A Framework for Systems Engineering of Energy Systems

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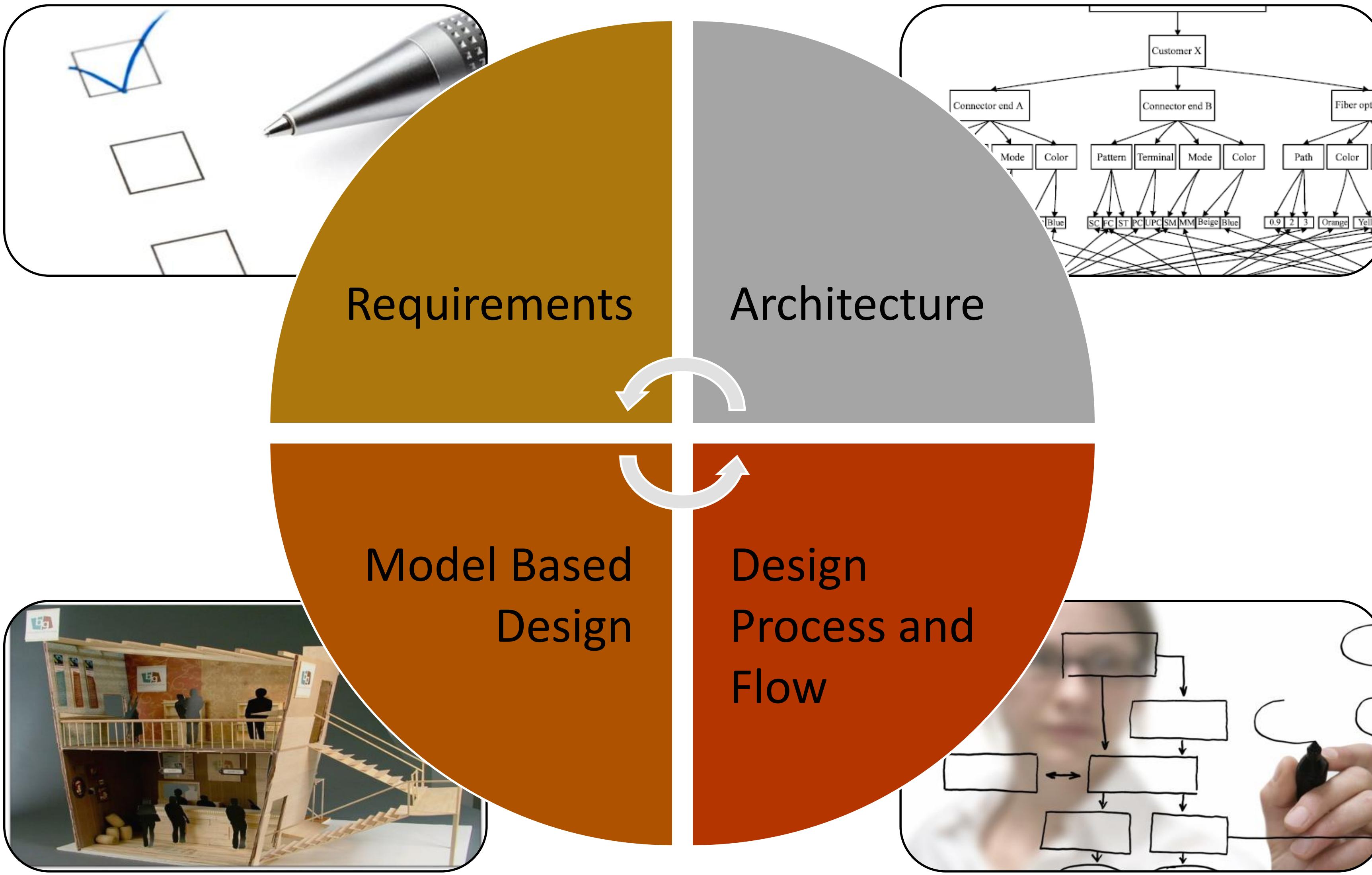
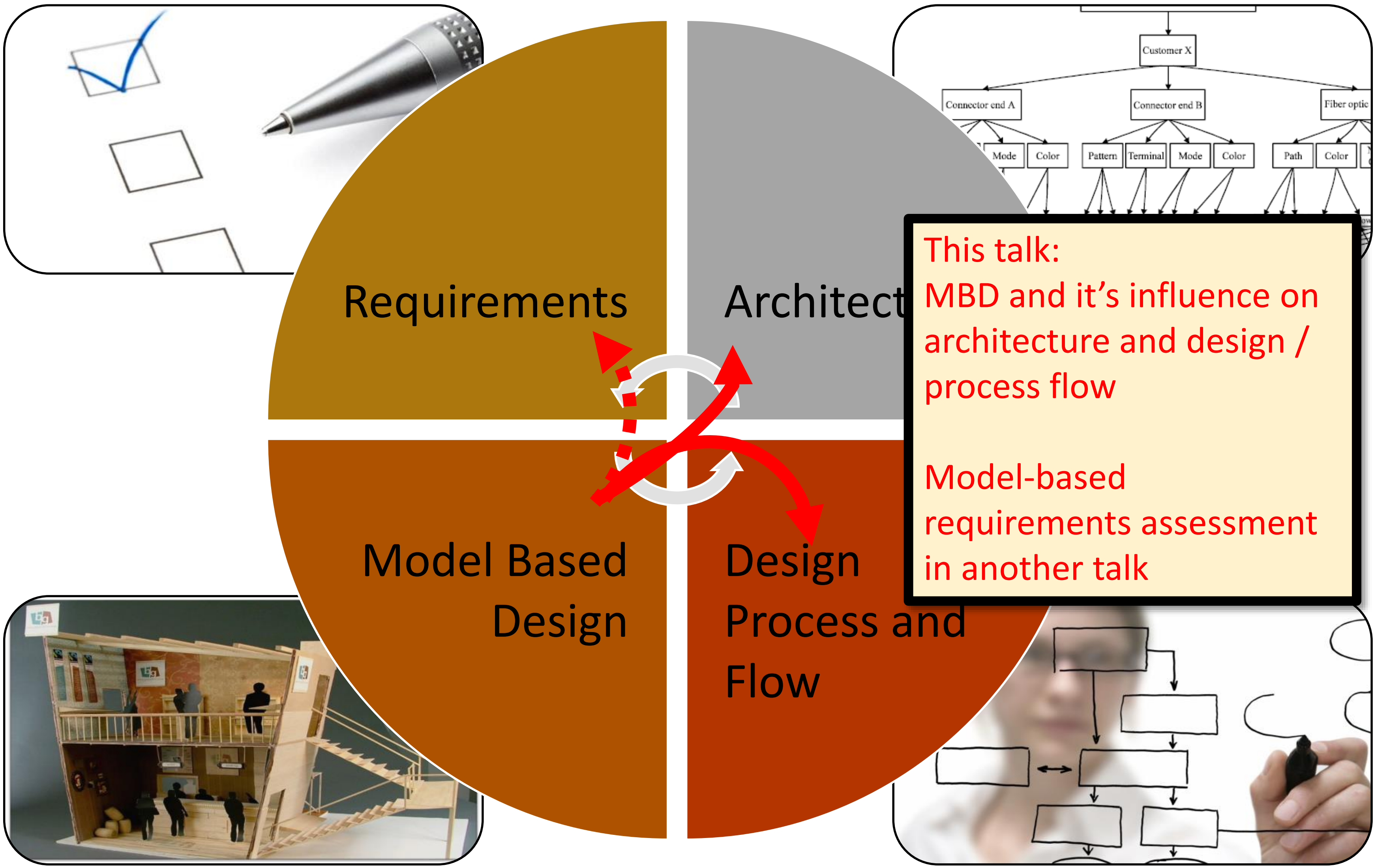
February 2015

the INSTITUTE for ENERGY EFFICIENCY

Elements of Systems Engineering



Elements of Systems Engineering



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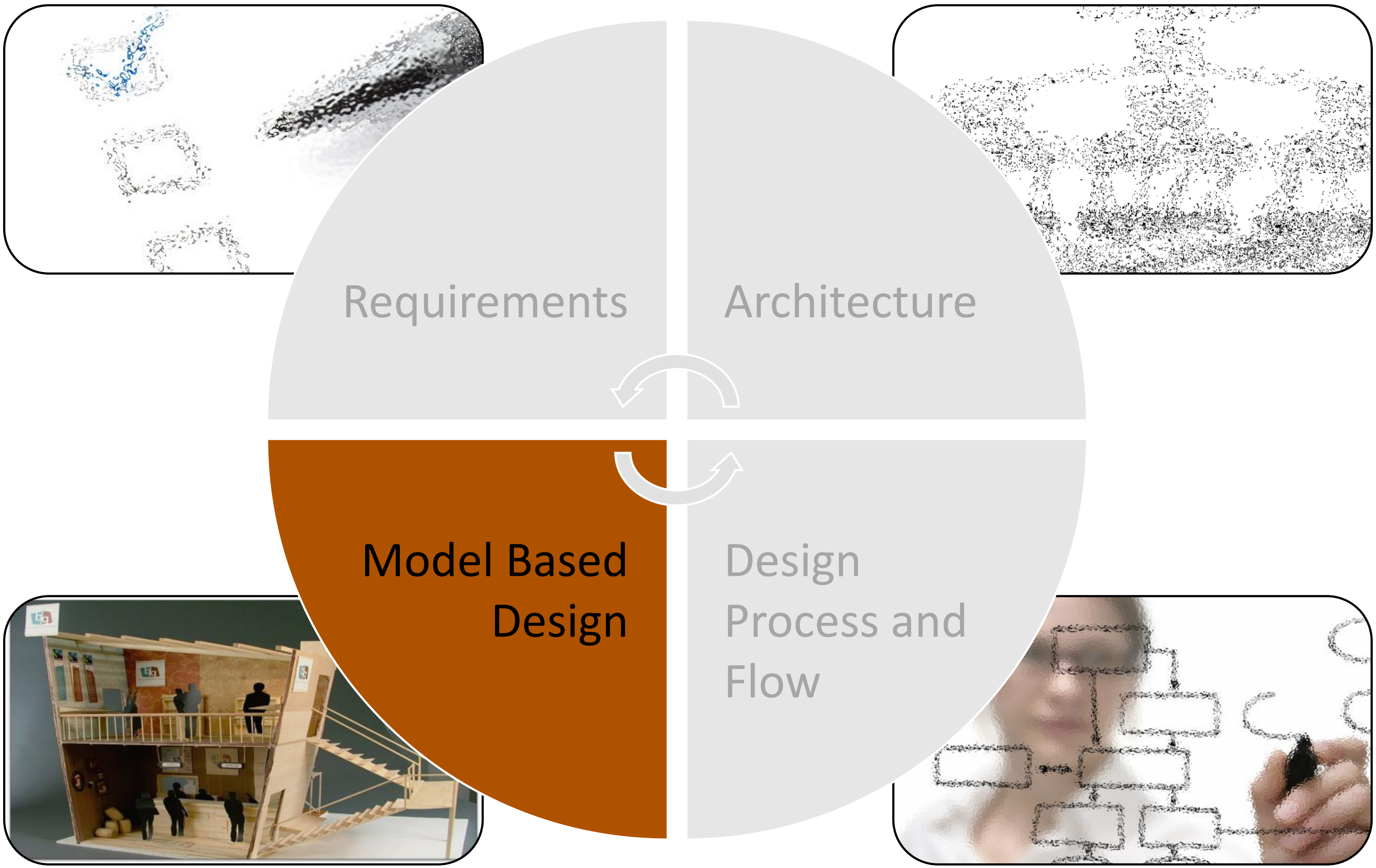

Summary Messages:

Model-based Design (MBD)
“Addressing design with computation”

- Time domain simulations rarely lead to design evolution
- More can be done with time domain simulations (wrappers)
- Dynamics matter!
- Continuity needed when modeling at different stages / fidelity
- Models need be appropriate for the intended use and user base
- Uncertainty analysis up front and throughout
- Critical parameter management at all levels
- The decomposability of a system cannot be ignored
- New curricula needed that addresses all of this
- …

We’ll come back to these topics throughout the talk.

Sections

1. Motivation
2. Uncertainty Analysis / Critical parameter management
3. Analysis of dynamics
4. Verification
5. Decomposition
6. How its done

- Discussed in the context of either an academic pursuit or industry/field collaboration.
- Lessons learned and opportunities will be discussed for each

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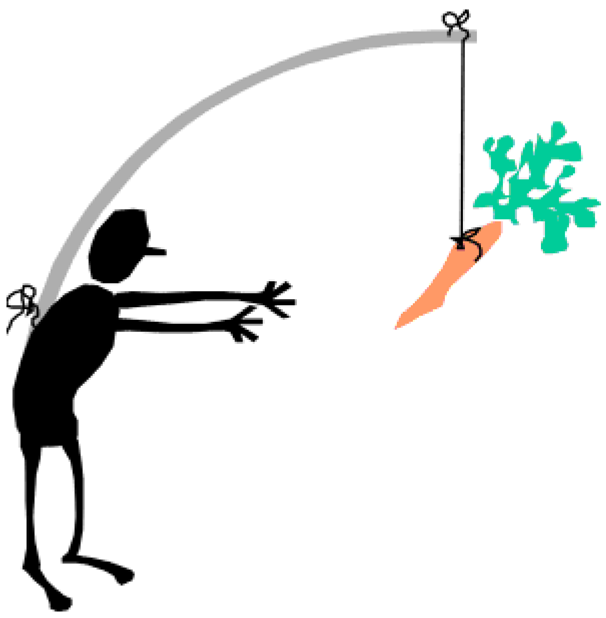
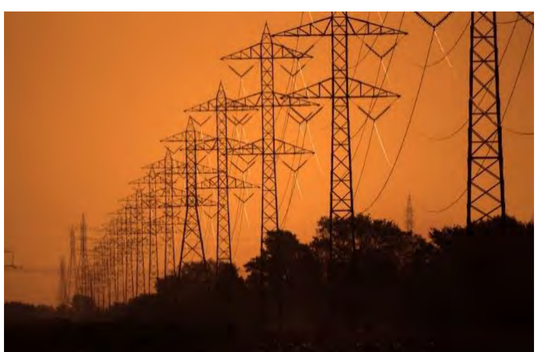
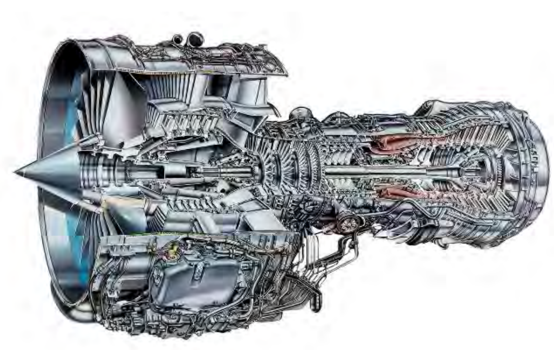
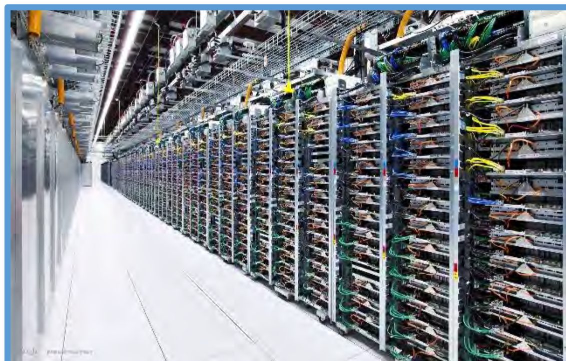


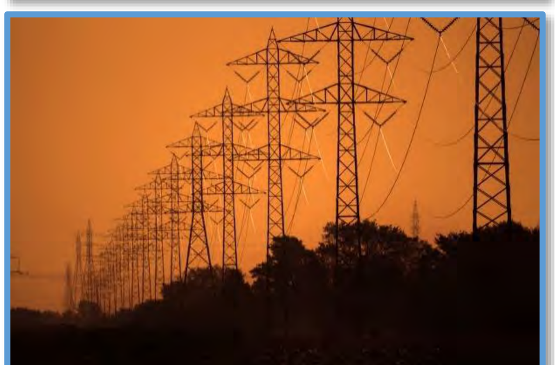
Everything we touch in the western world is a result of energy
- There is a huge potential for advancing humankind by optimizing energy systems
- Unfortunately *system theory* is only partially used in their design

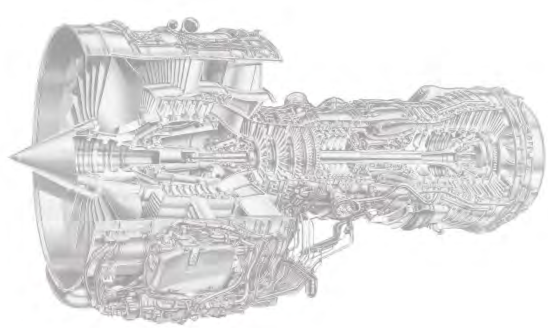




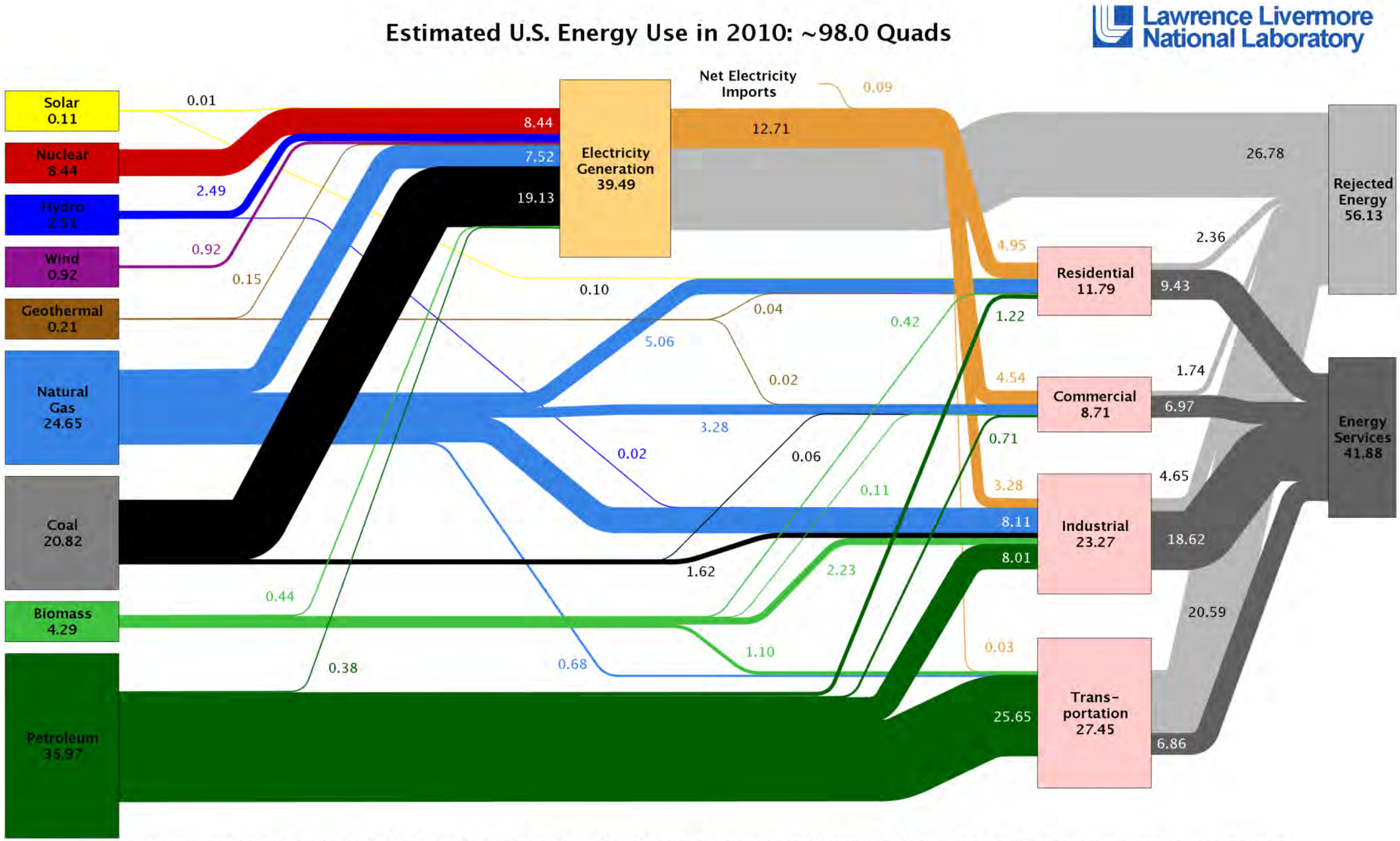
Commercial and residential buildings are a large portion of the energy sector





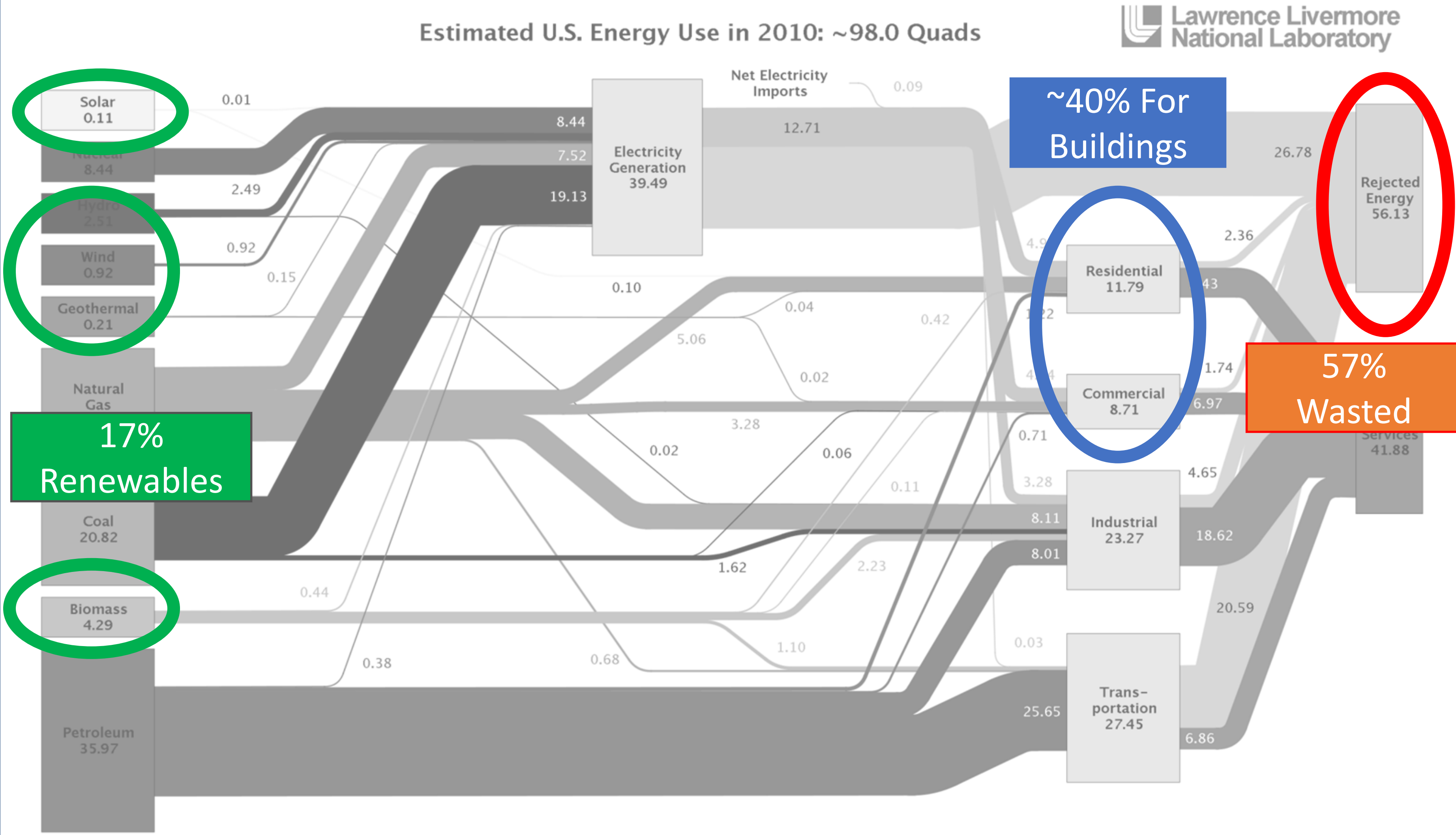


Energy Demand



Source: LLNL 2011. Data is based on DOE/EIA-0384(2010), October 2011. 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 hydro, wind, solar and geothermal in BTU-equivalent values by assuming a typical fossil fuel plant "heat rate." (see EIA report for explanation of change to geothermal in 2010). 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

Energy Demand



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Motivation

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

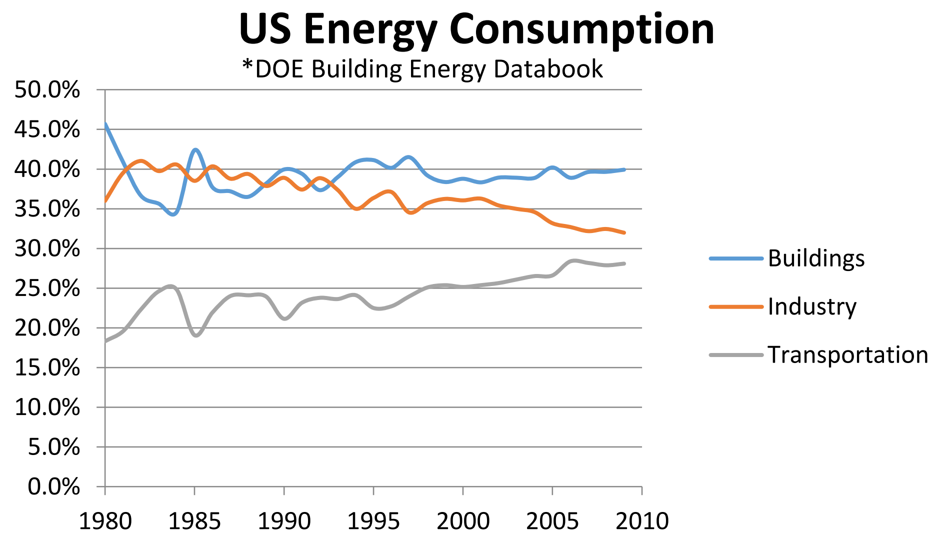
- ❑ ~30% reduction can be achieved by occupancy based lighting control (0.8 QBTU) ← DoD Spends ~3.4Billion Annual on ~1 QBTU
- ❑ A 47% reduction in buildings energy use will take ALL cars off the road!

