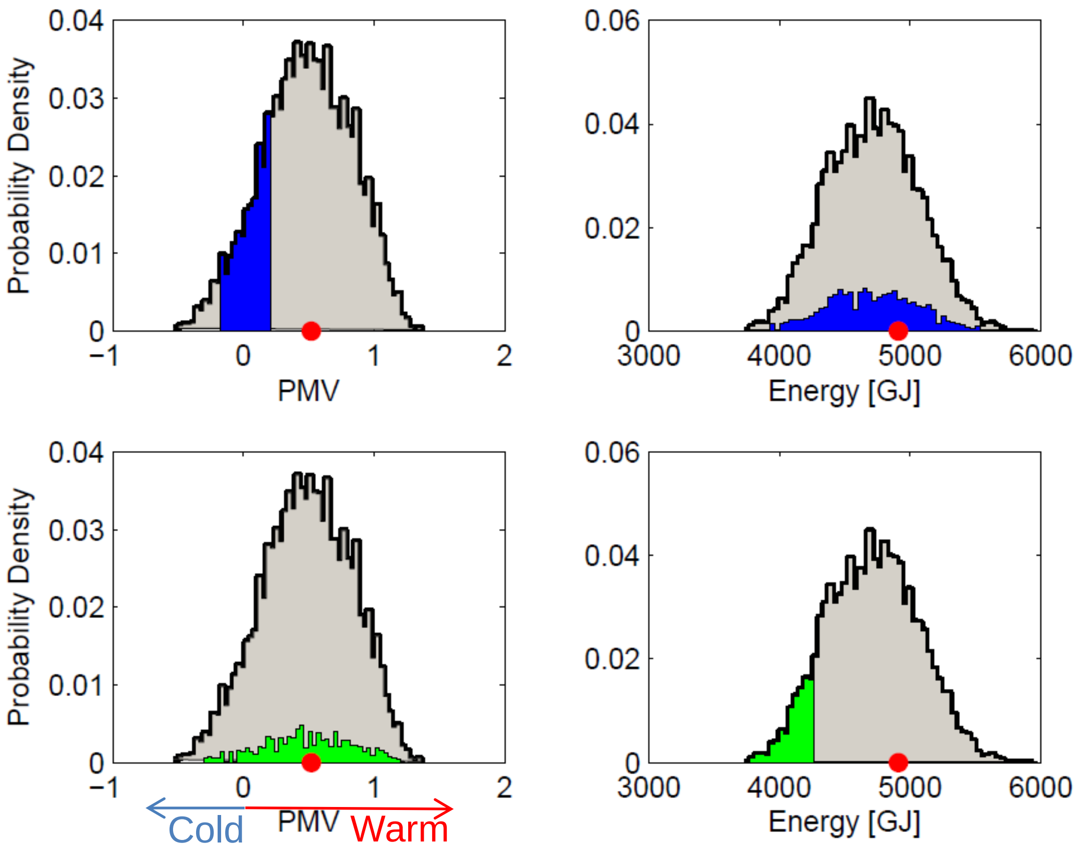
engineering

- Use of meta-models for multi-criteria optimization methods avoids pitfalls in EnergyPlus and TRNSYS of discontinuous cost surfaces, etc.