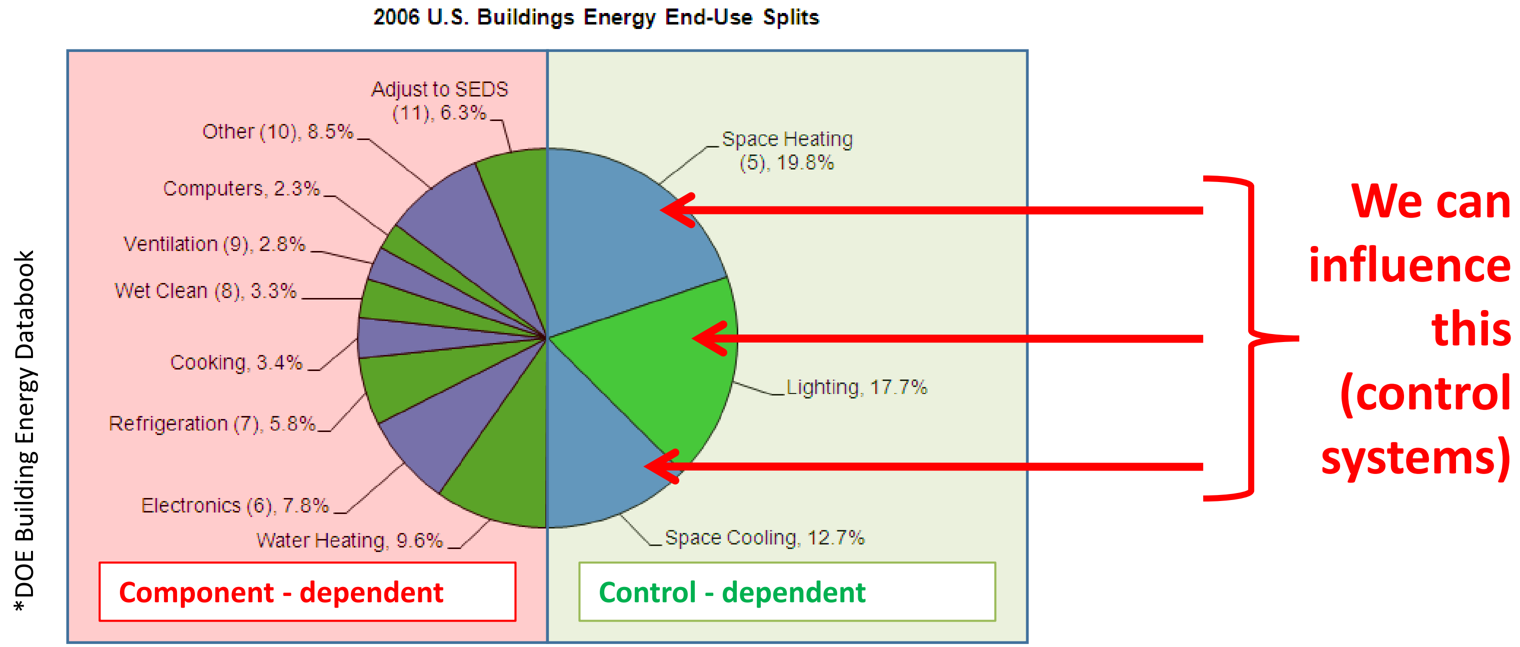
Source: Buildings Energy Data Book & US EIA

Energy Demand

No drastic changes over time.

Most consumption is *controllable*

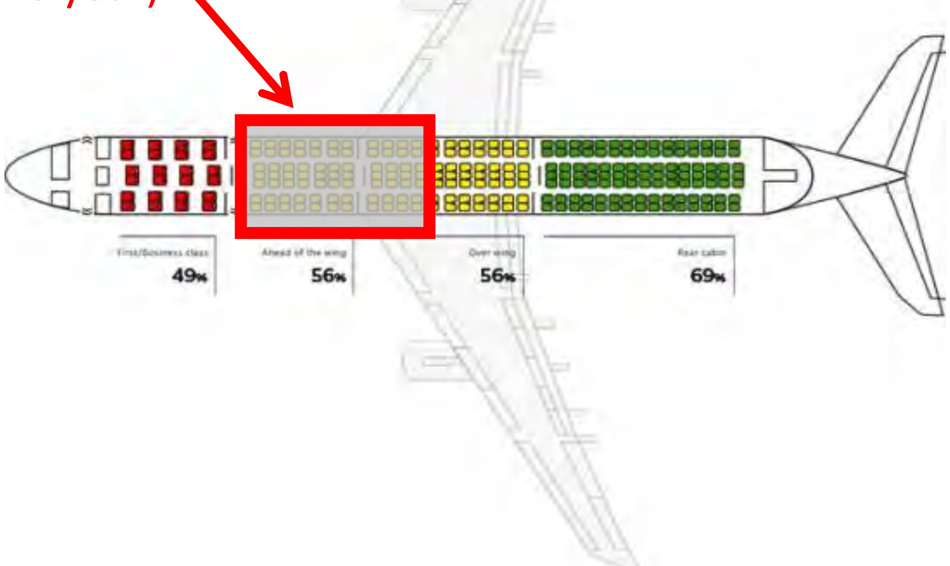


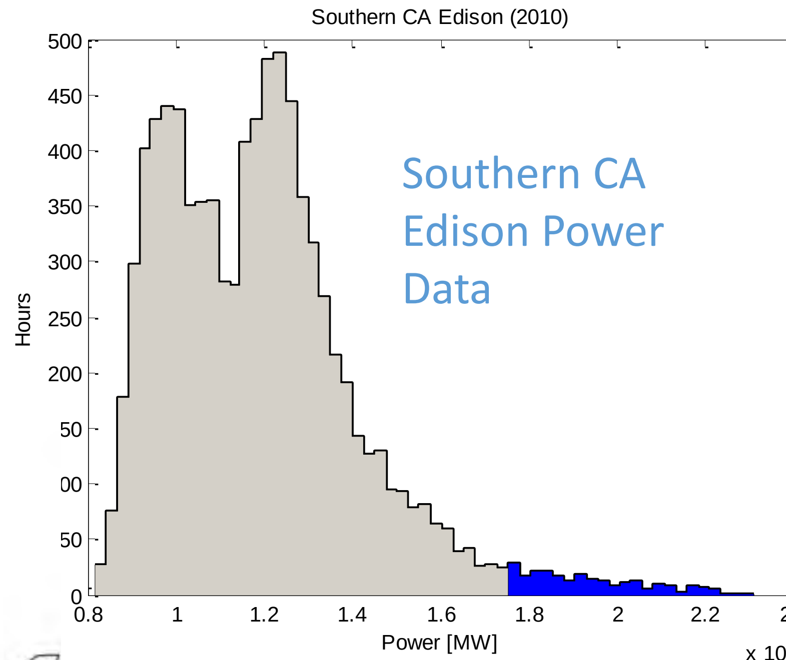


Energy – Peak Demand

- ❑ Power grid design constraints based on *peak* loading, which occurs very *infrequently*

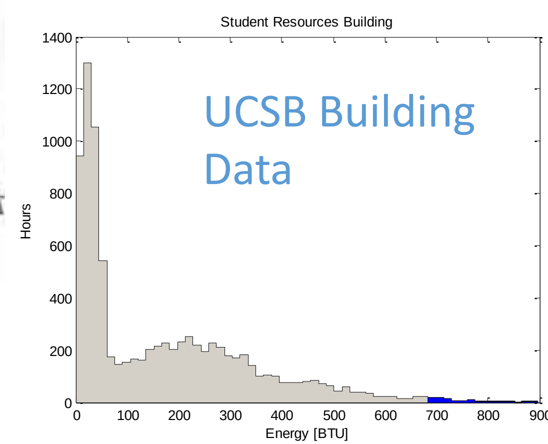
Analogy:
Only used 10 days a year
(25% capacity @2.75% of the year)





Data: CA OASIS

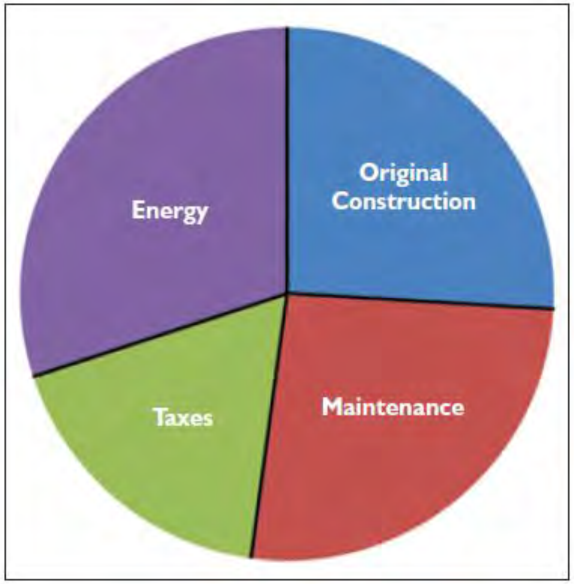
Top 25% of power only 2.74% of year.

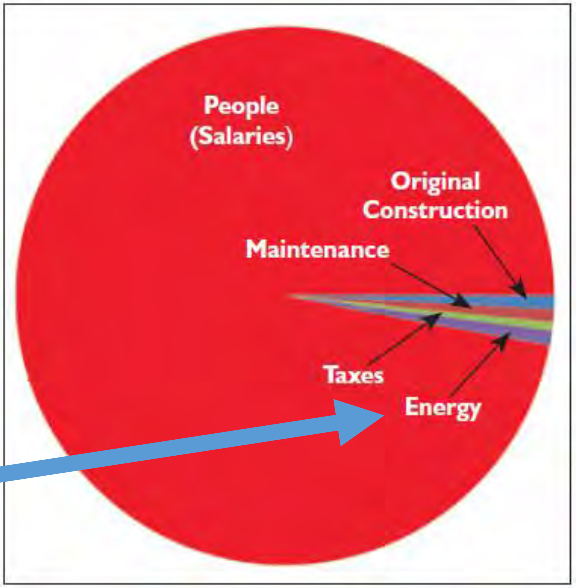


Top 25% of power only 0.41% of year.

Comfort

Approximate breakdown of building expenses



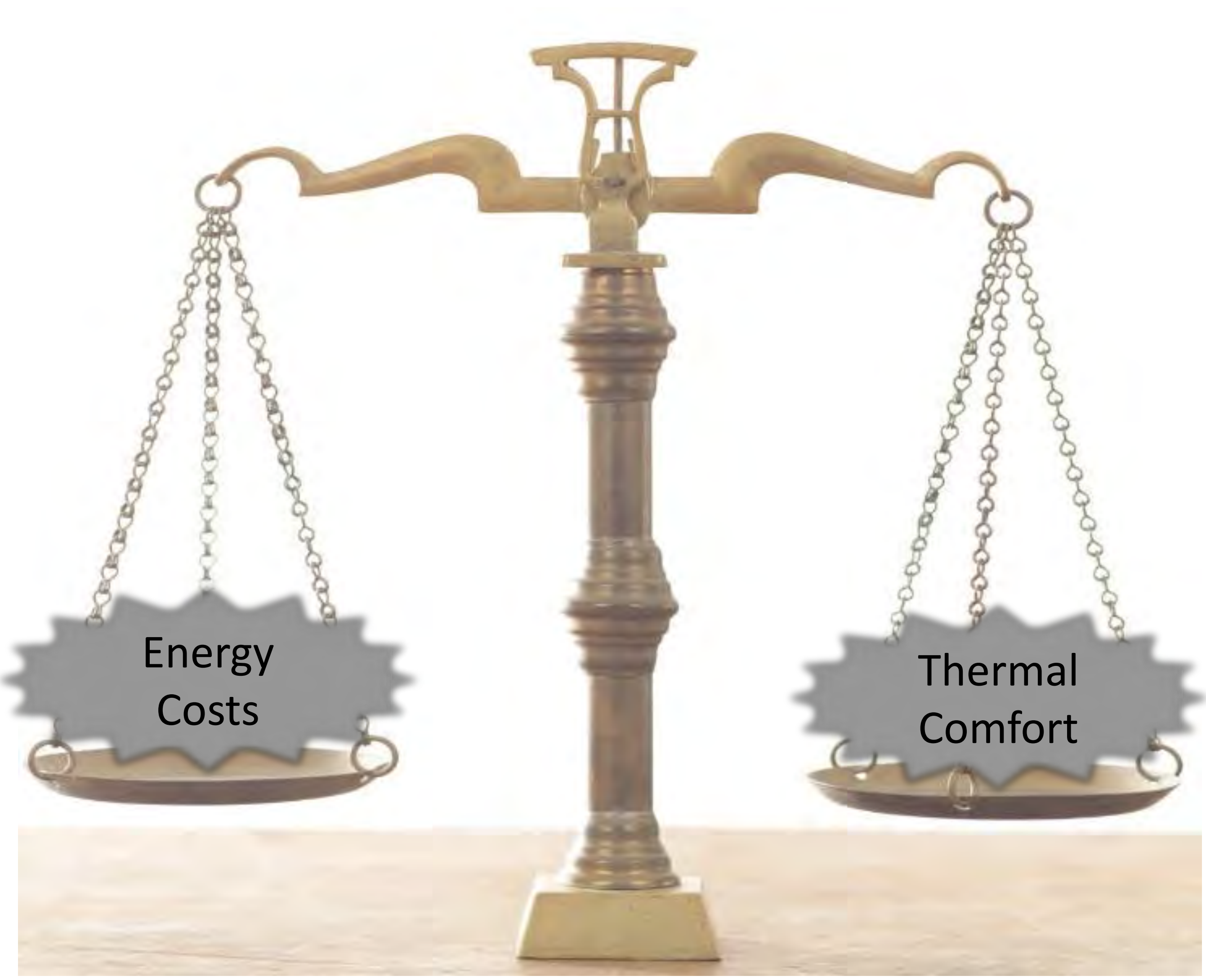


[Tom, ASHRAE 2008]

- ➢ The easy solution to the energy problem is to *'turn the building off'*
- ➢ Conditioning is needed to:
  - Develop products
  - Earn degrees
  - Sell products
  - Heal people (hospitals)
  - Maintain computers
  - ...

Energy < 5% of expenses

Balance



Success

….It can be done

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
- 1^{st} year generated 2x electricity that it used

Success

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A Grander View, Ontario
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a

in 11 months.

1-off examples

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- 5.9Kft^2 Educational
- **75% Energy savings** compared to CBECS
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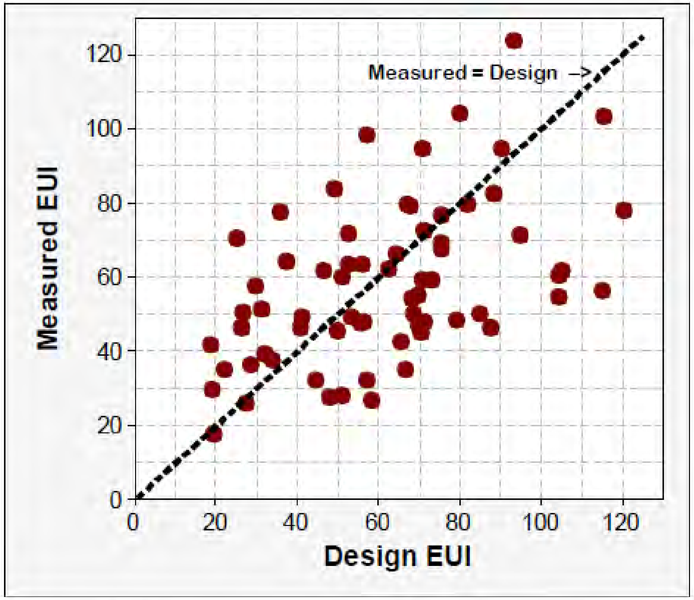
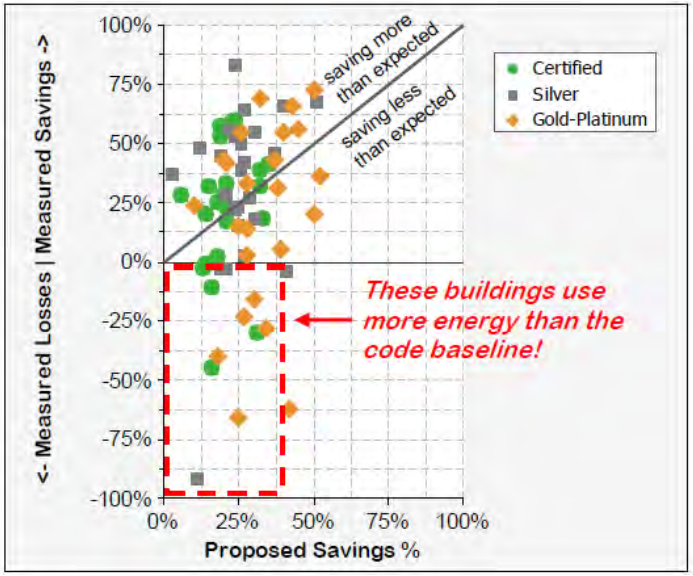
Struggle





[Frankel 2008]

Modeling:

"….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. "

Monitoring:

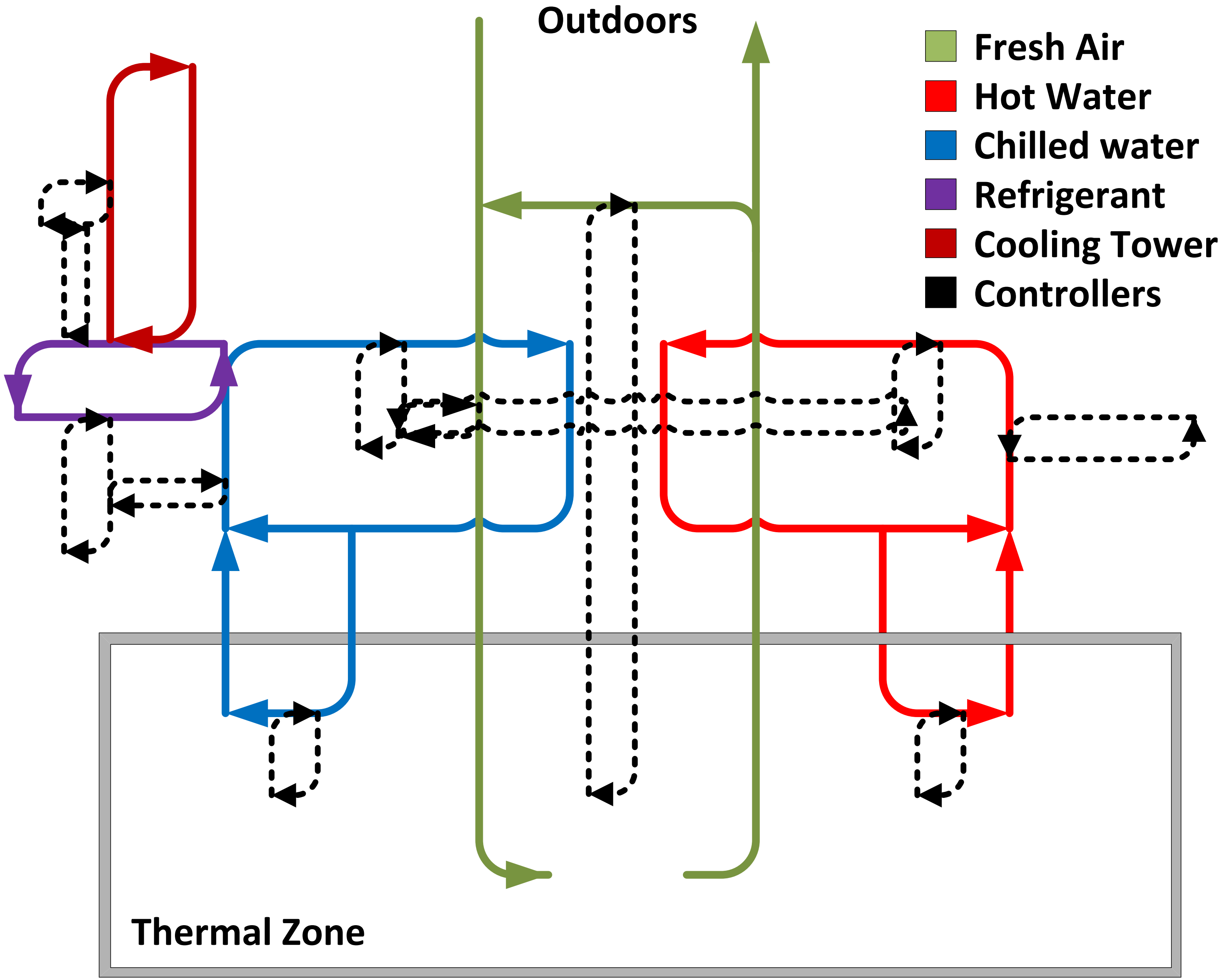
"… dramatic improvement in performance with monitoring and correcting some problem areas identified by the metering "

Control:

"There was often a lack of control software or appropriate control logic to allow the technologies to work well together "

[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.]

Systems - of - Systems



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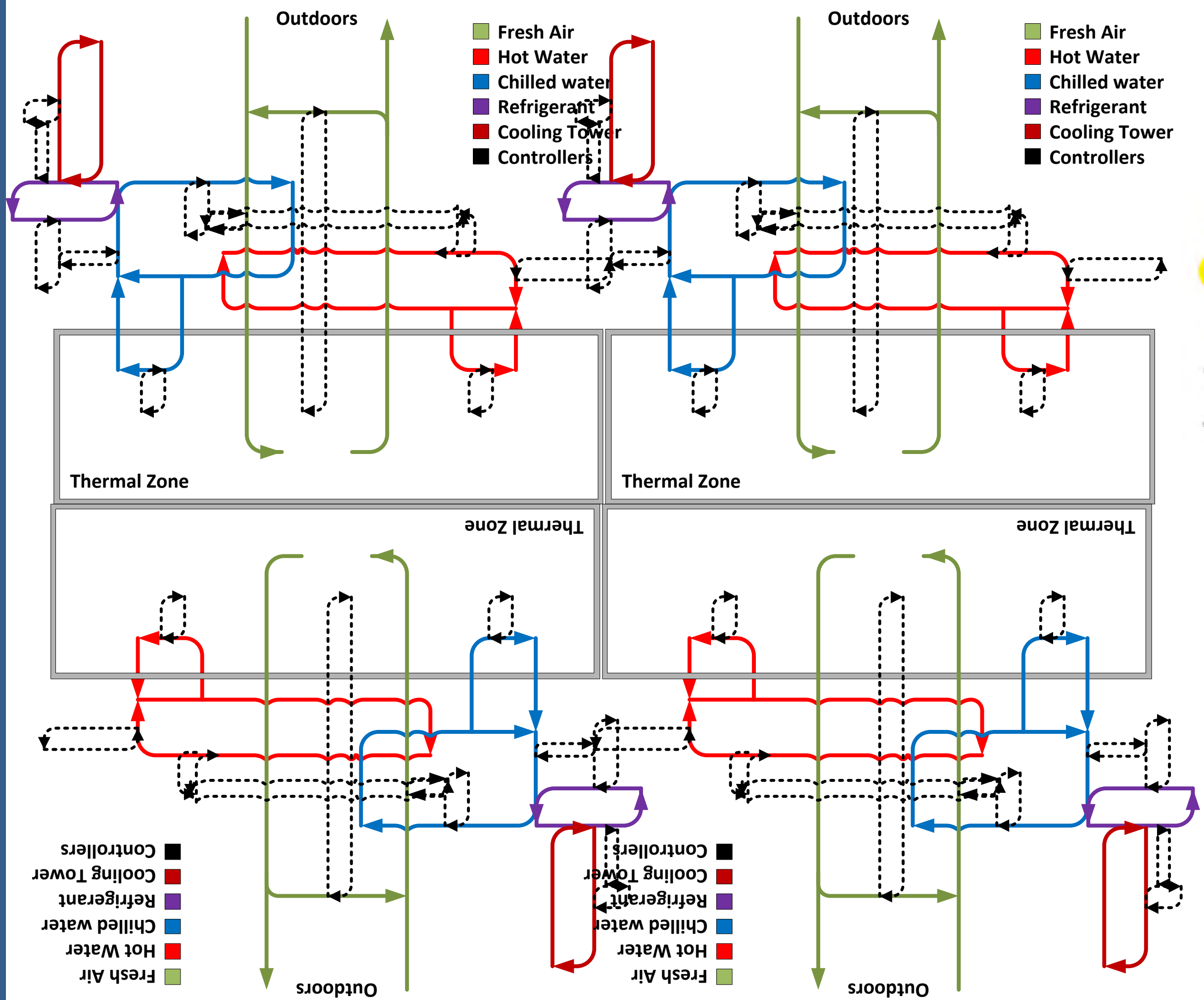
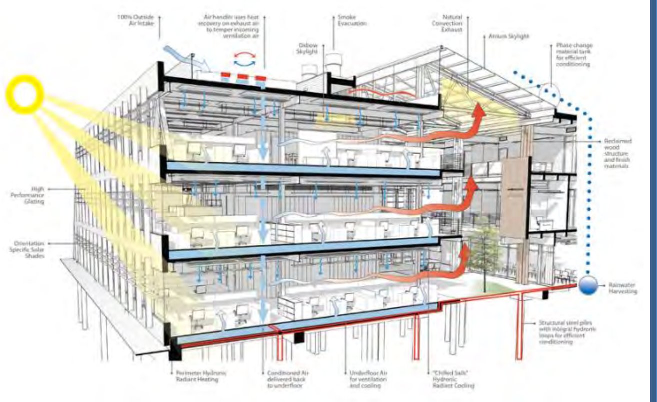


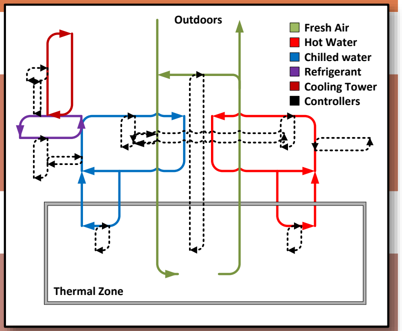


http://www.aiatopten.org/

Systems - of - Systems

Systems of systems don't scale well!

- Numerous zones in a single building
- Loops operate at different time scales
- Loops are spread through different spatial scales
- Stochastic disturbance on every system
- Heterogeneous media (water, air, refrigerant)
- Heterogeneous manufacturers / protocols



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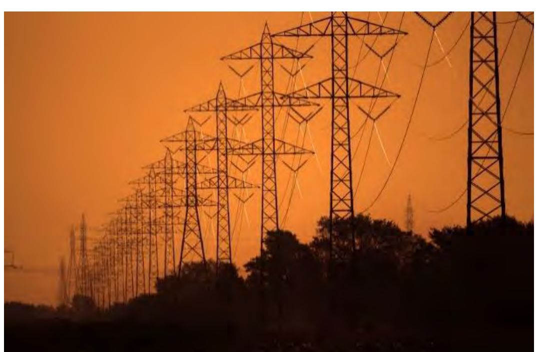

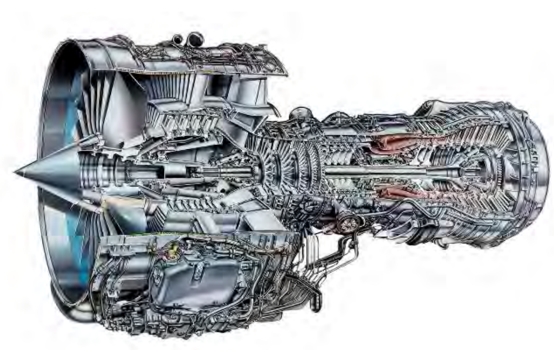

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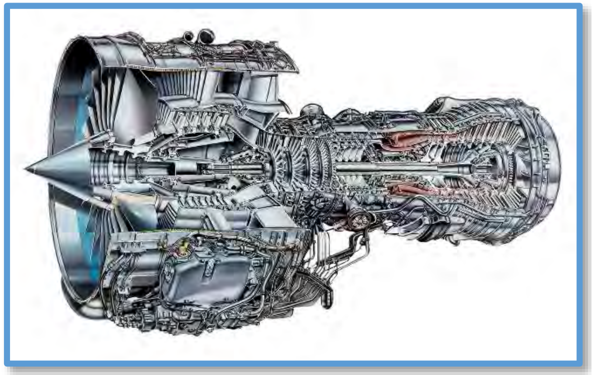
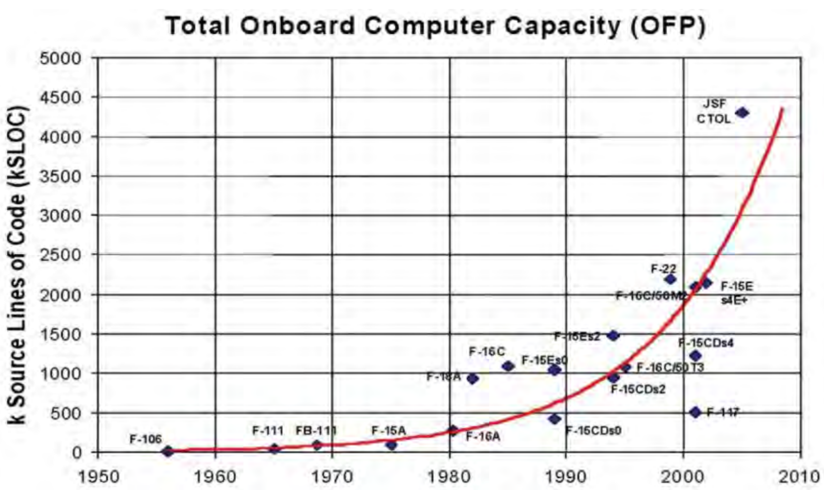


Aerospace

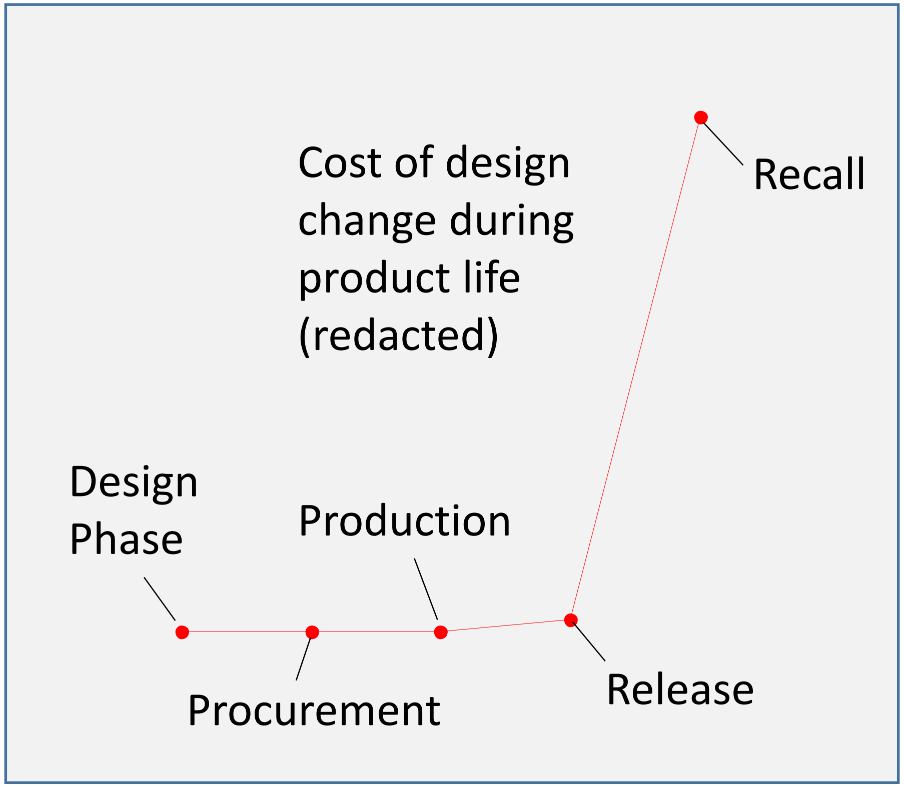
- Aerospace and automotive systems suffer similar issues
- However, more data available because of ‘fleets / product line’

<u>As with buildings, complexity is increasing with time</u>



Sangiovanni-Vincentelli, 2007

<u>Cost of correction increases strongly with time</u>



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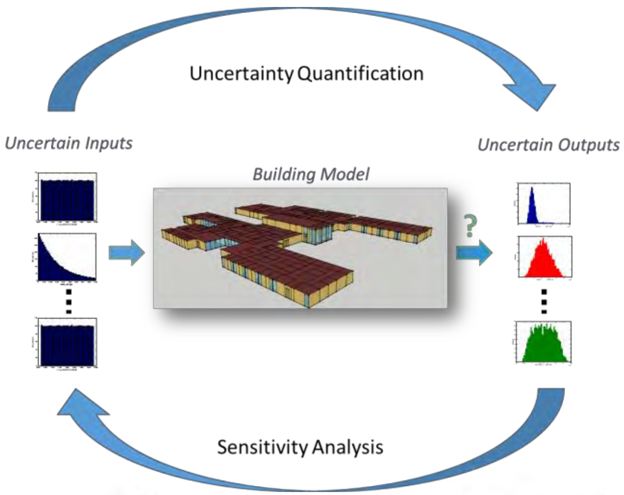
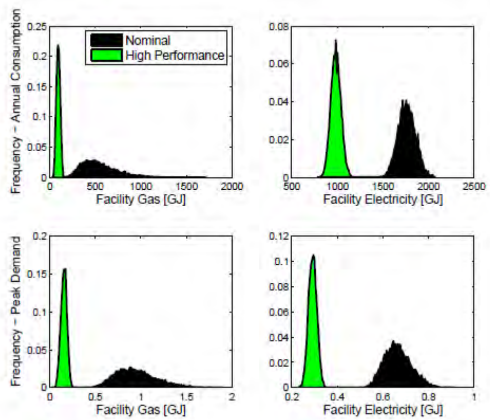
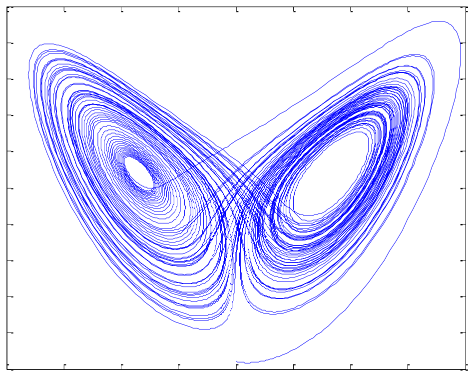
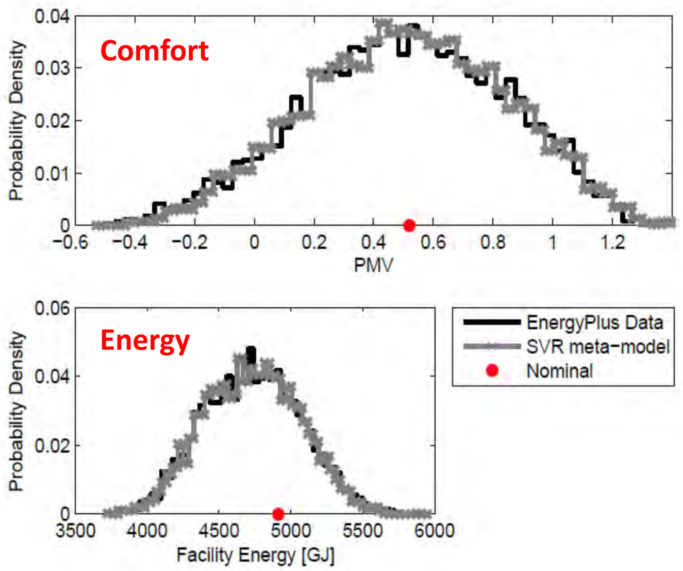
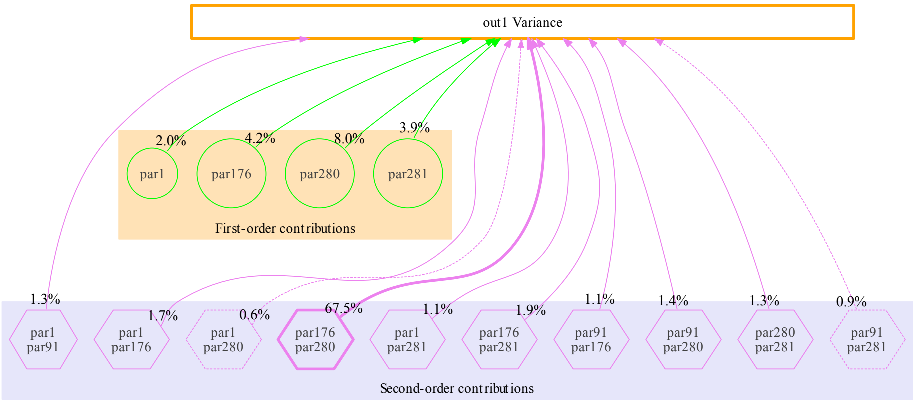
Uncertainty Management and Critical Parameter Tracking











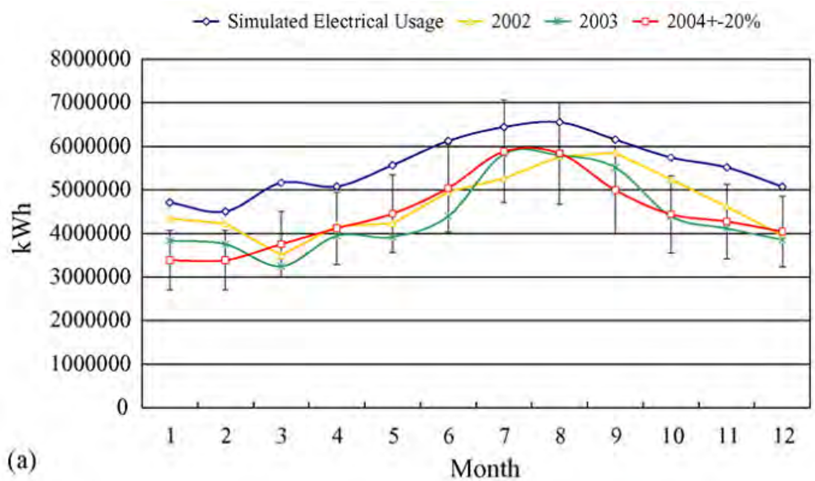
Assimilation

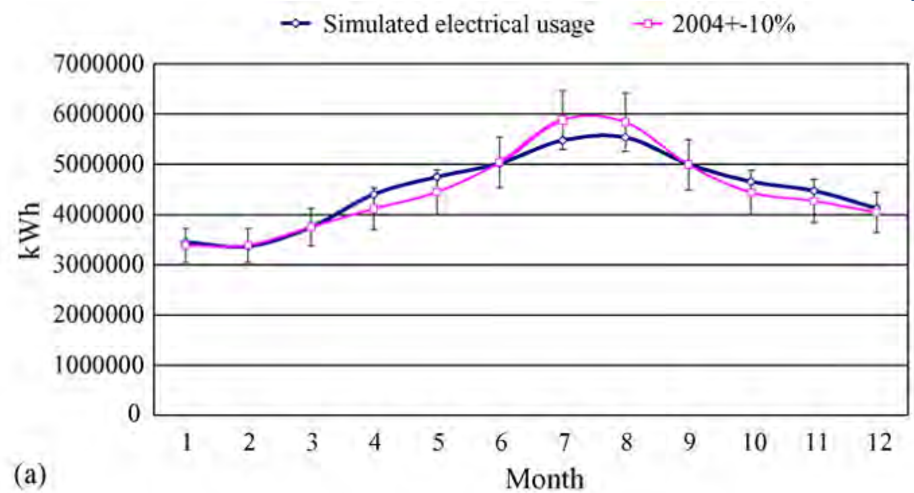
High Rise building in China, modeled in DOE2

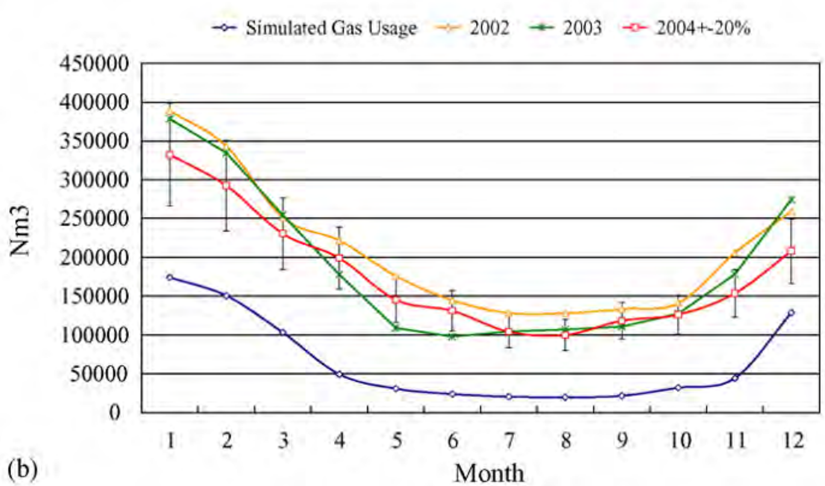
After construction and measurement, the models *can* be assimilated to data

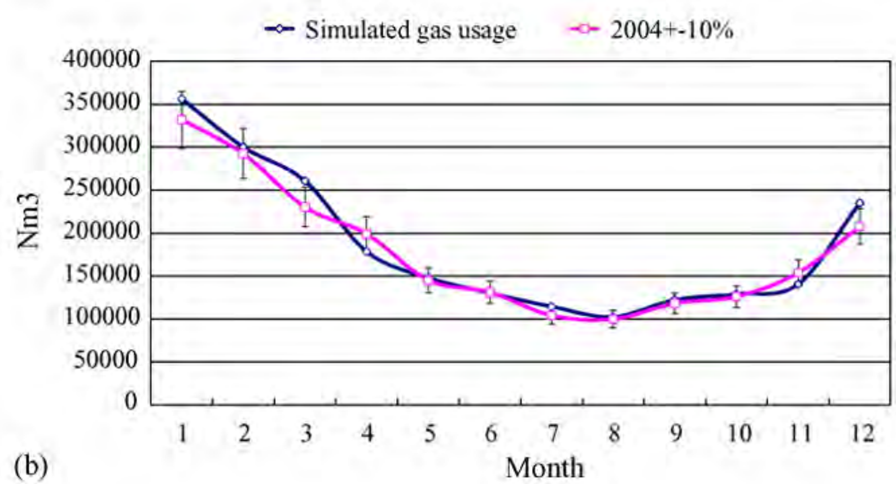
Prediction

After Assimilation





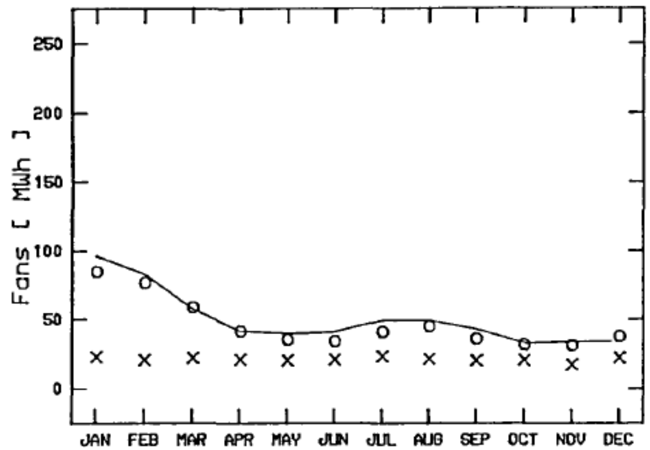


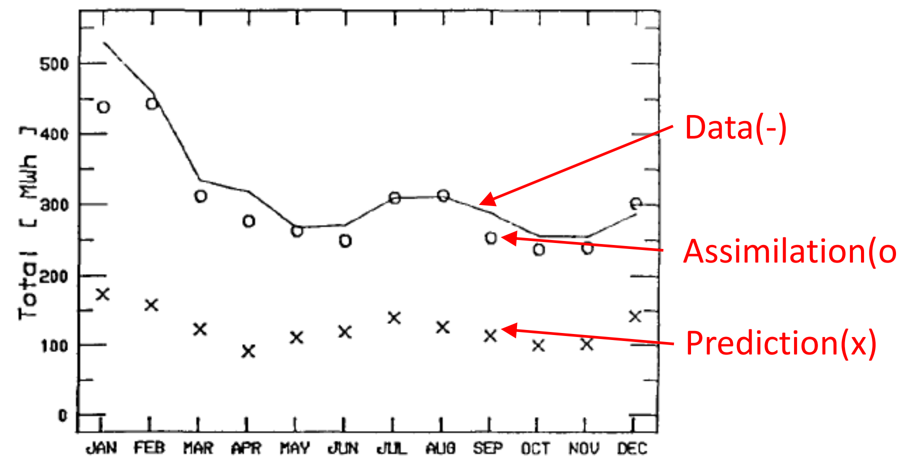


Pan, Energy and Buildings 2007

Assimilation

Again, even though predictions may be off by 200%, the model can be eventually tuned (office building)





[Norford, 1994]

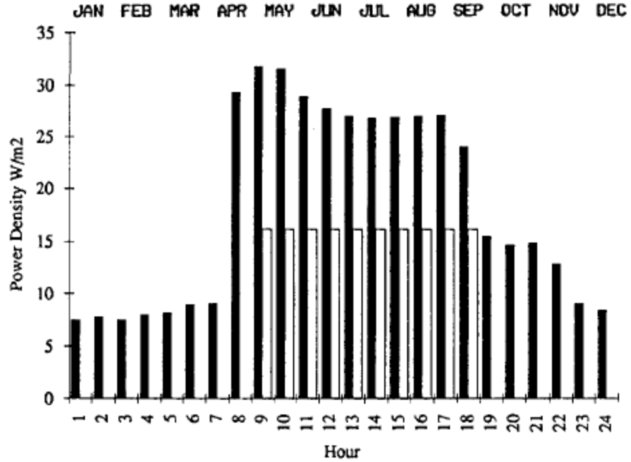


Fig. 2. Occupant office electricity use: ■ measured; □ design assumption.

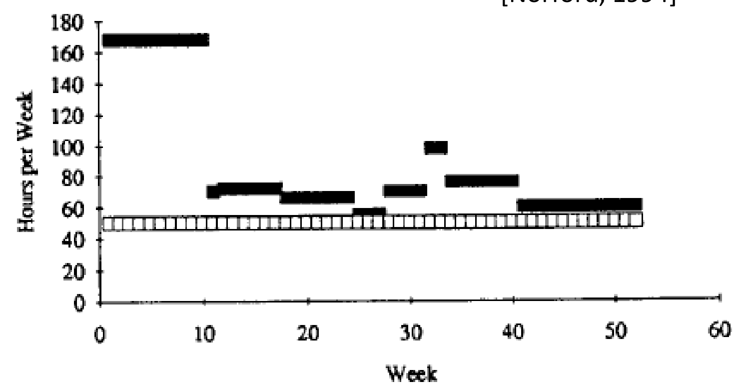


Fig. 3. Hours of HVAC operation: ■ hours of HVAC operation; □ design assumption.

Detailed analysis provided insight into what parameters in the model had bad assumptions

Typical Parameters

Fixed in time

Parameter Type	Examples
Heating source	Furnace, boiler, GSHP etc
Cooling source	Chiller, GSHP, etc
AHU	Coil parameters etc
Air Loop	Fans
Water Loop	Pumps
Terminal unit	VAV boxes, chilled beams, radiant heating
Zone external	Envelope, outdoor conditions
Zone internal	Occupant usage
Sizing parameters	Design parameters for zone, system, plant

Time-varying:

Parameter Type	Examples
AHU	AHU SAT setpoint
Zone internal	Internal heat gains schedule
Zone setpoint	Zone temp setpoint

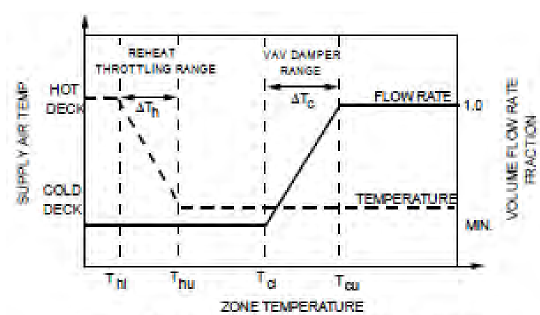
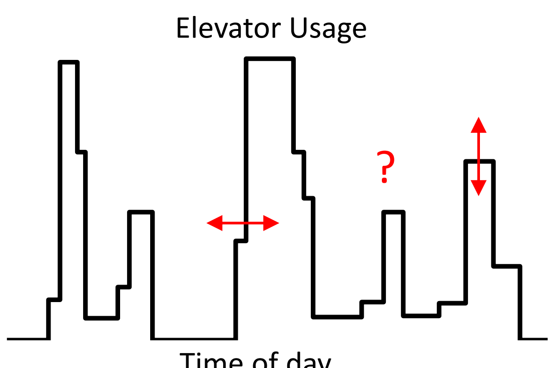


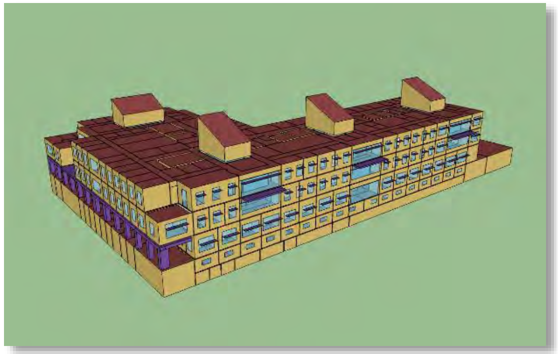
Figure 6. Idealized Variable Volume System Operation.