Wetter & Polak 2004



B. Eisenhower, et al Metamodel-based Optimization of Building Energy Systems *In preparation*

Optimization Results

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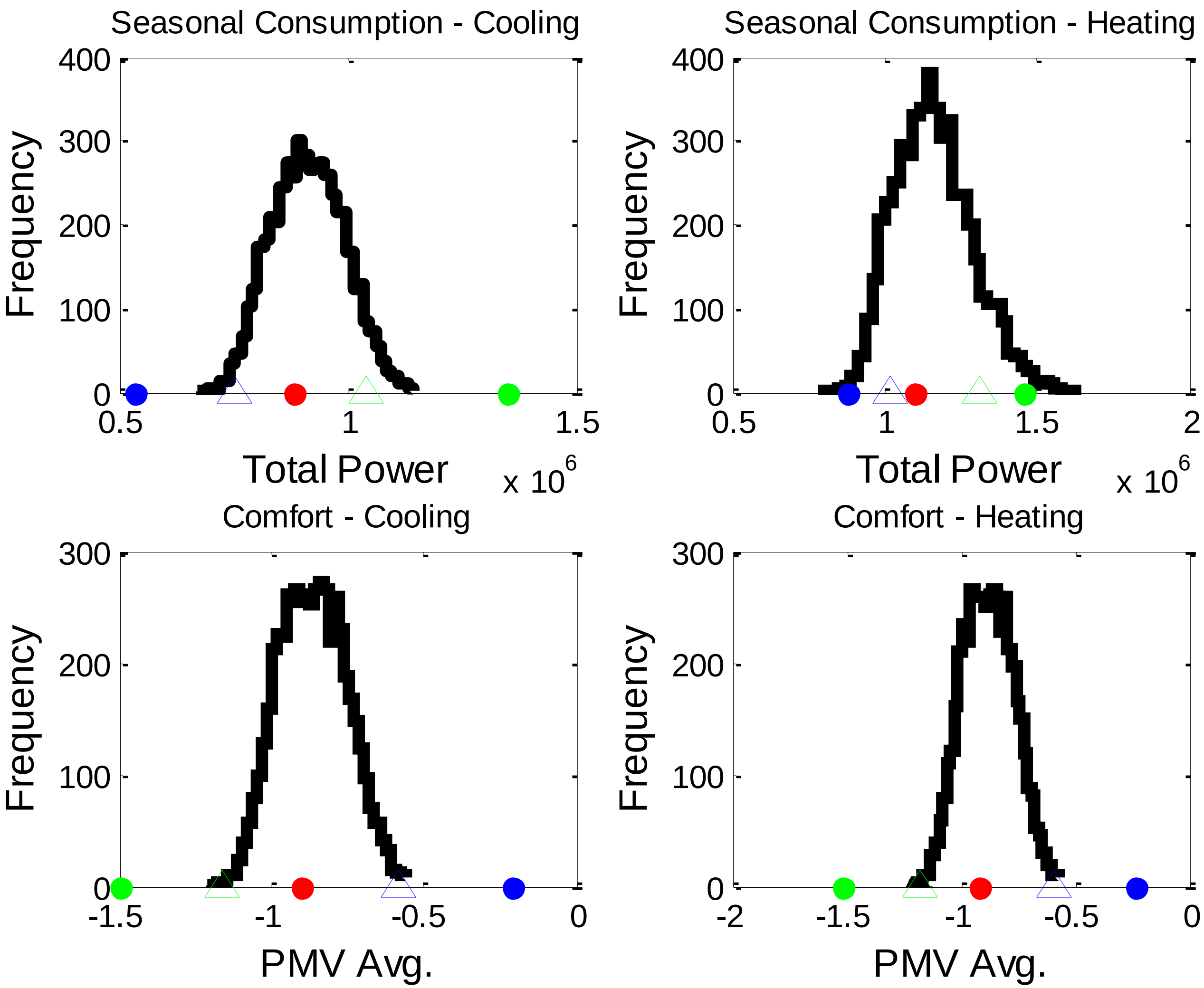
- Optimization results compared to uncertainty distributions