Large Models

Large models can contain thousands of partially certain parameters

Parameter Type	Quantity
Material	205
Material:AirGap	34
Material:NoMass	65
People	1201
Lights	1741
ElectricEquipment	1641
ZoneInfiltration:DesignFlowRate	216
ZoneVentilation:DesignFlowRate	559
ZoneMixing	477
ZoneHVAC:Baseboard:Convective:Water	153
ZoneInfiltration:DesignFlowRate	216
ZoneVentilation:DesignFlowRate	559
AirTerminal:SingleDuct:ConstantVolume:FourPipeInduction	1033
Coil:Heating:Water	1096
Coil:Cooling:Water	1196
Fan:VariableVolume	61
AirLoopHVAC	4
Schedule:Compact	2162
Total	**12,338**

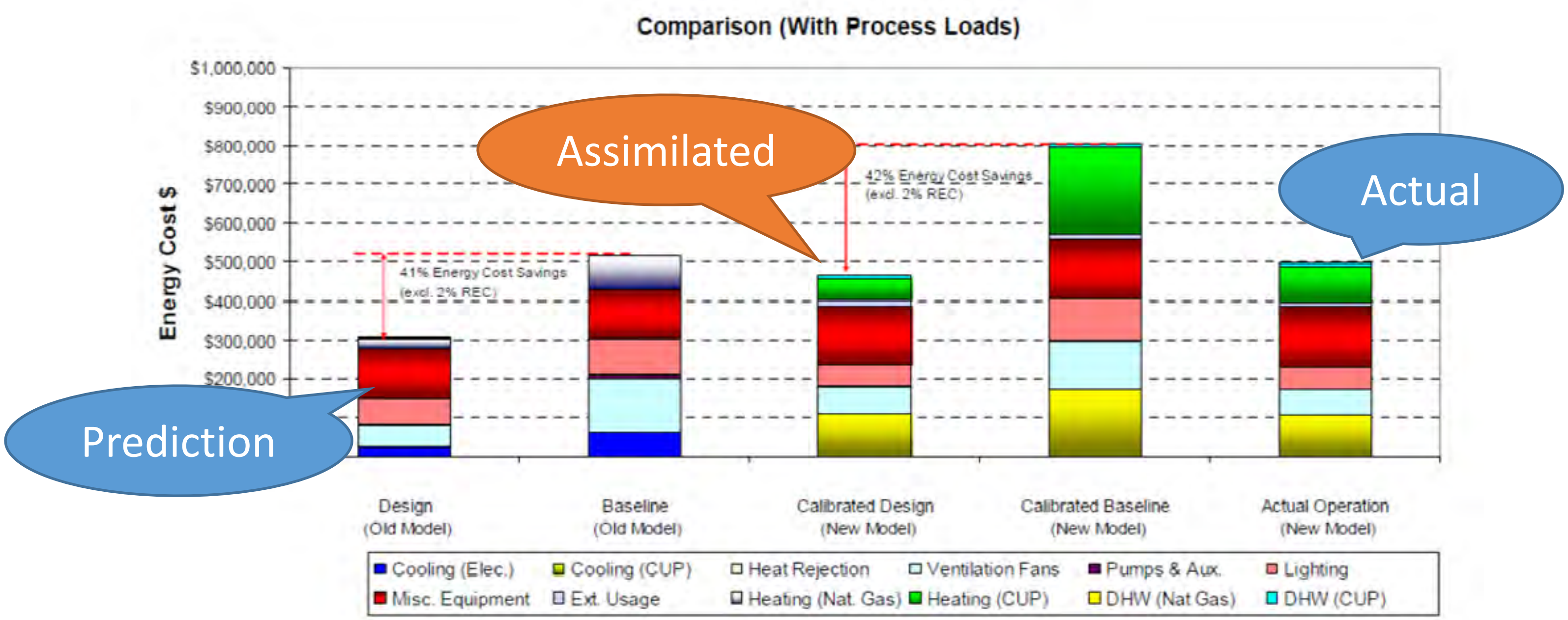


Model of T. Maile, E+ annual simulation = 51 minutes

Large Models

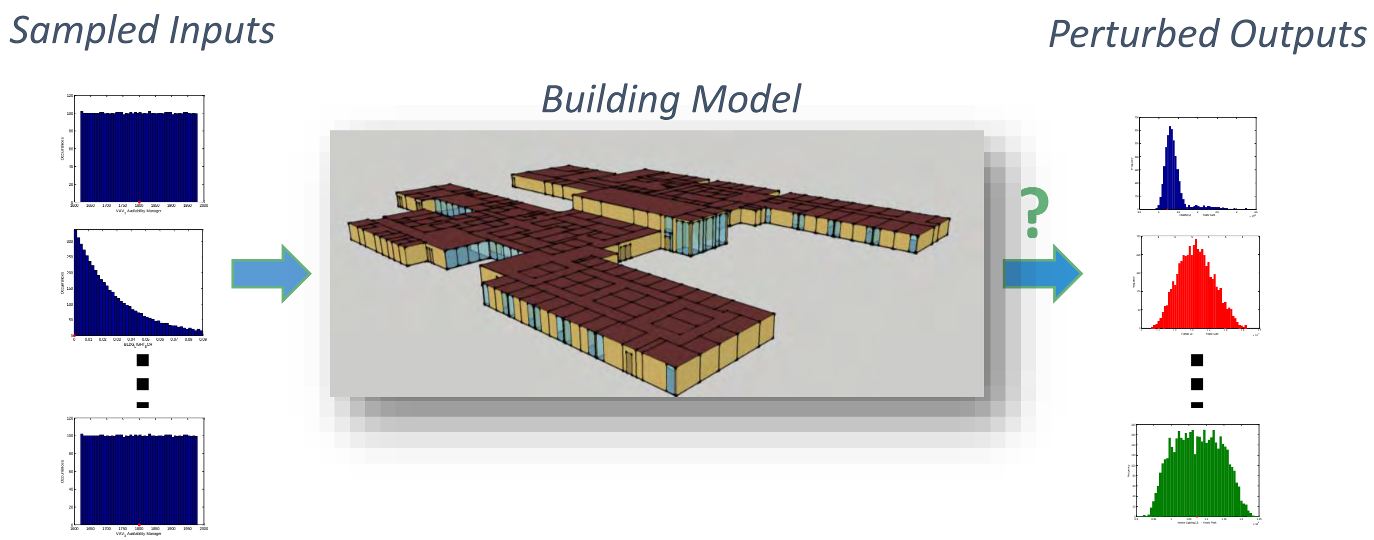
Even large models can be assimilated to data

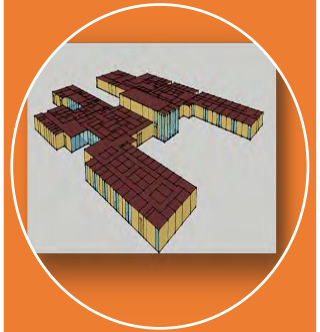
….this process takes a long time



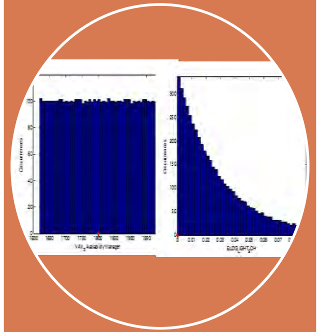
* Stanford Y2E2 Building

Sampled System Analysis

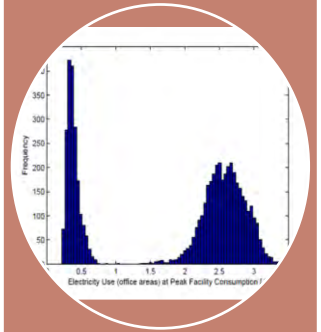




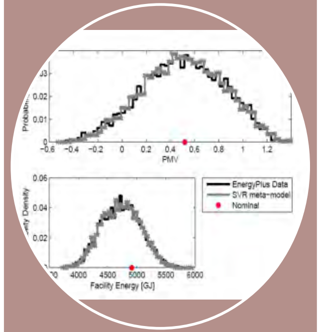
Create Energy Model E+, TRNSYS, Modelica



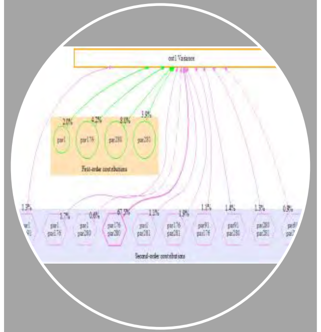
Identify key parameters, perform sampling



Calculate simulation results, study uncertainty in output



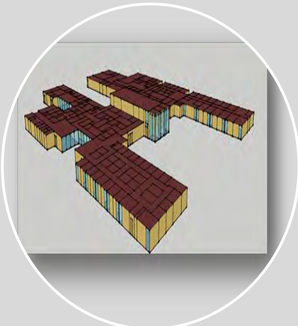
Calculate full order meta-model



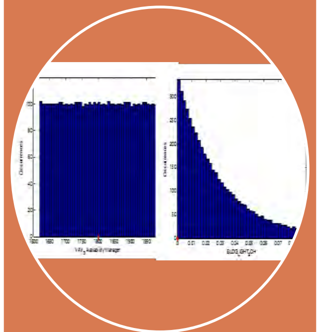
Perform Sensitivity Analysis

- Model Reduction
- Optimization
- Calibration
- Failure Mode Effect Analysis

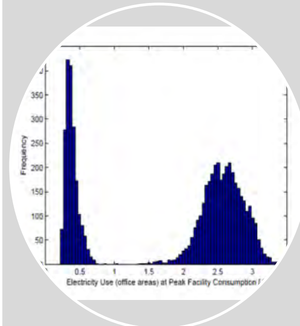
Model-based design flow



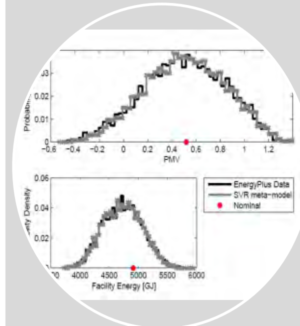
Create Energy Model E+, TRNSYS, Modelica



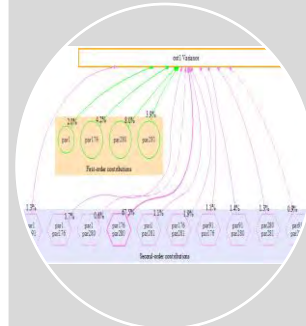
Identify key parameters, perform sampling



Calculate simulation results, study uncertainty in output



Calculate full order meta-model

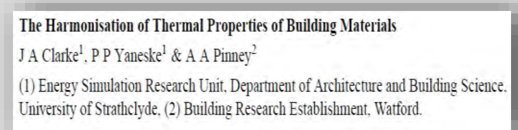


Perform Sensitivity Analysis

- Model Reduction
- Optimization
- Calibration
- Failure Mode Effect Analysis

Parameter Selection & Variation

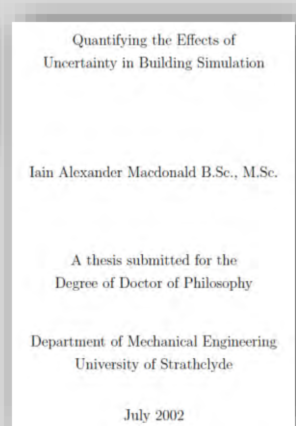
- All *non-architectural* parameters selected in the model
- Parameters varied 20-30% of their mean (sometimes %75)
- Parameters are varied simultaneously
- There are inequality constraints on some subsets (e.g. a+b < 1)



The Harmonisation of Thermal Properties of Building Materials

J A Clarke[1], P P Yaneske[1] & A A Pinney[2]

(1) Energy Simulation Research Unit, Department of Architecture and Building Science, University of Strathclyde, (2) Building Research Establishment, Watford.



Quantifying the Effects of Uncertainty in Building Simulation

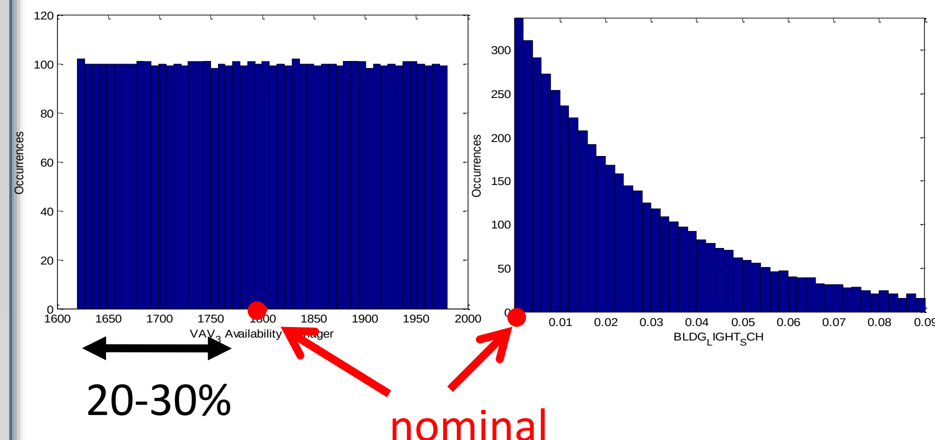
Iain Alexander Macdonald B.Sc., M.Sc.

A thesis submitted for the Degree of Doctor of Philosophy

Department of Mechanical Engineering University of Strathclyde

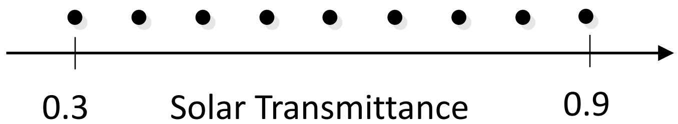
July 2002

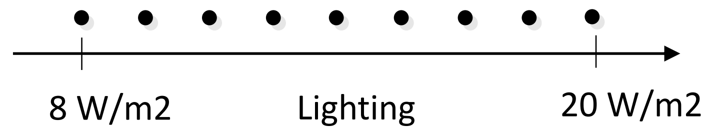
Distribution types are available in literature but not applied because of the large number of parameters



Sampling

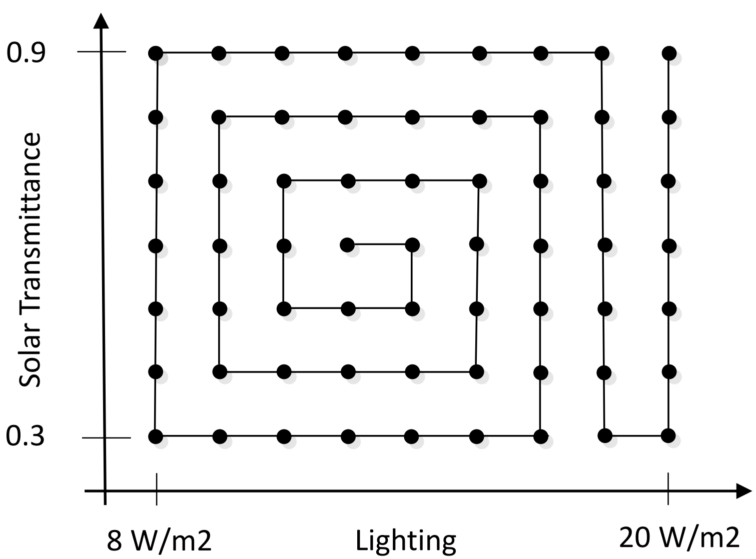
Example: 1 – parameter at a time

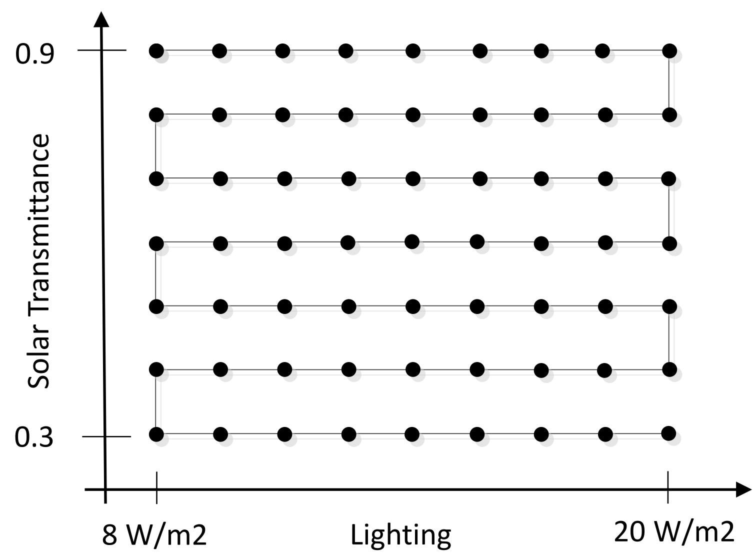




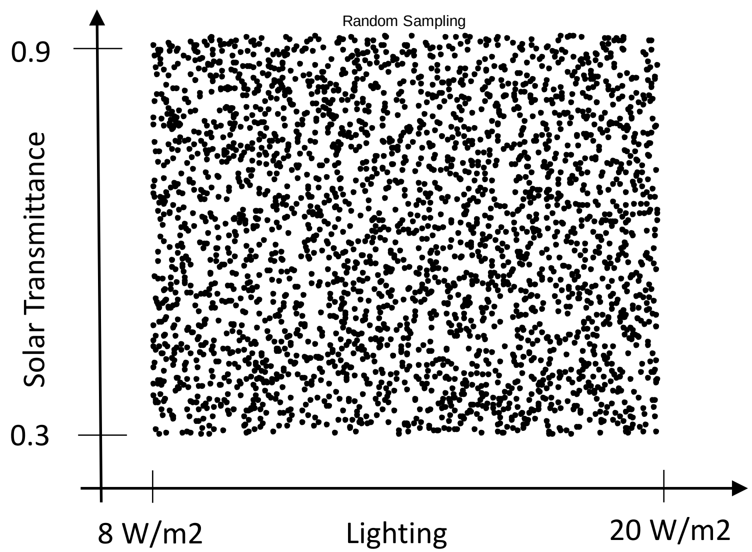
One parameter at a time takes too long and does not capture combinatorial effects

Example: 2 – parameters at a time

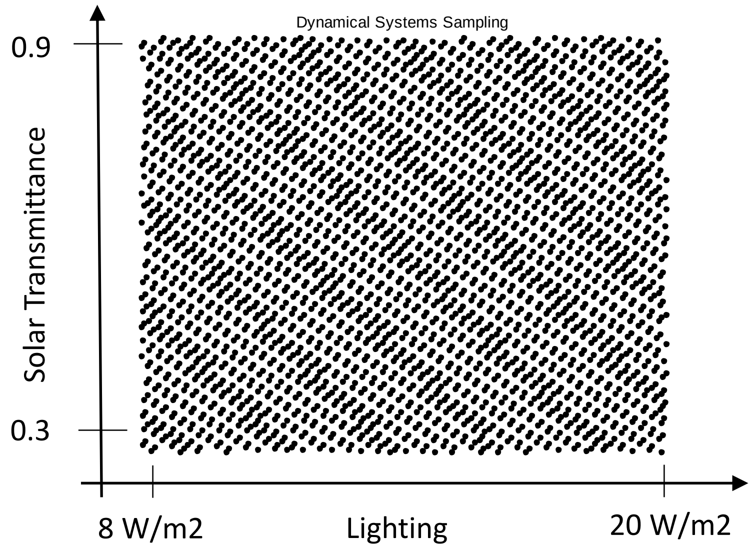




Sampling

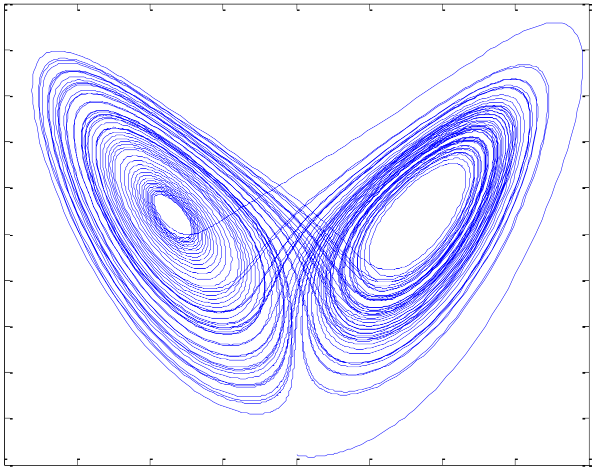


- Traditional methods use random sampling
- This results in ‘clumps’ in the parameter space

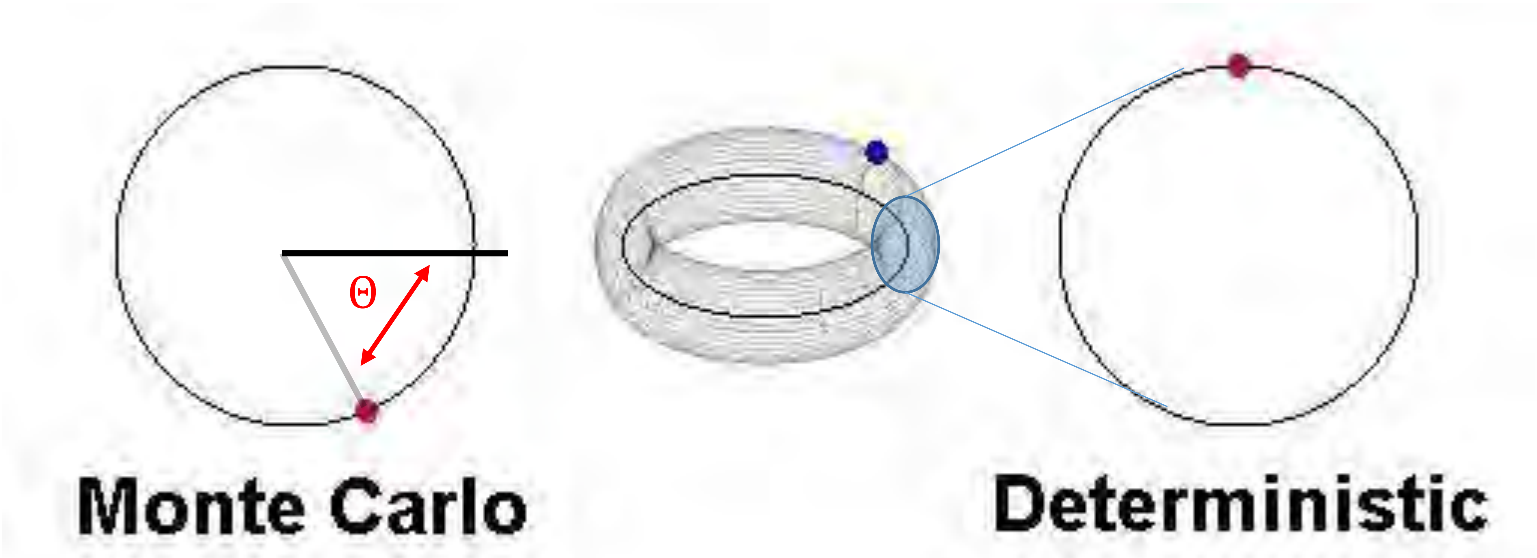


Use chaotic dynamics we can get much better sampling coverage

Lorenz Attractor



Deterministic Sampling



In one dimension:

- ❑ Random approach: pick random angles on the circle
- ❑ Deterministic approach: design a chaotic trajectory on a torus

Deterministic Sampling

Movie of sampling on a taurus

Resonance / Anti-resonance conditions

$$|(\kappa, \widetilde{\omega})| < \frac{1}{c|\kappa|^{v}}$$

$(\kappa, \widetilde{\omega}) = \kappa_0\omega_0 + \kappa_1\omega_1 + \cdots + \kappa_M\omega_M$

$\kappa \in \mathbb{Z}$,

$c, v \in \mathbb{R}^{+}$

ω_i = Frequencies

Ergodic:

- ❑ Time average and space average distributions are equal
- ❑ Originated in 1930's (von Neumann)

$$\hat{f}(x) = \lim_{n\to\infty} \frac{1}{n} \sum_{k=0}^{n-1} f\left(T^{k}x\right)$$

These are equal

$$\bar{f} = \frac{1}{\mu}\int f \, d\mu$$

T: Measure preserving transformation on measure space

x: Initial point

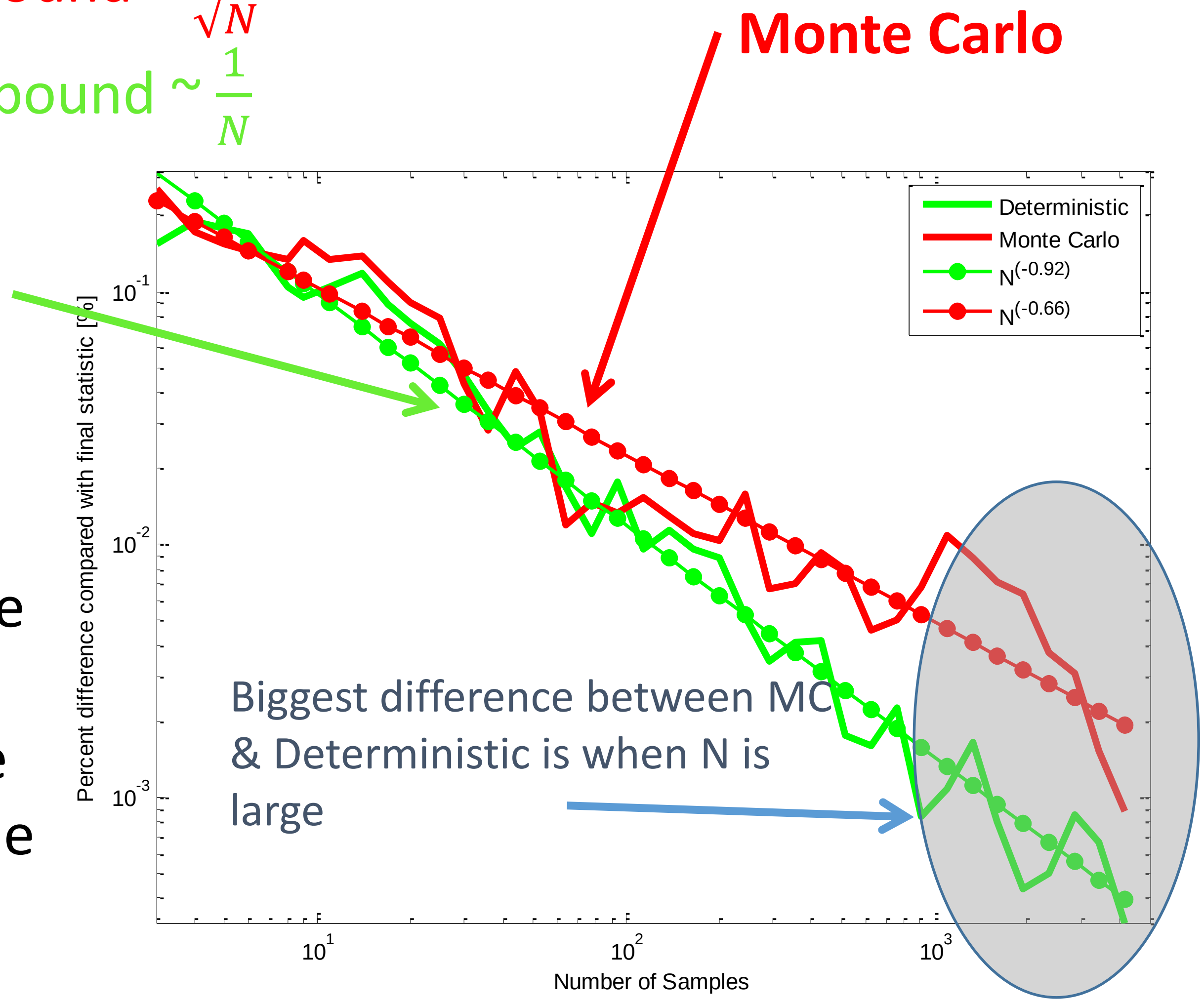
$\hat{f}$: Time average

μ: Measure

$\bar{f}$: Space average

Convergence Properties

- Monte Carlo bound $\sim \frac{1}{\sqrt{N}}$
- Deterministic bound $\sim \frac{1}{N}$



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

For whole-building analysis, N must be large

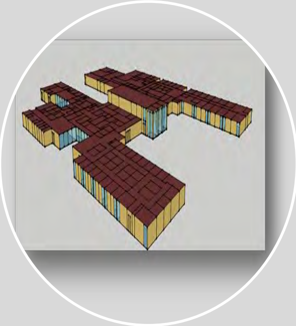
* Work with Igor Mezic

[Eisenhower, JBPS 2012]

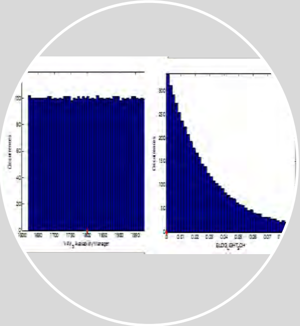
Scalability

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

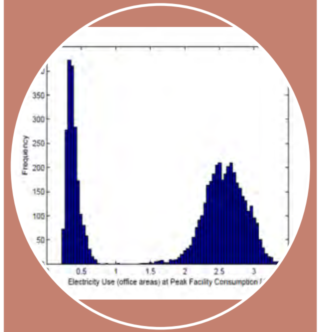
Refinement of old Mathematics leads to discontinuity in tool effectiveness



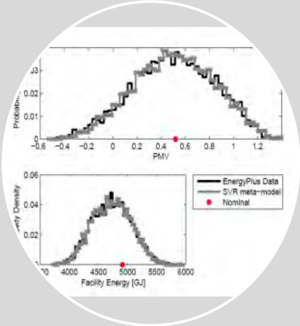
Create Energy Model E+, TRNSYS, Modelica



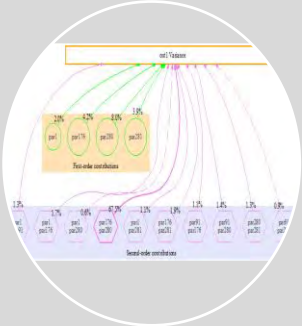
Identify key parameters, perform sampling



Calculate simulation results, study uncertainty in output

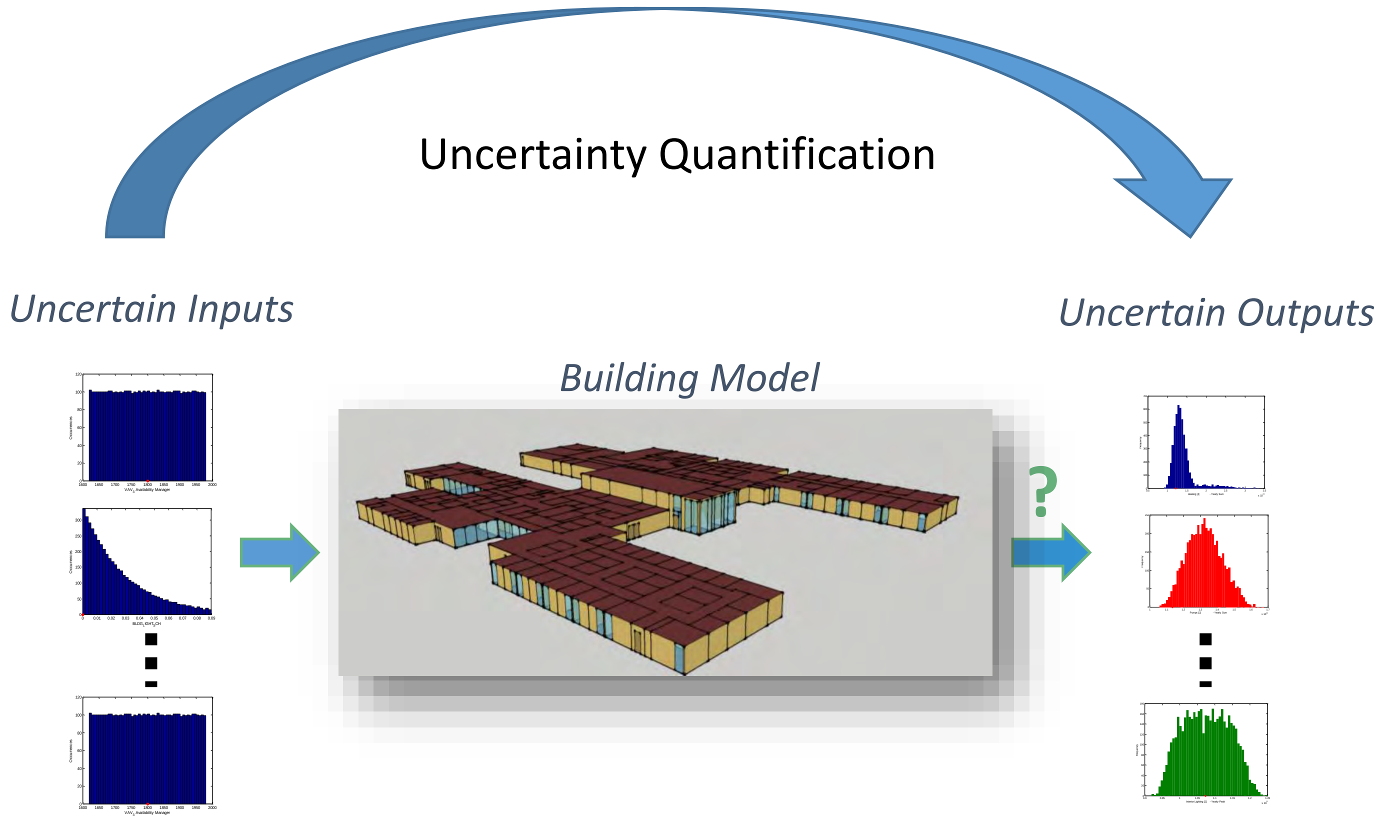


Calculate full order meta-model



Perform Sensitivity Analysis

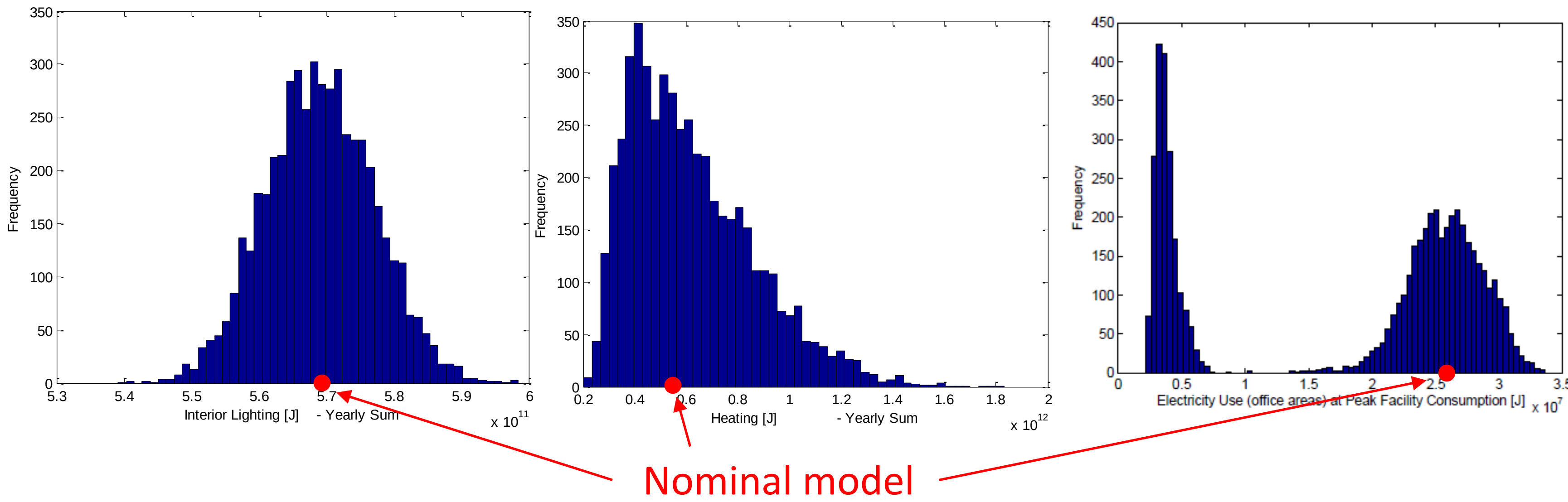
- Model Reduction
- Optimization
- Calibration
- Failure Mode Effect Analysis


Uncertainty Quantification
Uncertain Inputs
Building Model
Uncertain Outputs
?

Typical Outputs

Facility Outputs
Averaged Thermal Comfort
Gas Facility
Electricity Facility
Sub-metered
Heating
Cooling
Pumps
Fans
Interior Lighting
Interior Equipment

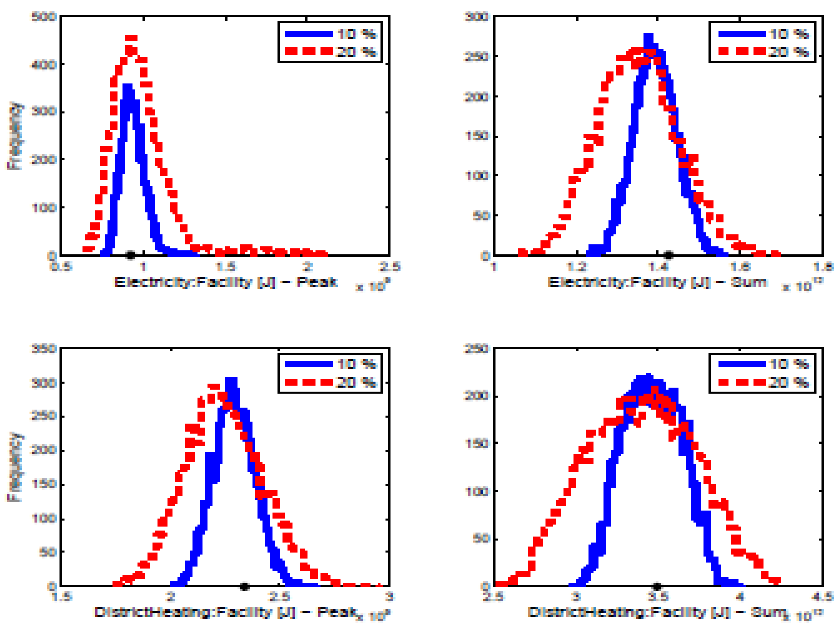
- Data assessed in different ways:
  - Peak demand
  - Seasonal demand
  - Monthly demand
  - ....
- The 'control' mechanisms in the model drive distributions towards Gaussian although others exist as well



Uncertainty Quantification

Different Inputs:

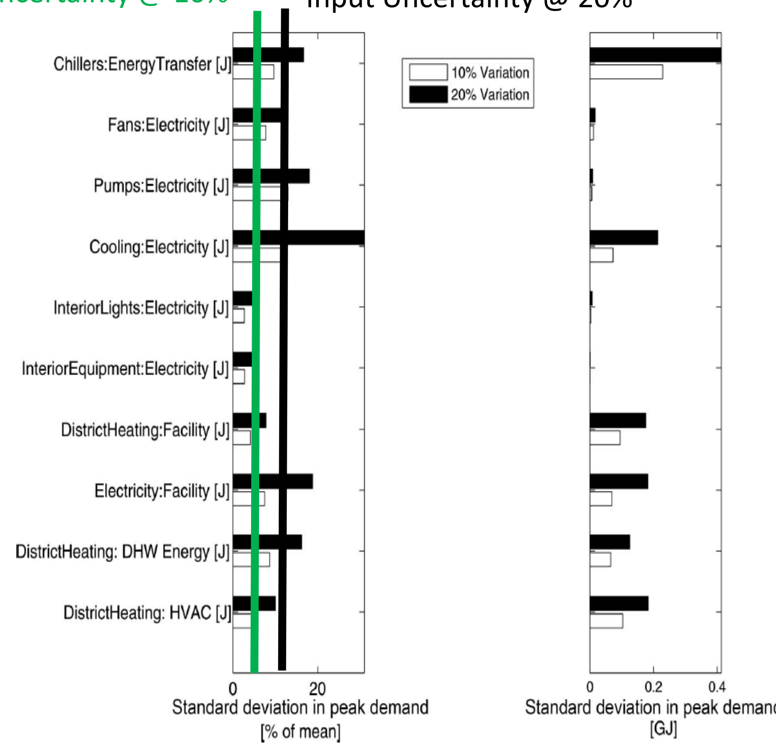
Influence of Different Parameter Variation size



[E+ Drill Hall]

Input Uncertainty @ 10%

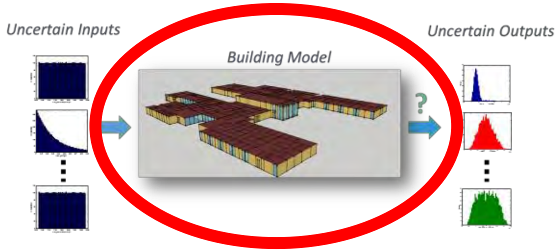
Input Uncertainty @ 20%



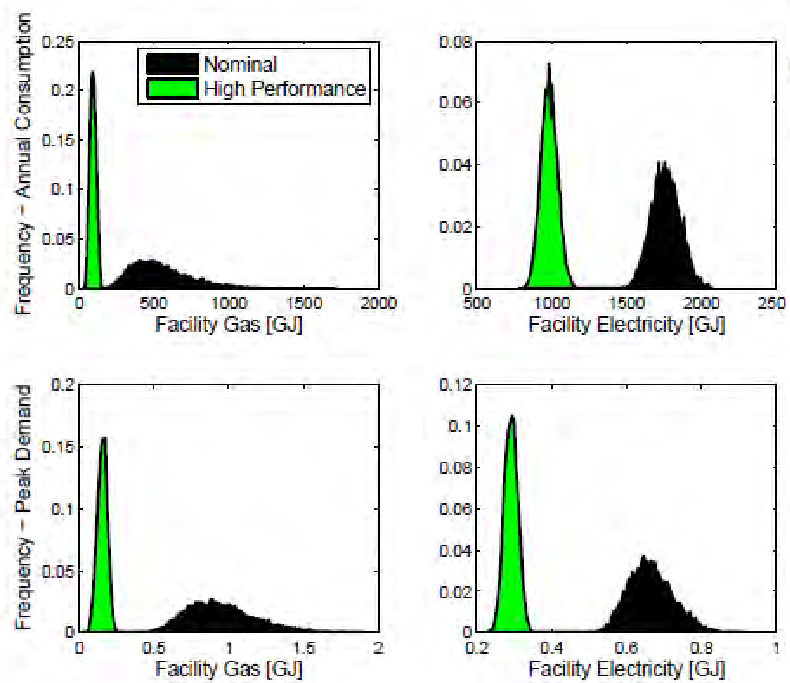
[Eisenhower, JBPS 2012]

Uncertainty Quantification

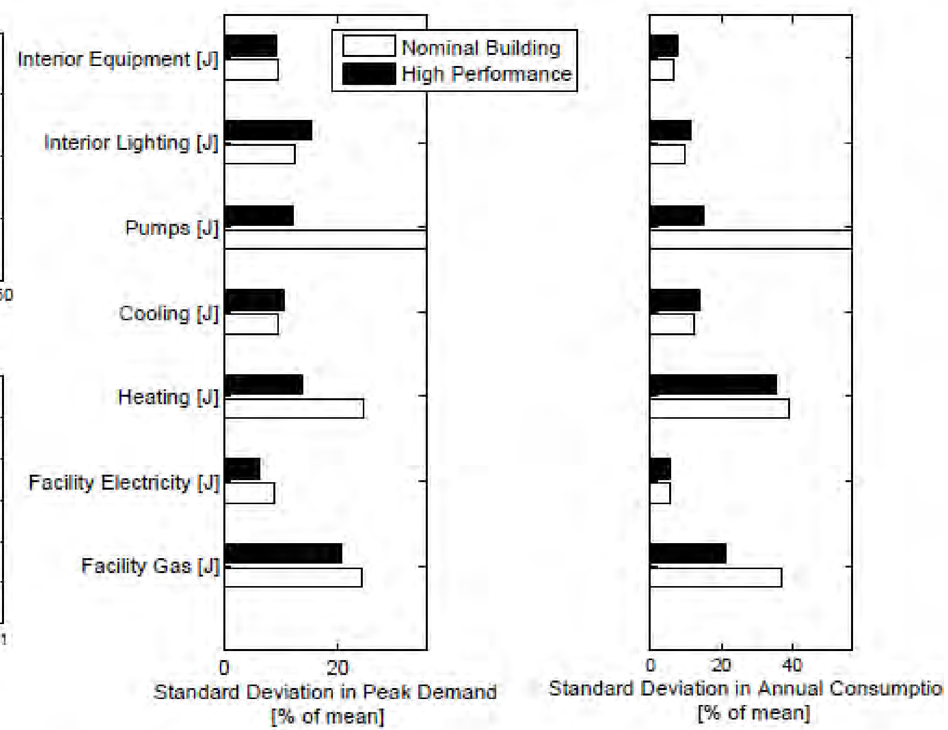
Different Designs:



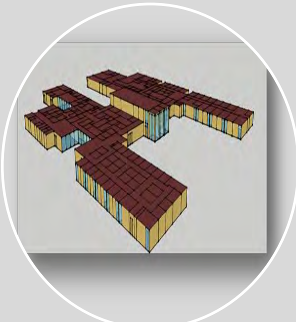
Nominal vs. High Efficiency Design



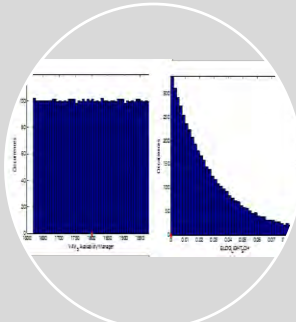
[E+ DOE Models]



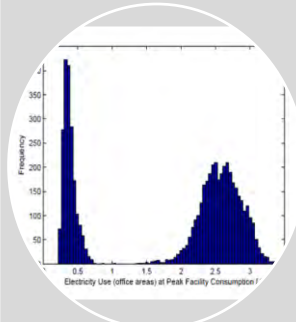
[Eisenhower, Simbuild 2011]



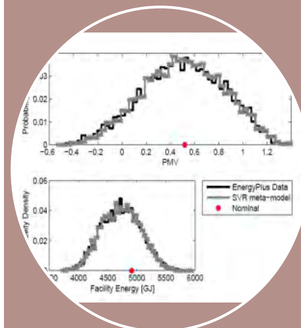
Create Energy Model E+, TRNSYS, Modelica



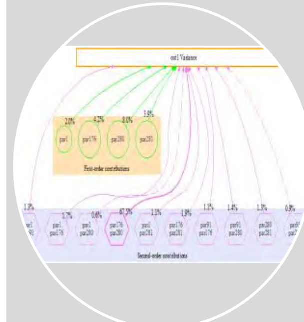
Identify key parameters, perform sampling



Calculate simulation results, study uncertainty in output



Calculate full order meta-model



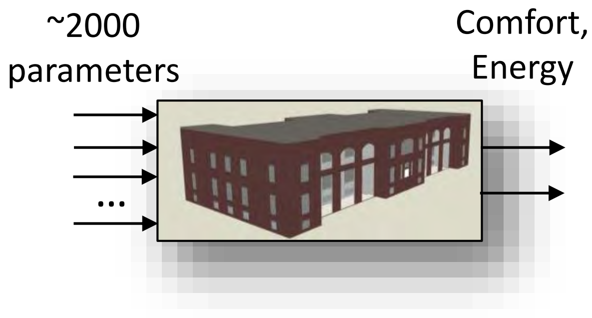
Perform Sensitivity Analysis

- Model Reduction
- Optimization
- Calibration
- Failure Mode Effect Analysis

Meta-Modeling

Original Model

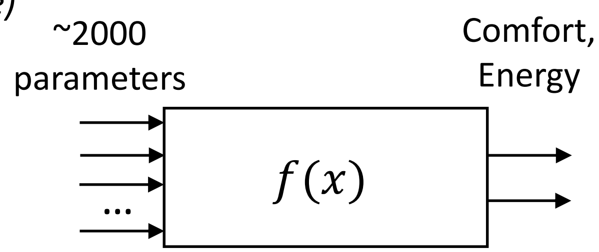
- ❑ Can test many building configurations
- ❑ All modeled dynamics exist
- ❑ Usually black box
- ❑ Expensive evaluations
- ❑ Discontinuous functions



Meta-Model (model of a model)

(same structure)

- ❑ Configurations limited to data that is used for fit
- ❑ Known functional form
- ❑ Rapid evaluations
- ❑ Continuous functions



Machine Learning / Regression

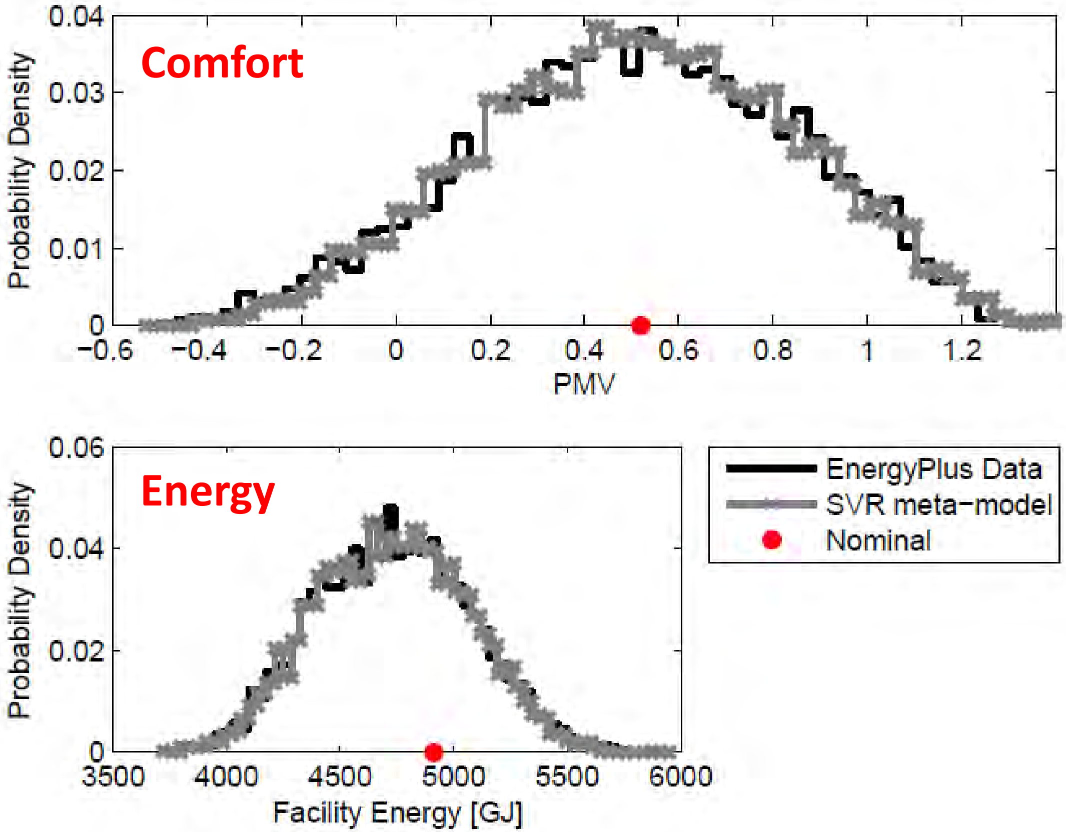
- Support Vector Regression used to create analytical model from whole building energy model data
- Analytical model representation (Gaussian Kernel)