Red dot = nominal simulation

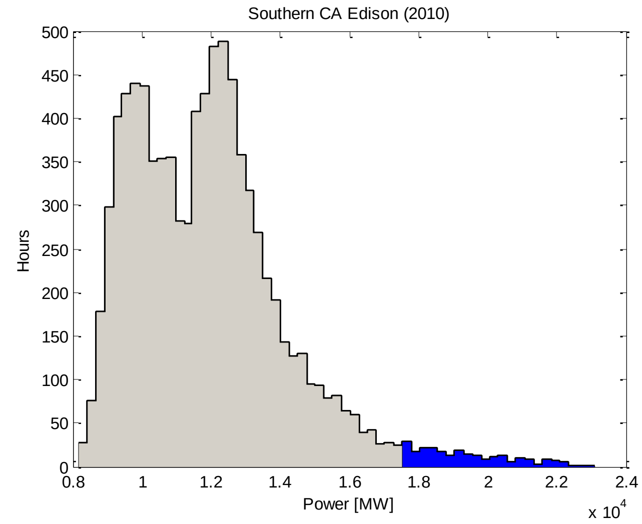
Green = Maximized solution

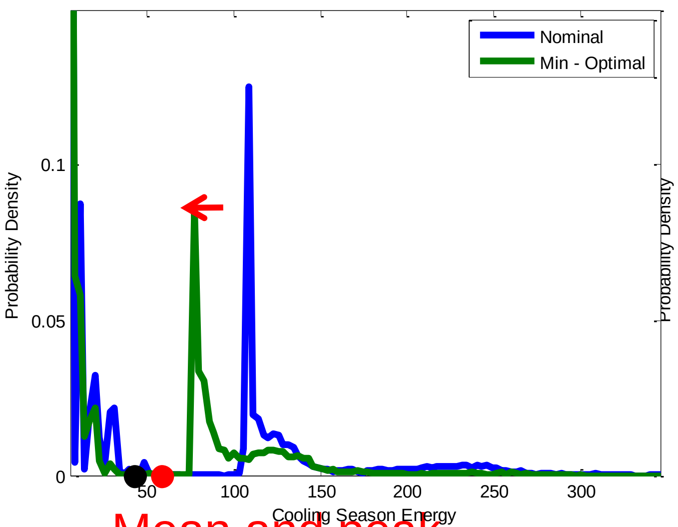
Blue = Minimized solution

Dot = 317 para
Triangle = 16 para

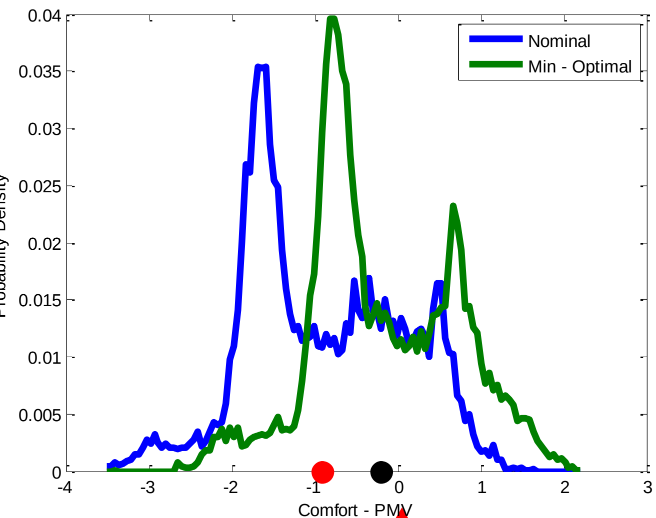
Optimization Results

❑ Optimization influence on peak demand





Mean and peak reduction



More Comfortable

Model-based Failure Mode Analysis