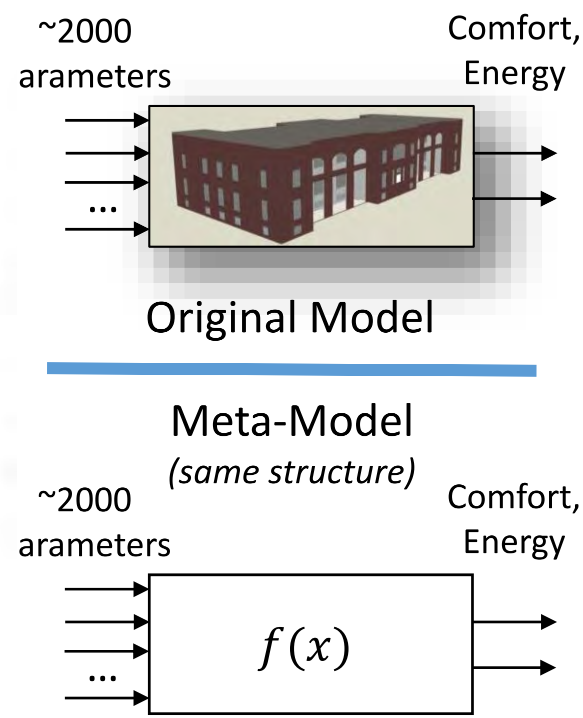
$$\mathrm{f}(\mathbf{x}) = \sum_{k=1}^{N} C_k \exp\left(-\gamma\left\{\left(x_1 - X_{1,k}^{0}\right)^2 + \left(x_2 - X_{2,k}^{0}\right)^2 + \left(x_3 - X_{3,k}^{0}\right)^2 + \ldots\right\}\right)$$

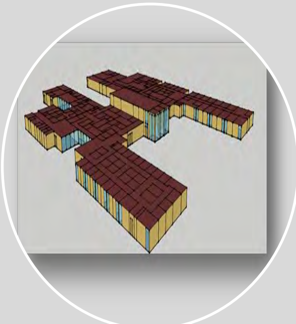
where $\mathbf{X}_k^0$ is k[th] input parameter sample, γ and C_k are fit using an optimizer

- Unique minima to the optimization used to identify its coefficients (from convexity)

Meta-modeling results







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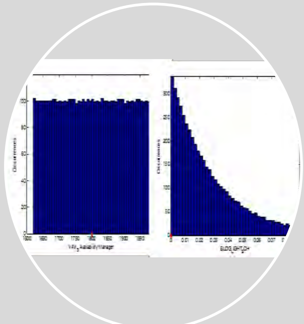

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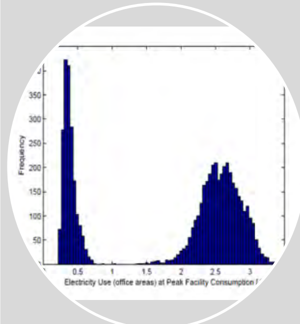

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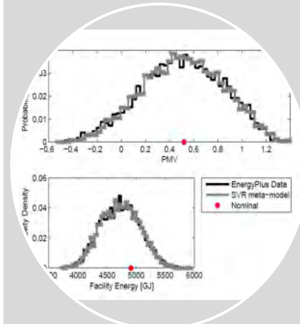
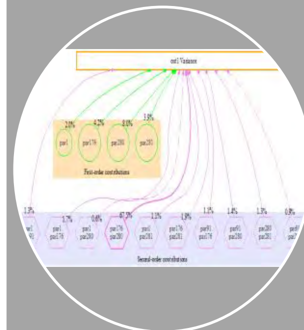


Calculate full order meta-model



Perform Sensitivity Analysis

- Model Reduction
- Optimization
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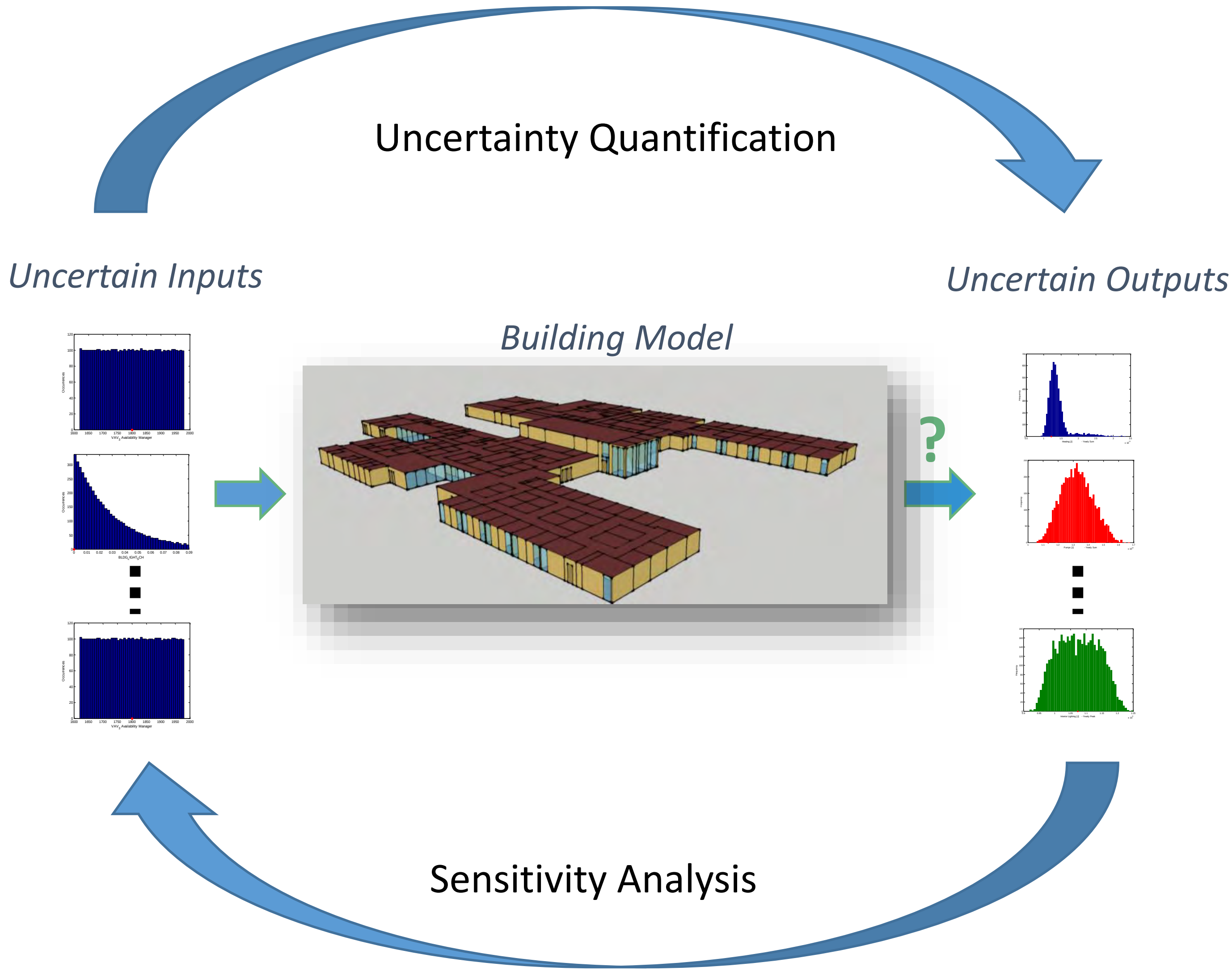
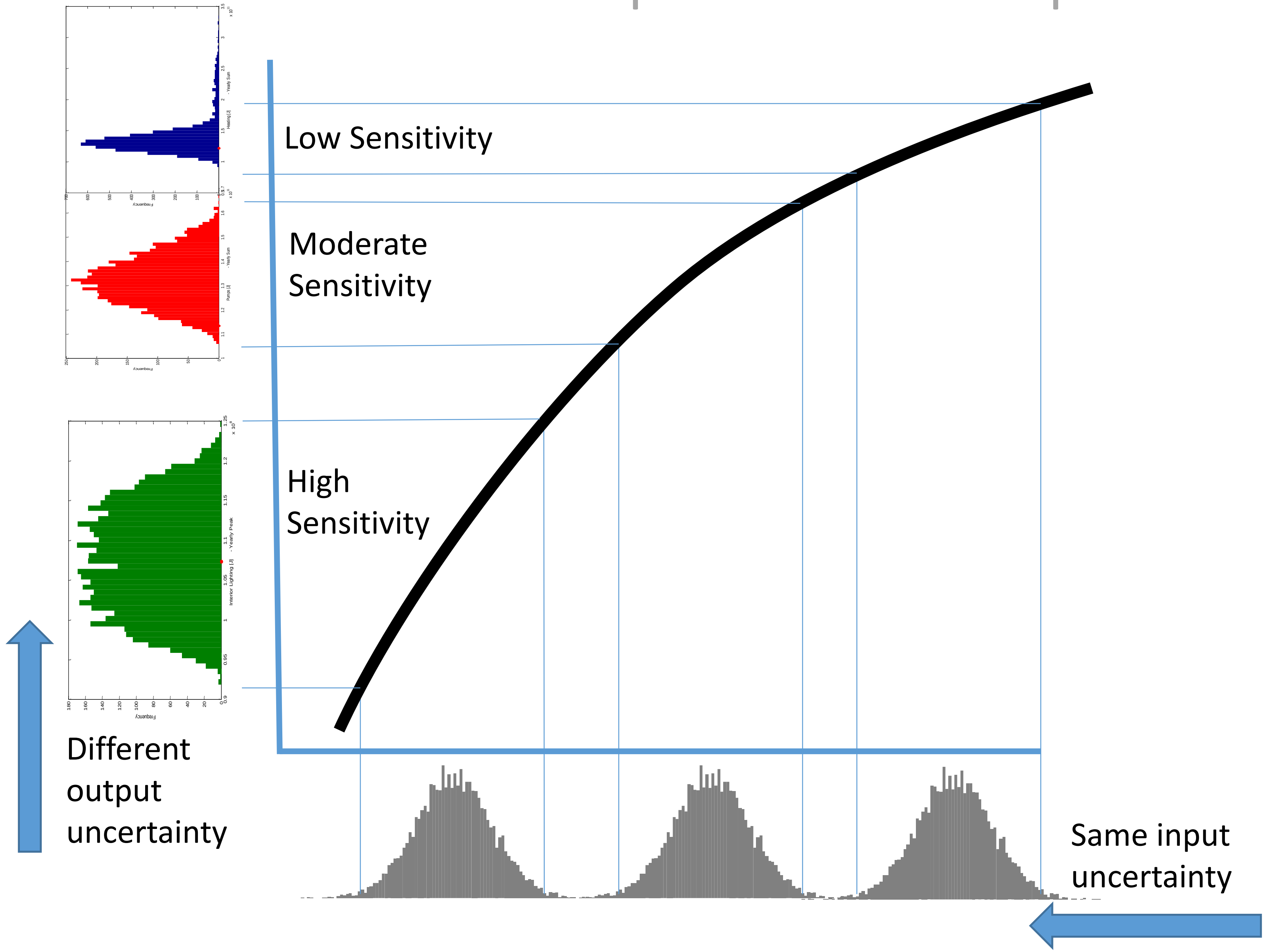

Uncertainty Quantification
Uncertain Inputs
Building Model
Uncertain Outputs
?
Sensitivity Analysis

Impact of sensitive processes



Calculating Sensitivities

ANOVA-based approach:

Functional decomposition

$$f(x) = f_0 + \sum_{i=1}^{k} f_i(x_i) + \sum_{j>i}^{k} f_{ij}(x_i, x_j) + \cdots + f_{12\ldots k}(x_1, \ldots, x_k),$$

$\boxed{2^k - 1 \text{ terms}}$

Variance decomposition

$$D = \sum_{i=1}^{k} D_i + \sum_{j>i}^{k} D_{ij} + \cdots + D_{12\cdots k},$$

Sensitivity indices

$$S_i = D_i / D \qquad S_{ij} = D_{ij} / D$$

Total individual sensitivity

$$S_{T_m} = S_m + \sum_{\substack{j>i \\ i \text{ or } j=m}}^{k} S_{ij} + \sum_{\substack{l>j>i \\ i \text{ or } j \text{ or } l=m}}^{k} S_{ijl} + \cdots + S_{1\cdots m \cdots k}.$$

Derivative-based approach:

- 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 $\rho(x_i)$

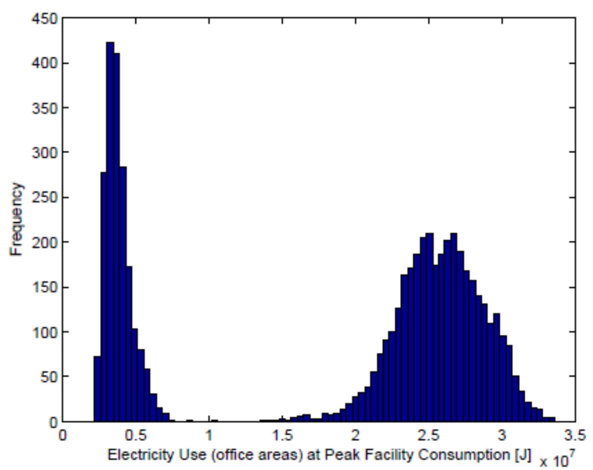
- L1-norm derivative sensitivity indices can be calculated as

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

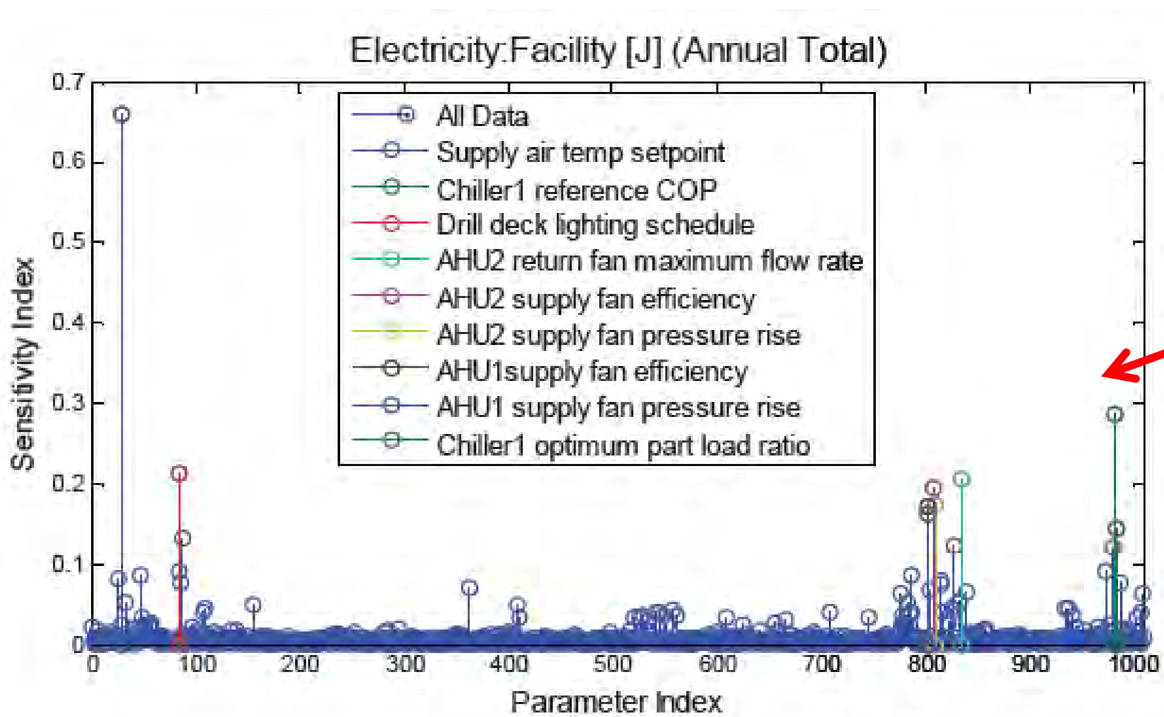
- Average derivatives can be calculated as

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

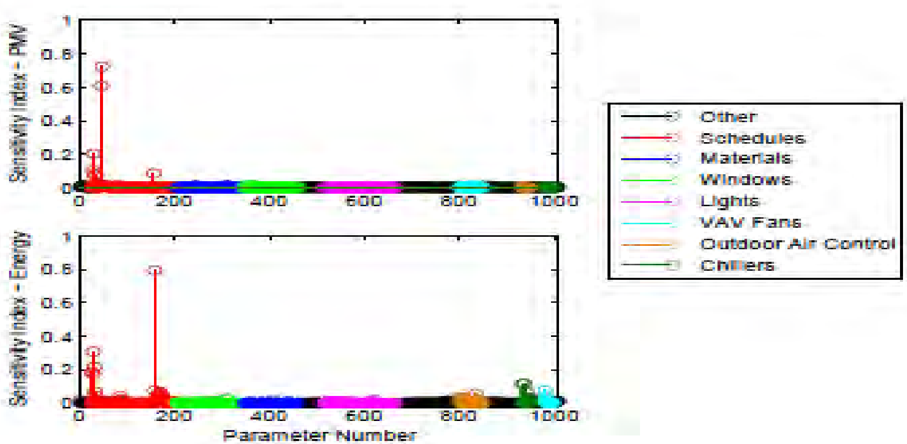
Variance is not always best to describe distribution

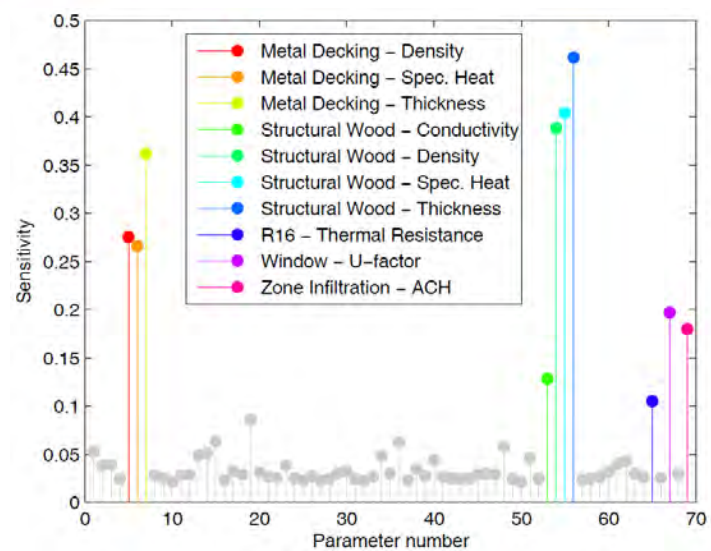


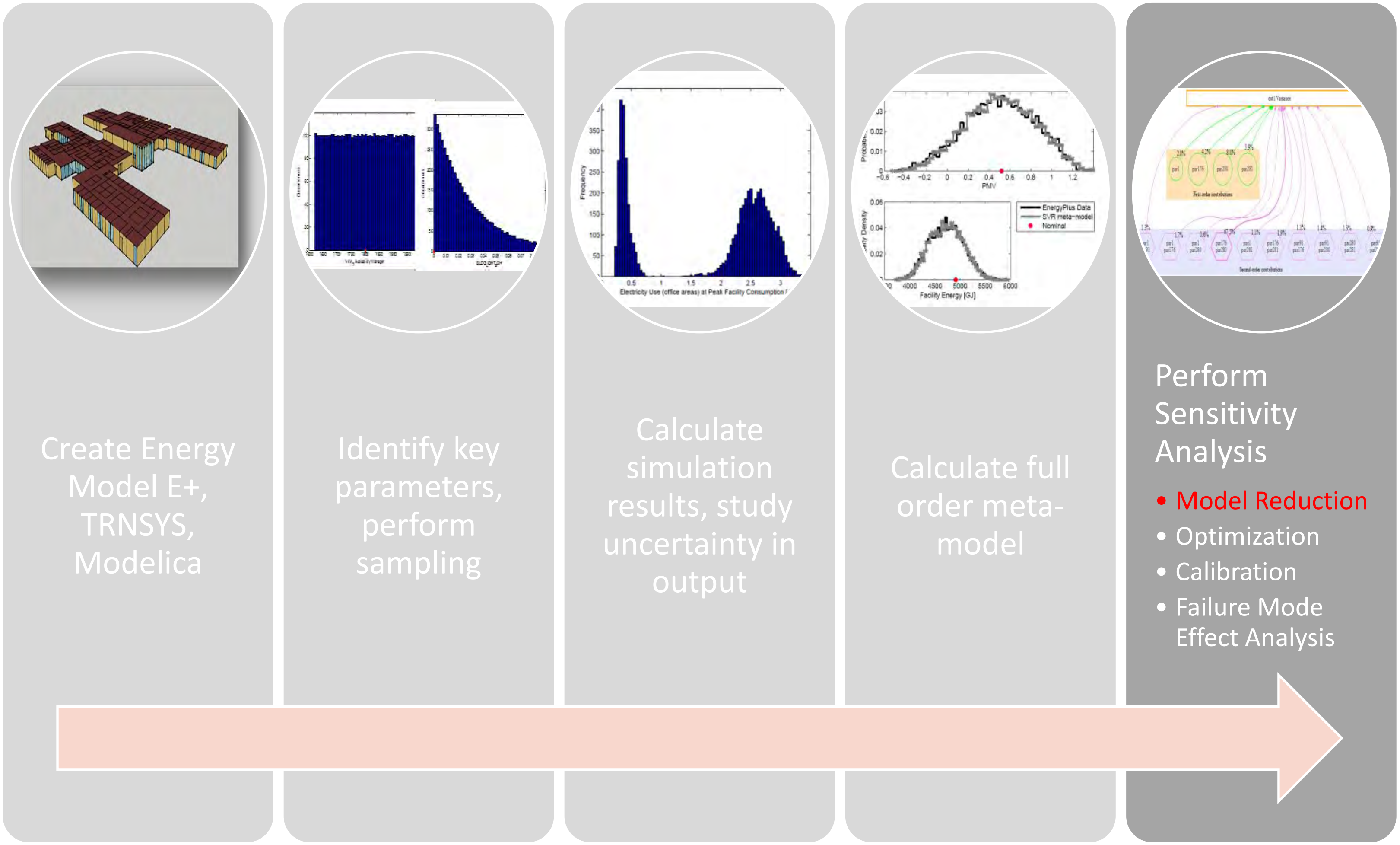
Sensitivity Indices (examples)



Typically only a few parameters drive uncertainty in output

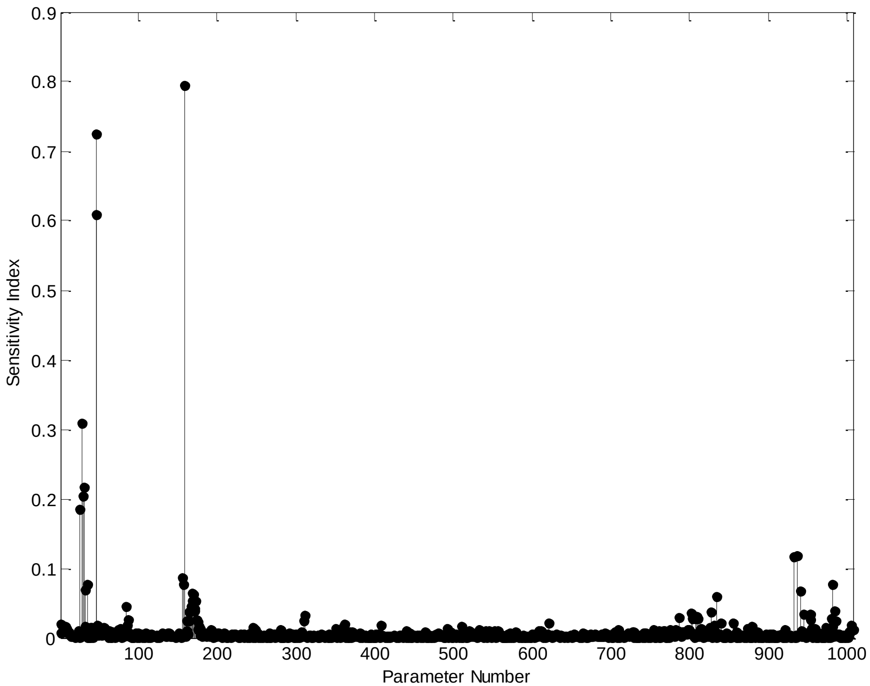


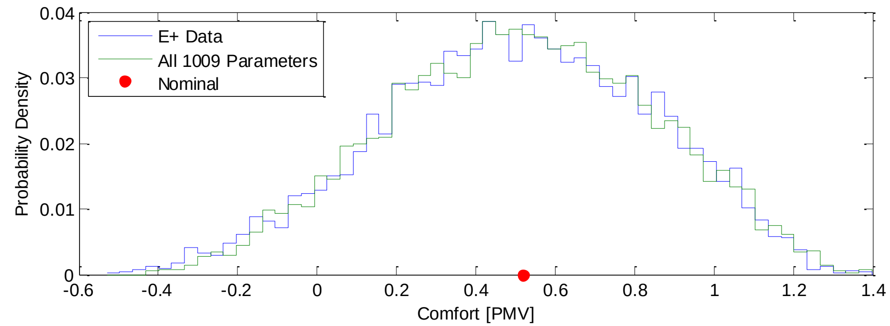


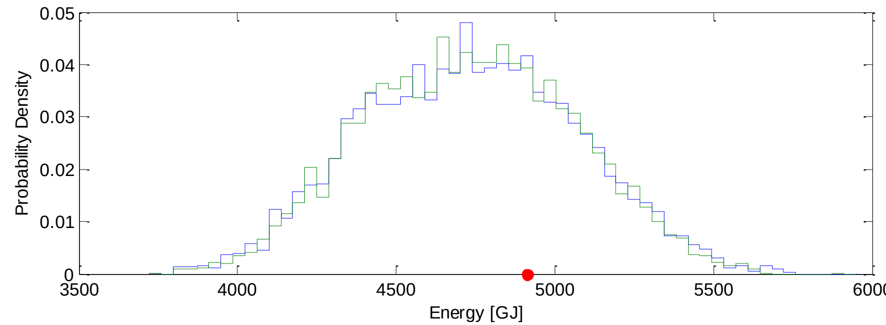


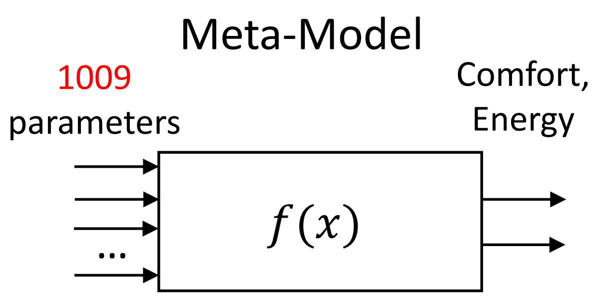
Create Energy Model E+, TRNSYS, Modelica
Identify key parameters, perform sampling
Calculate simulation results, study uncertainty in output
Calculate full order meta-model
Perform Sensitivity Analysis
• Model Reduction
• Optimization
• Calibration
• Failure Mode Effect Analysis

Model Reduction

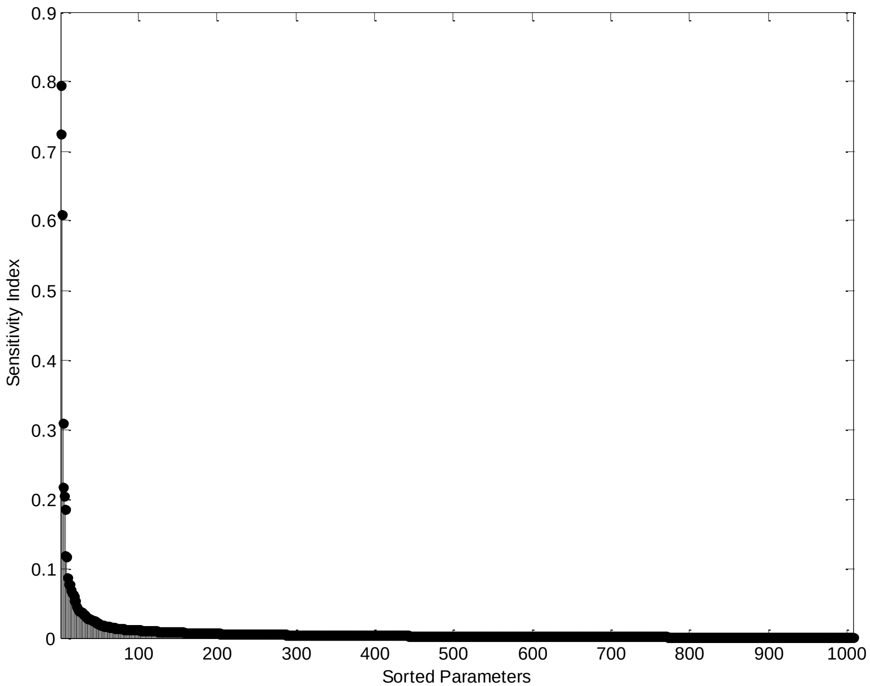


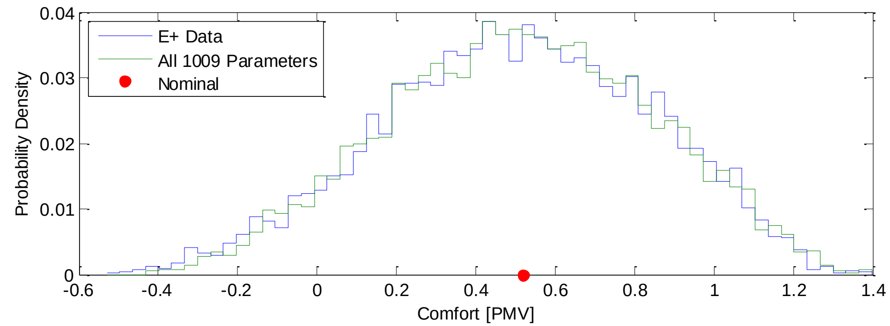


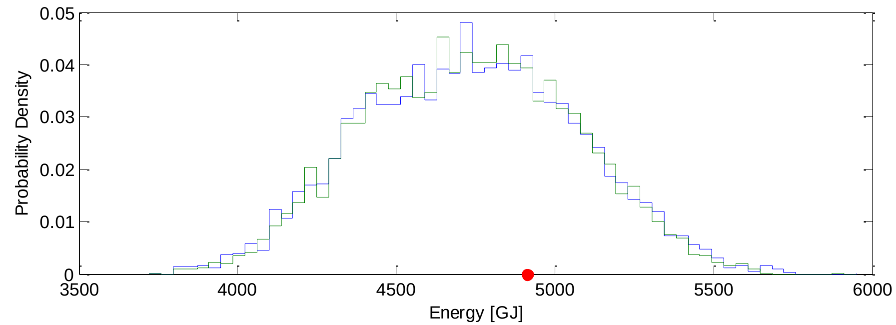


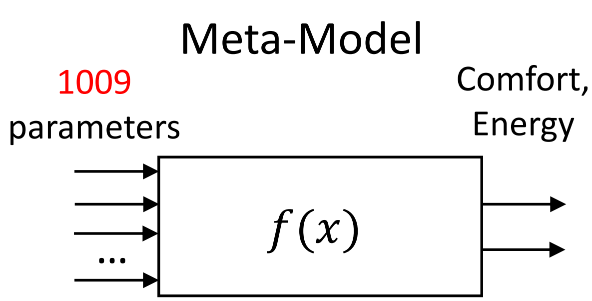


Model Reduction

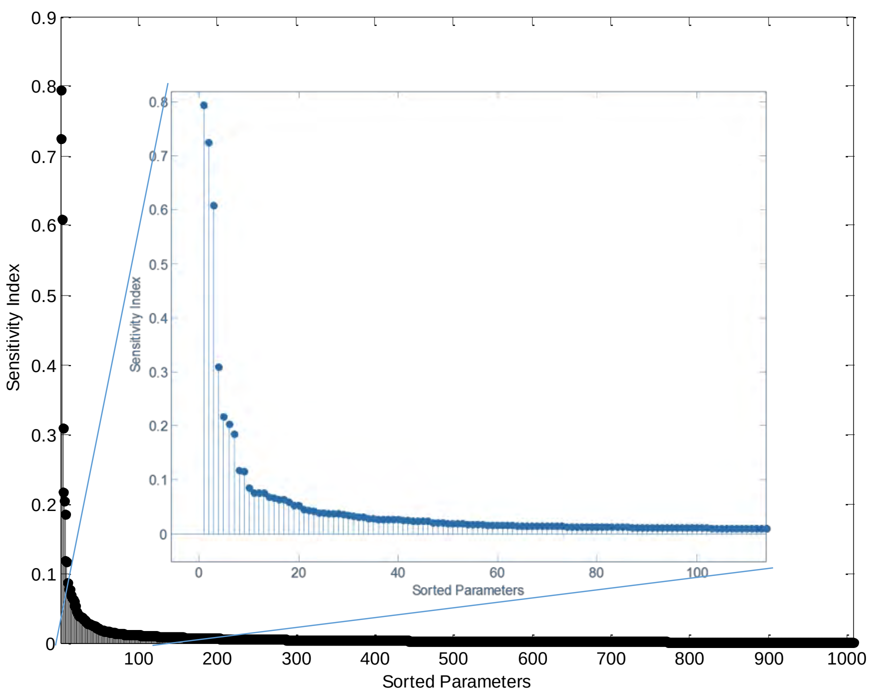


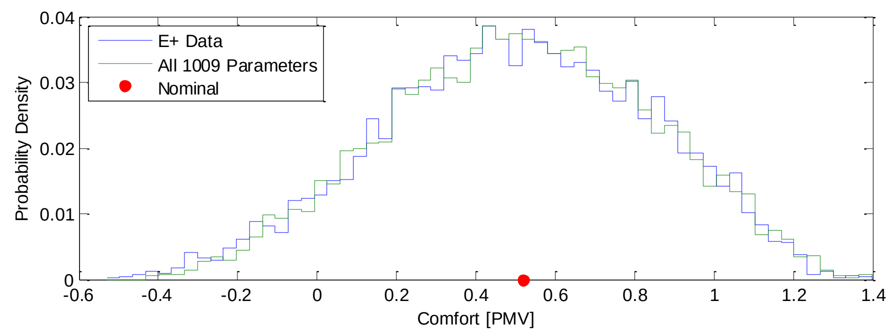


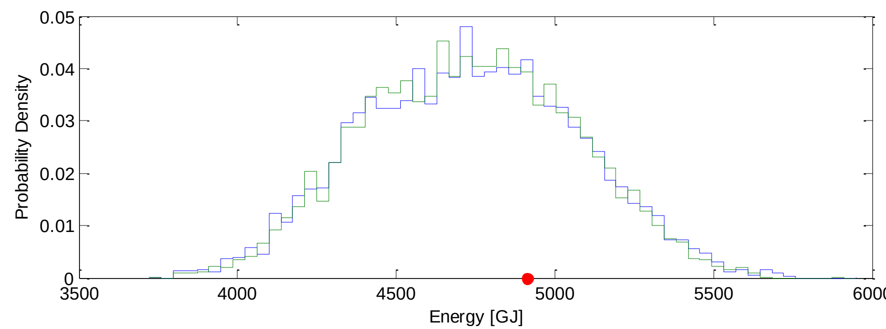




Model Reduction



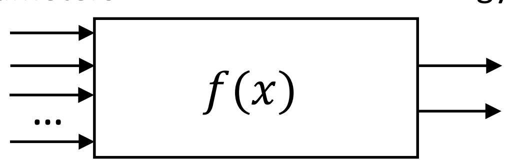




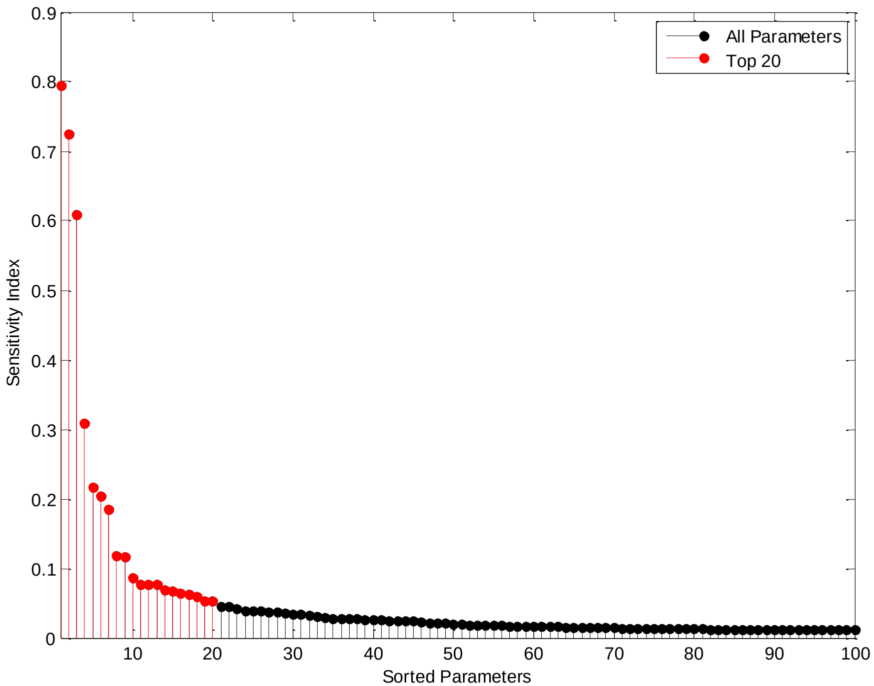
Meta-Model

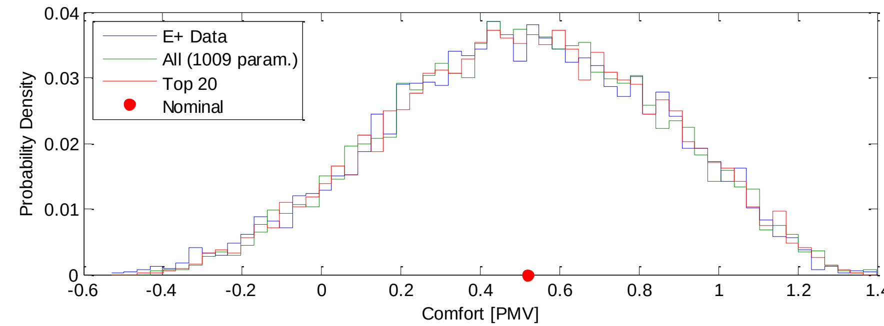
1009 parameters

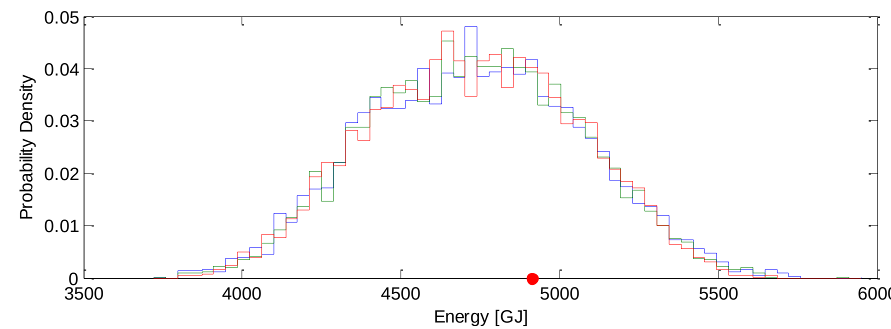
Comfort, Energy

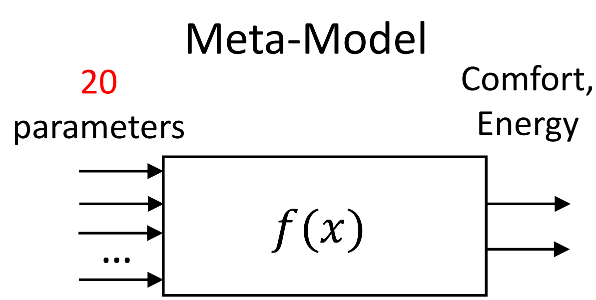


Model Reduction

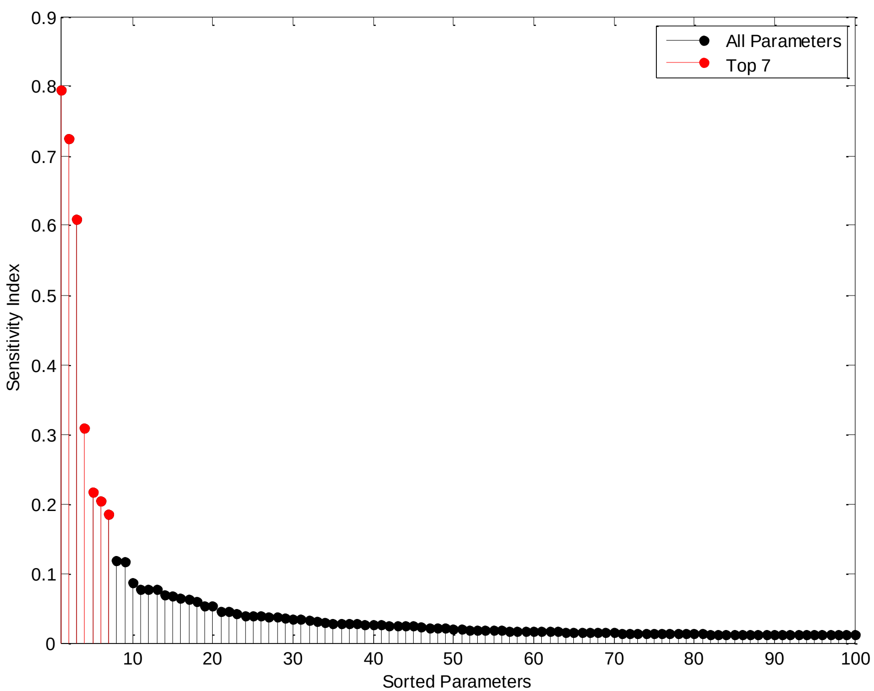


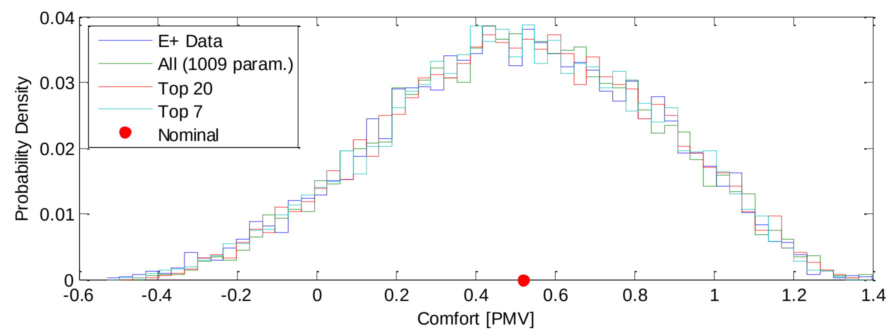


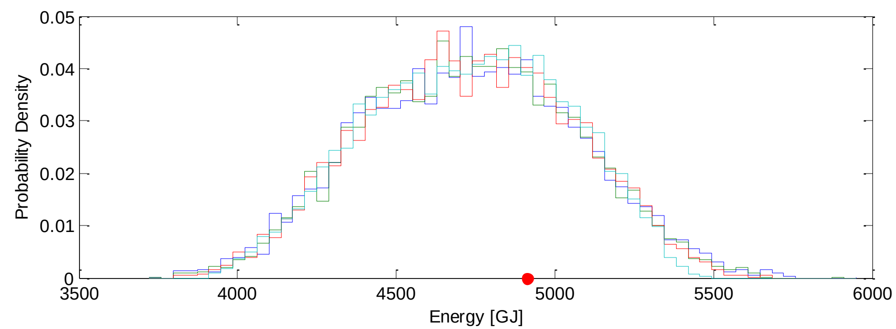




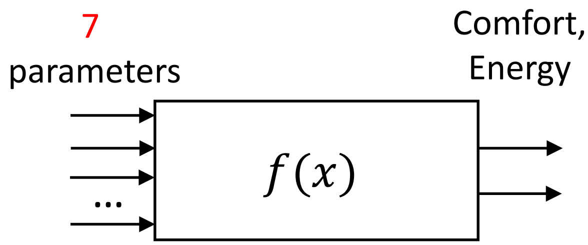
Model Reduction



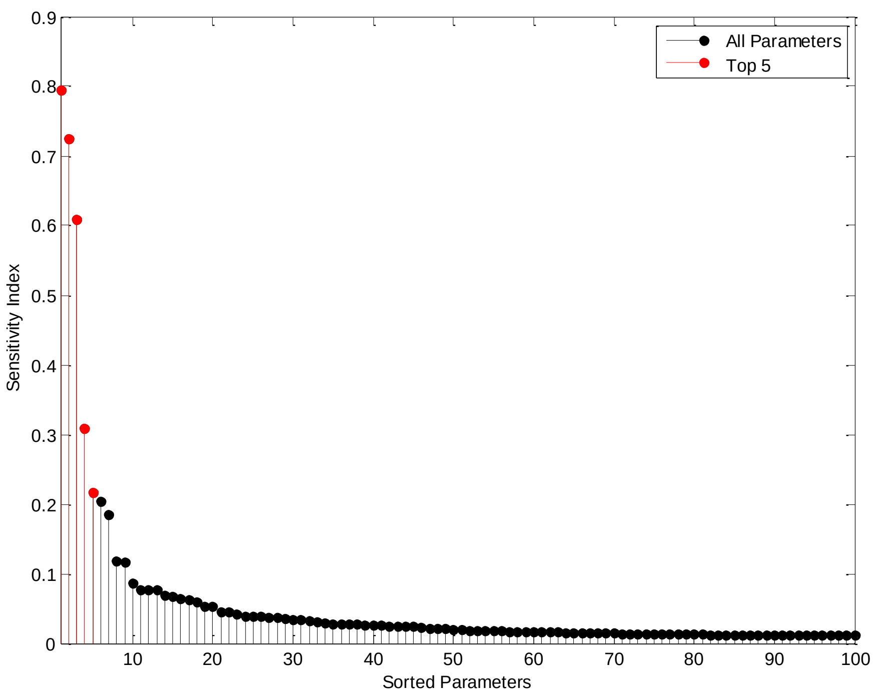


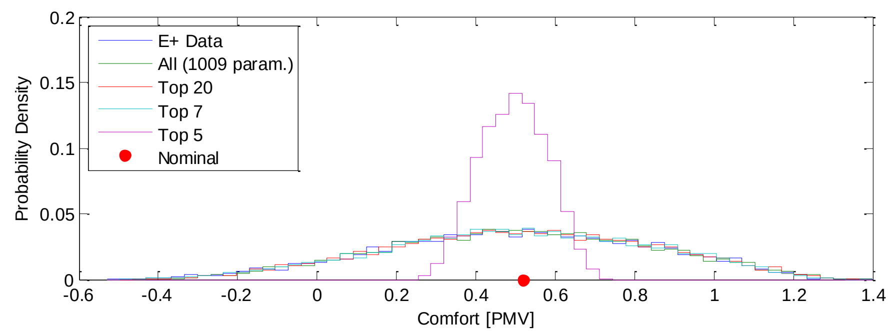


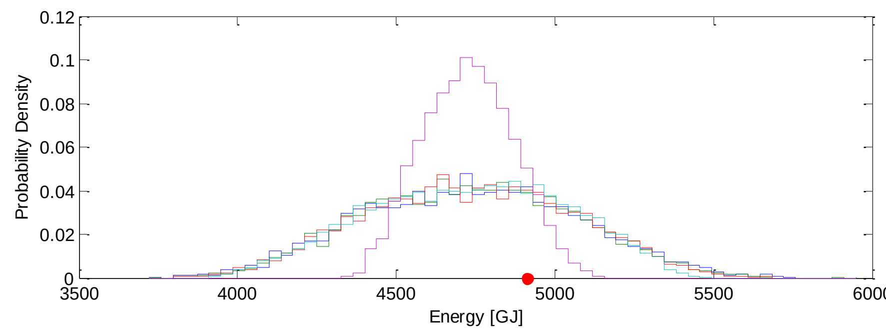
Meta-Model



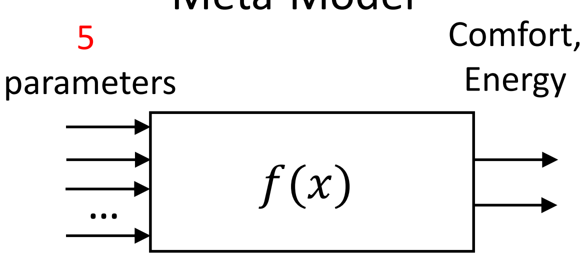
Model Reduction

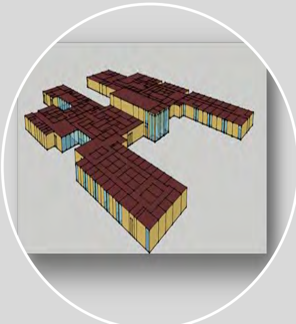




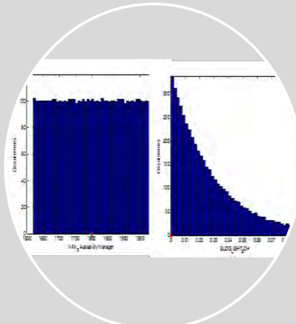


Meta-Model

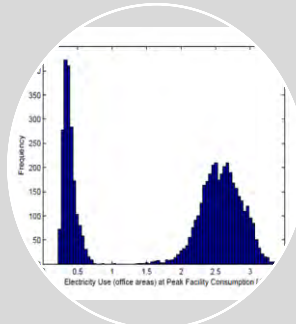




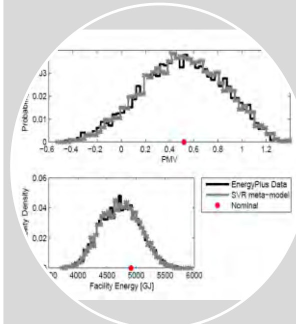
Create Energy Model E+, TRNSYS, Modelica