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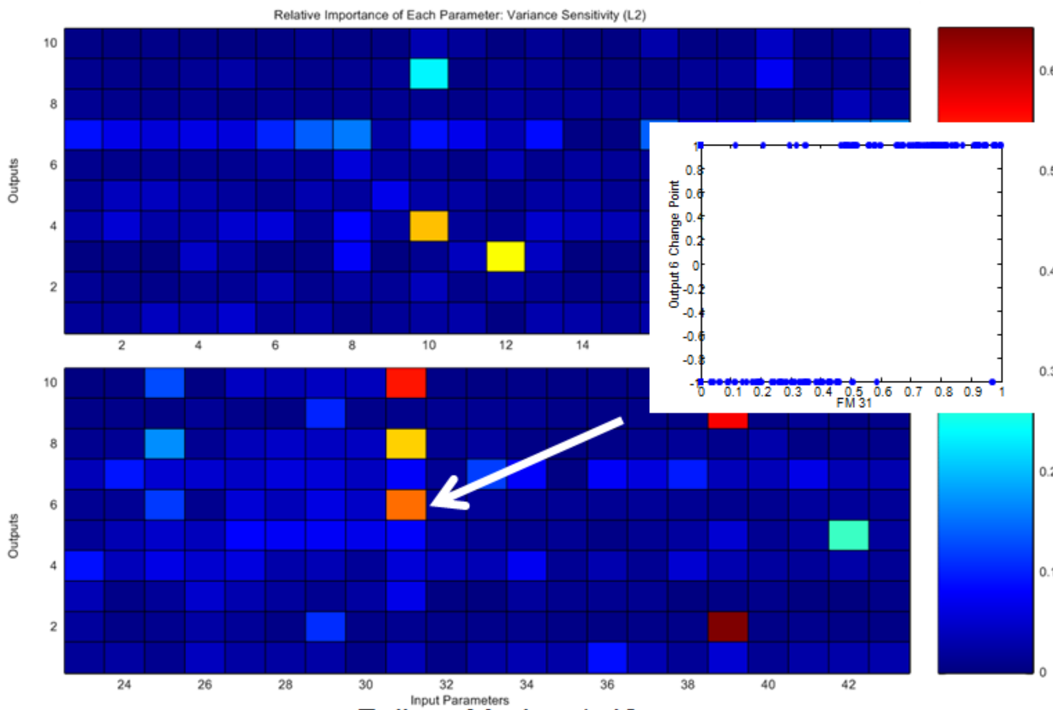
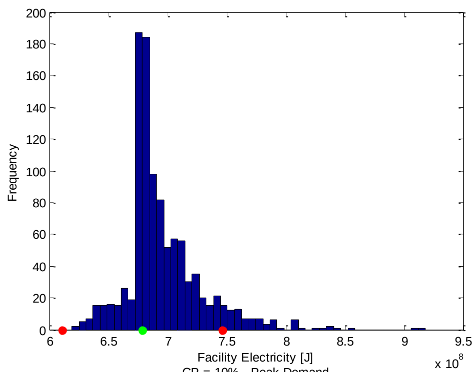
- ❑ Automated fault detection needed for continuous commissioning
- ❑ Current methods are at the component level (one at a time)
- ❑ All faults analyzed at same time

- Multiple faults physically possible at same time.
- Sensitivity index illustrates how influential each fault (or combination of) are on the particular output



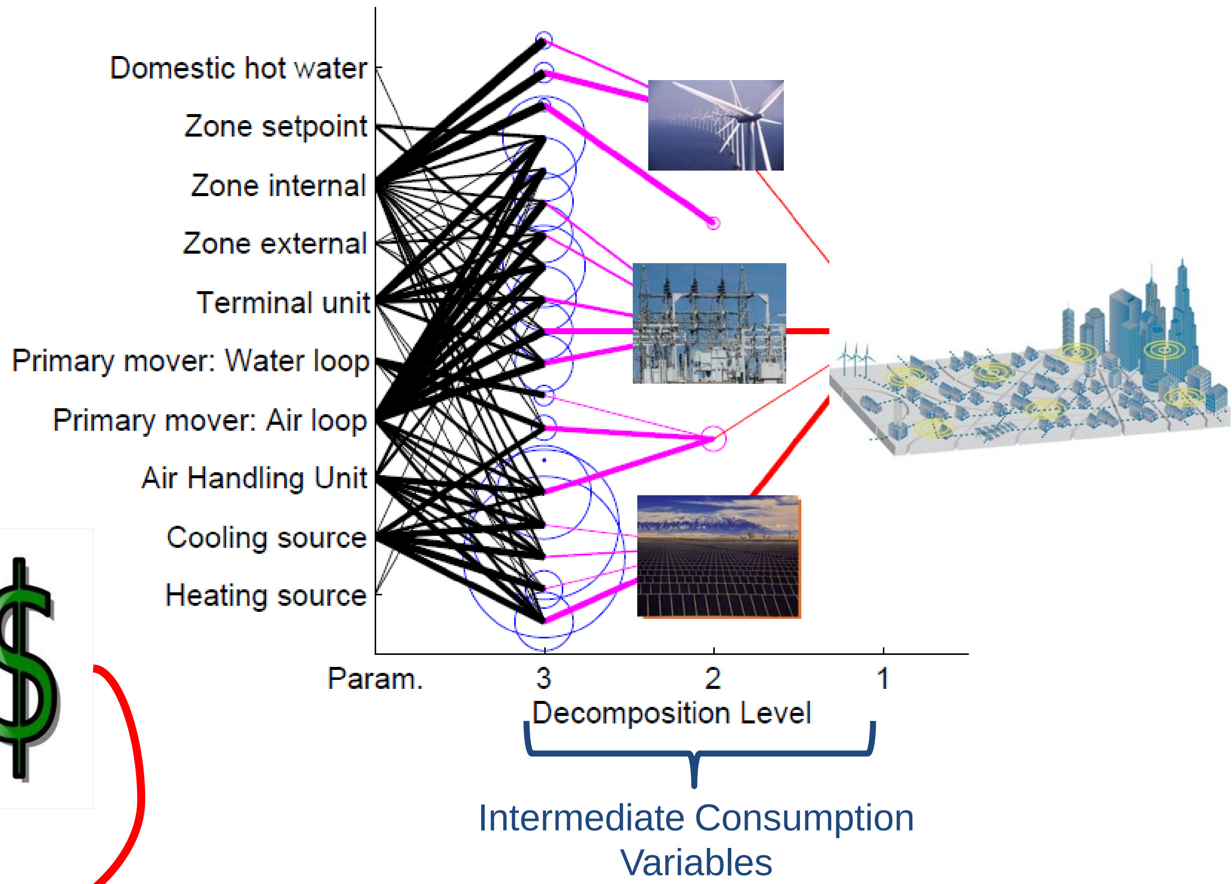
Failure Modes 1-43



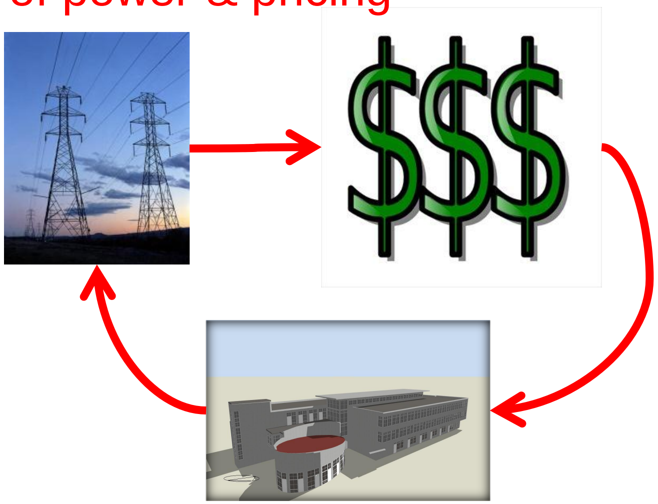
* With Kevin Otto & UTRC

Future Direction

Uncertainty management and decomposition on large scales (grid level)



Building dynamics in the feedback loop of power & pricing



Acknowledgements

This work was partially supported under the contract W912HQ-09-C-0054 (Project Number: SI-1709) administered by SERDP technology program of the Department of Defense.

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- Zheng O'Neill (United Technologies Research Center)
- Satish Narayanan (United Technologies Research Center – PL/PM)
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- Vladimir Fonoberov (AIMdyn Inc.)
- Kevin Otto (RSS)
- Igor Mezic (University of California, Santa Barbara)
- Michael Georgescu (University of California, Santa Barbara)

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