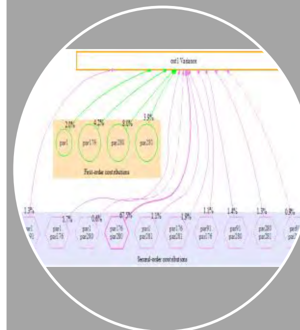
Identify key parameters, perform sampling



Calculate simulation results, study uncertainty in output



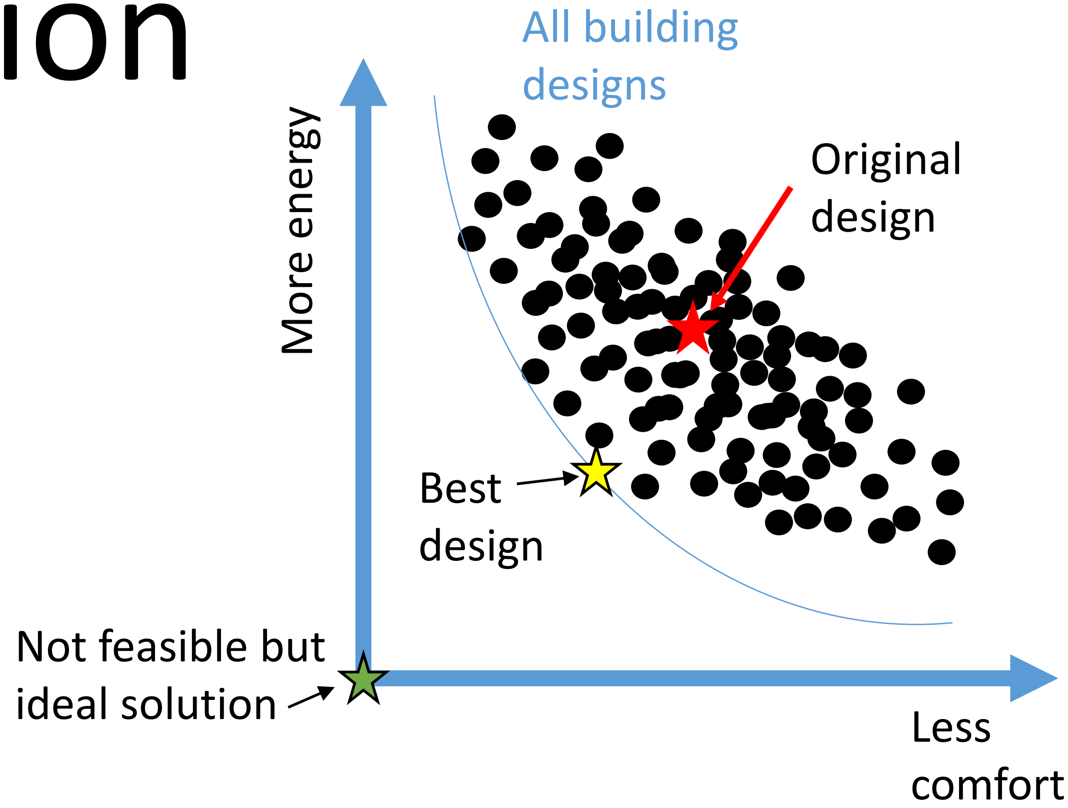
Calculate full order meta-model



Perform Sensitivity Analysis

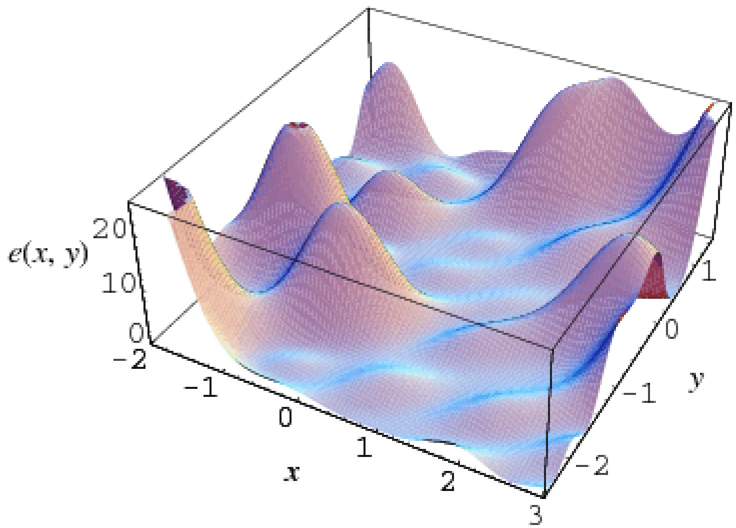
- Model Reduction
- Optimization
- Calibration
- Failure Mode Effect Analysis

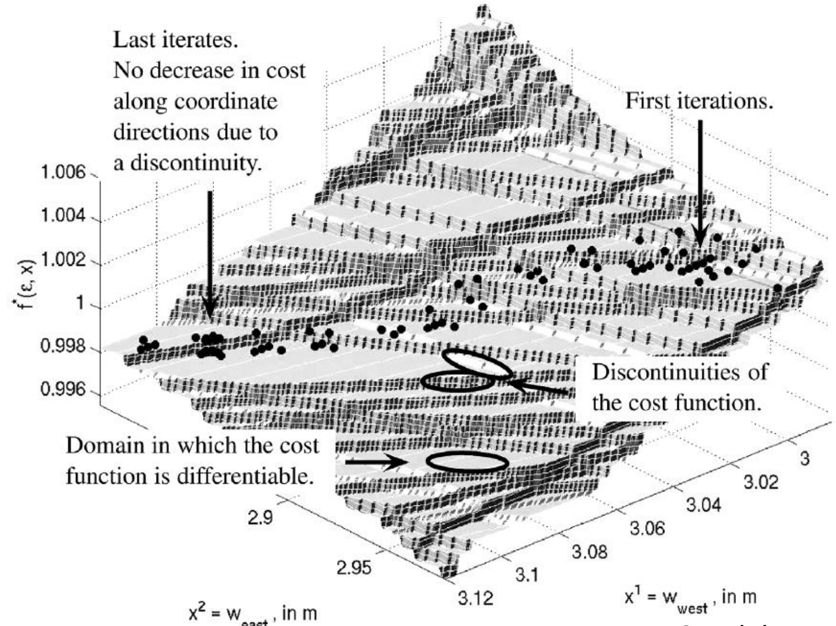
Optimization



....cost, weight, noise, emissions, sales, productivity, ...

Discontinuity & Uncertainty



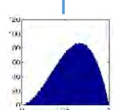


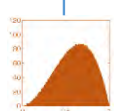
Wetter & Polak 2004

Not friendly to numerical optimization

Uncertainties in meta-model dealt with by uncertain cost function weights

$$\text{Cost} = \alpha_1 \text{Comfort} + \alpha_2 \text{Energy}$$





Methods:

1. **IPOPT** - Primal-Dual Interior Point algorithm with a filter line-search method for nonlinear programming *(Wachter - Carnegie Melon / IBM)*
2. **NOMAD** - Derivative free Mesh Adaptive Direct Search (MADS) algorithm *(Digabel - Ecole Polytechnique de Montreal)*

[Eisenhower, BSO 2012]

Optimization Results

Energy model created

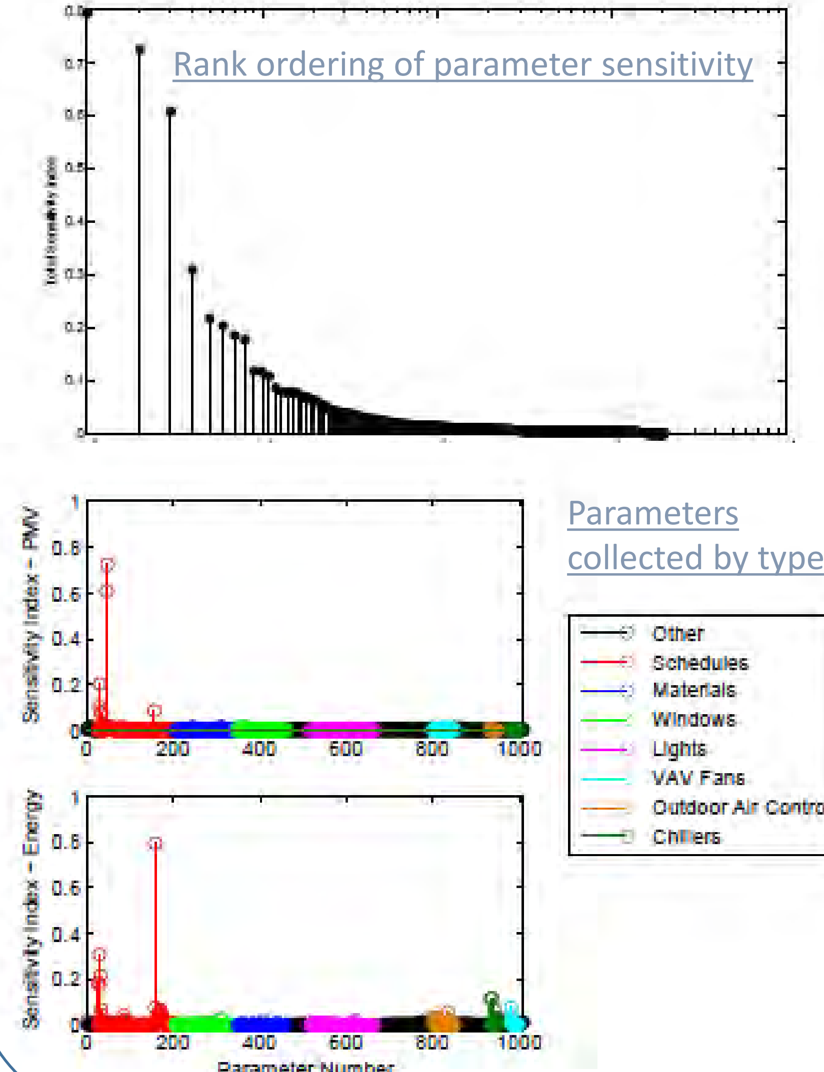
1009 parameters sampled

Subsets of parameters selected for different optimization experiments

Different cost functions evaluated

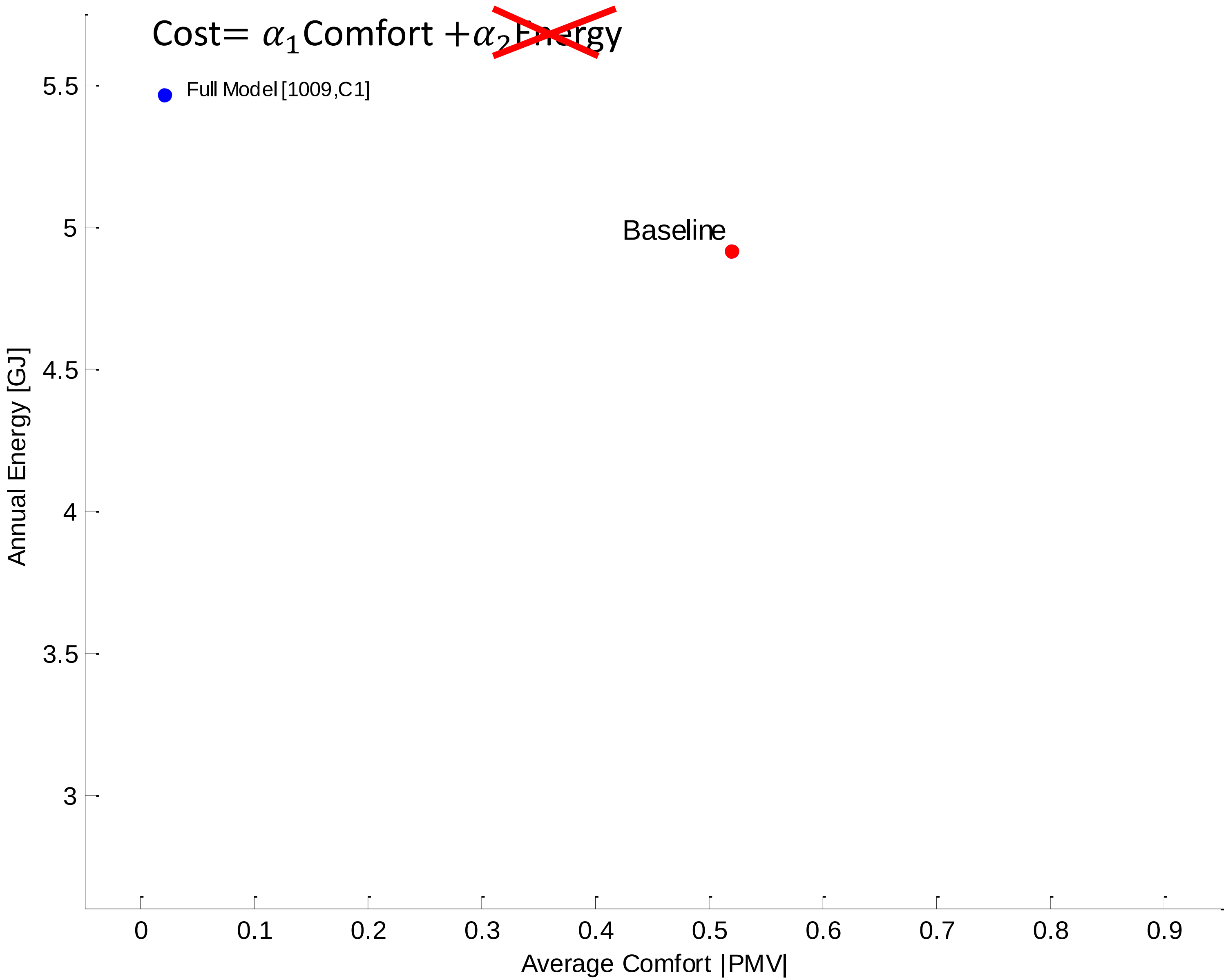
Compared to traditional optimization methods

Model reduction based on parameter type or parameter influence

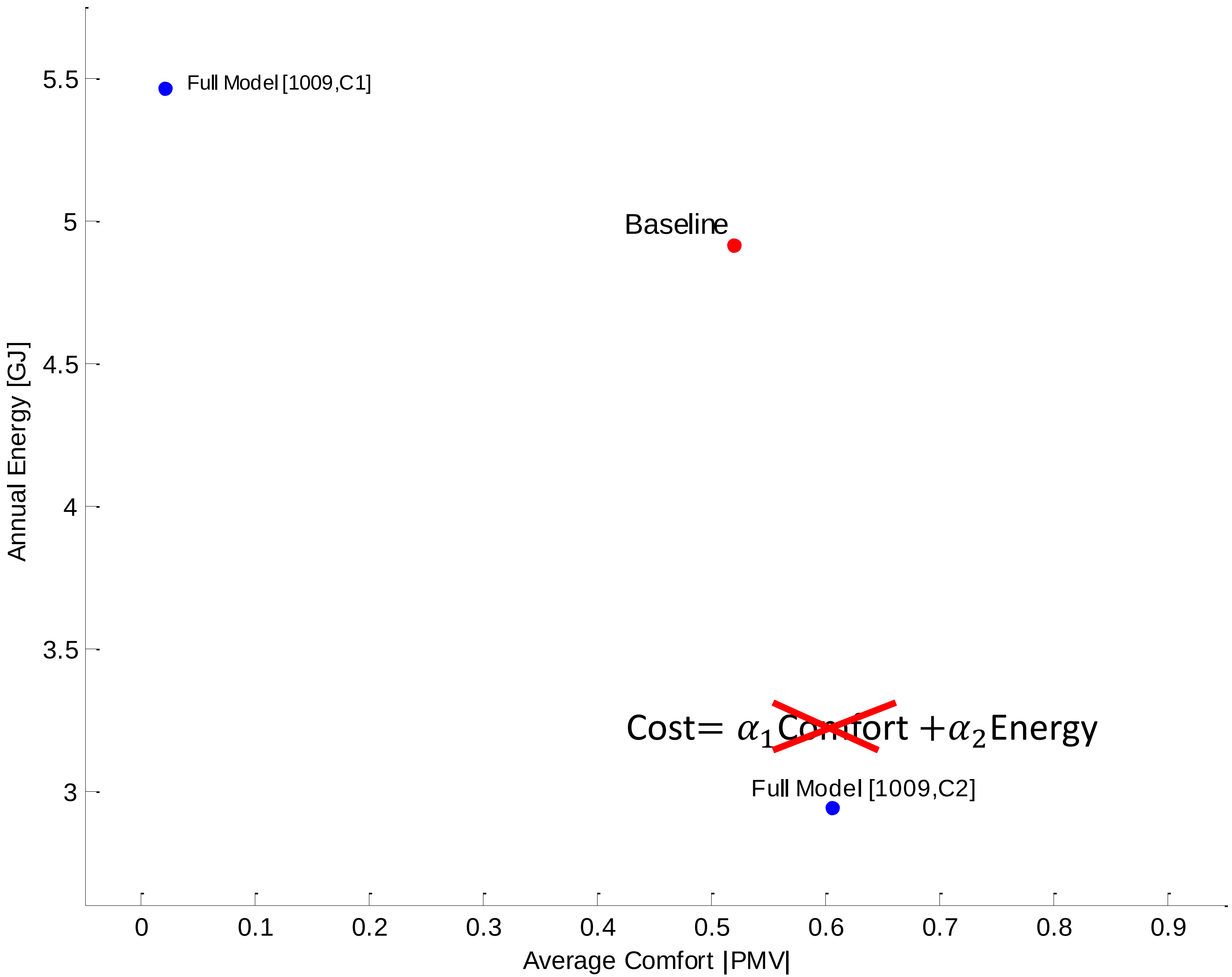


[Eisenhower, E&B 2012]

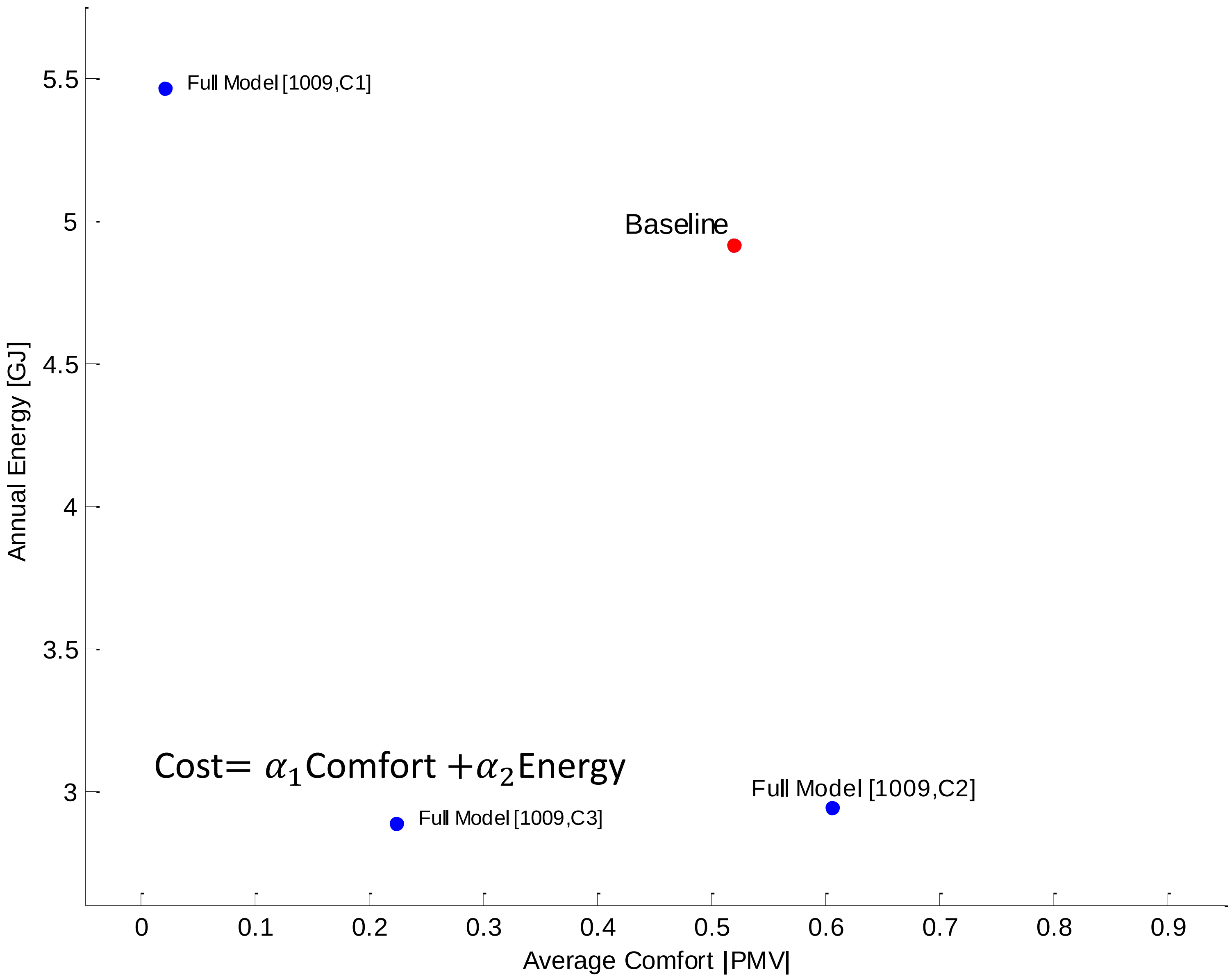
Optimization Results



Optimization Results



Optimization Results



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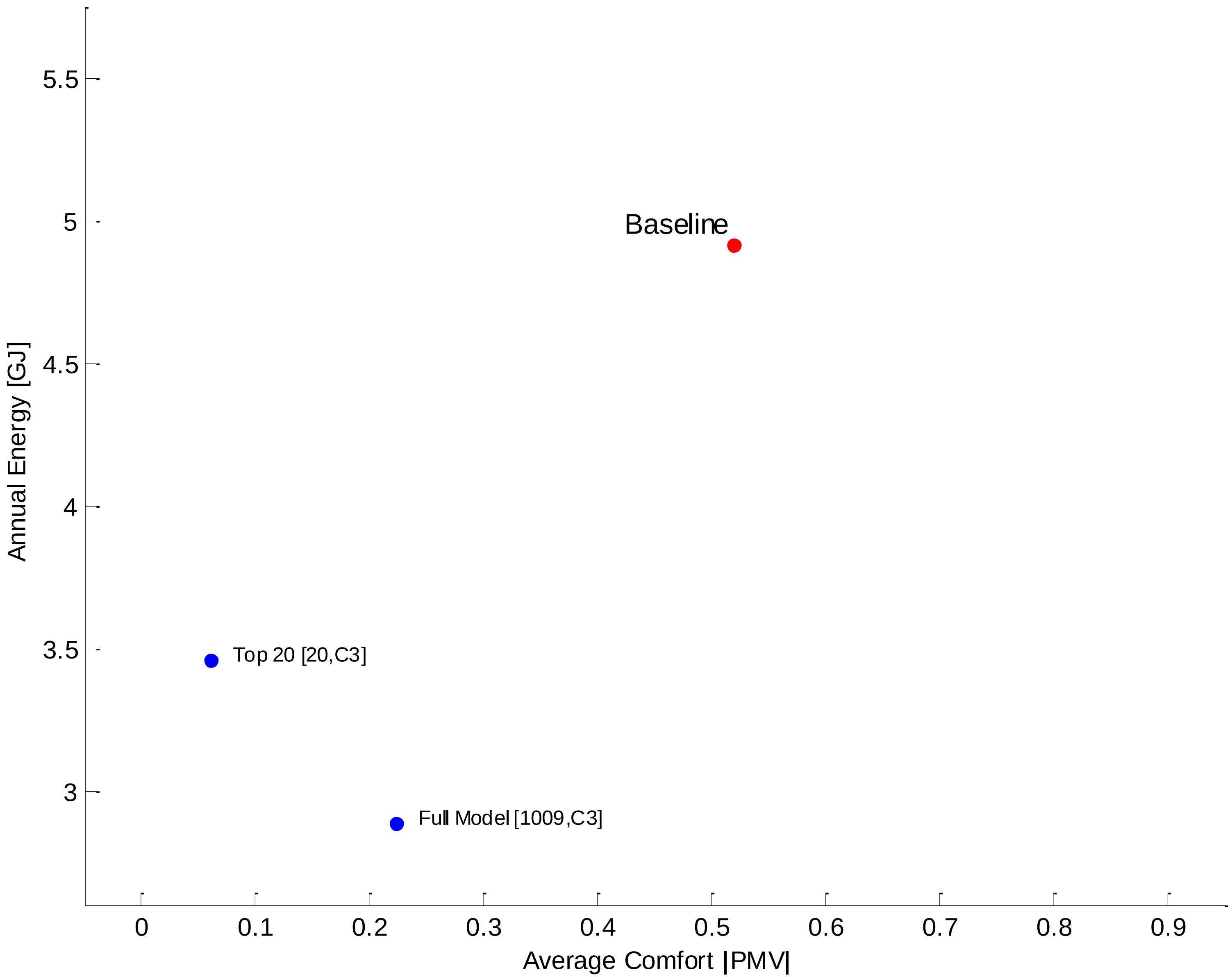

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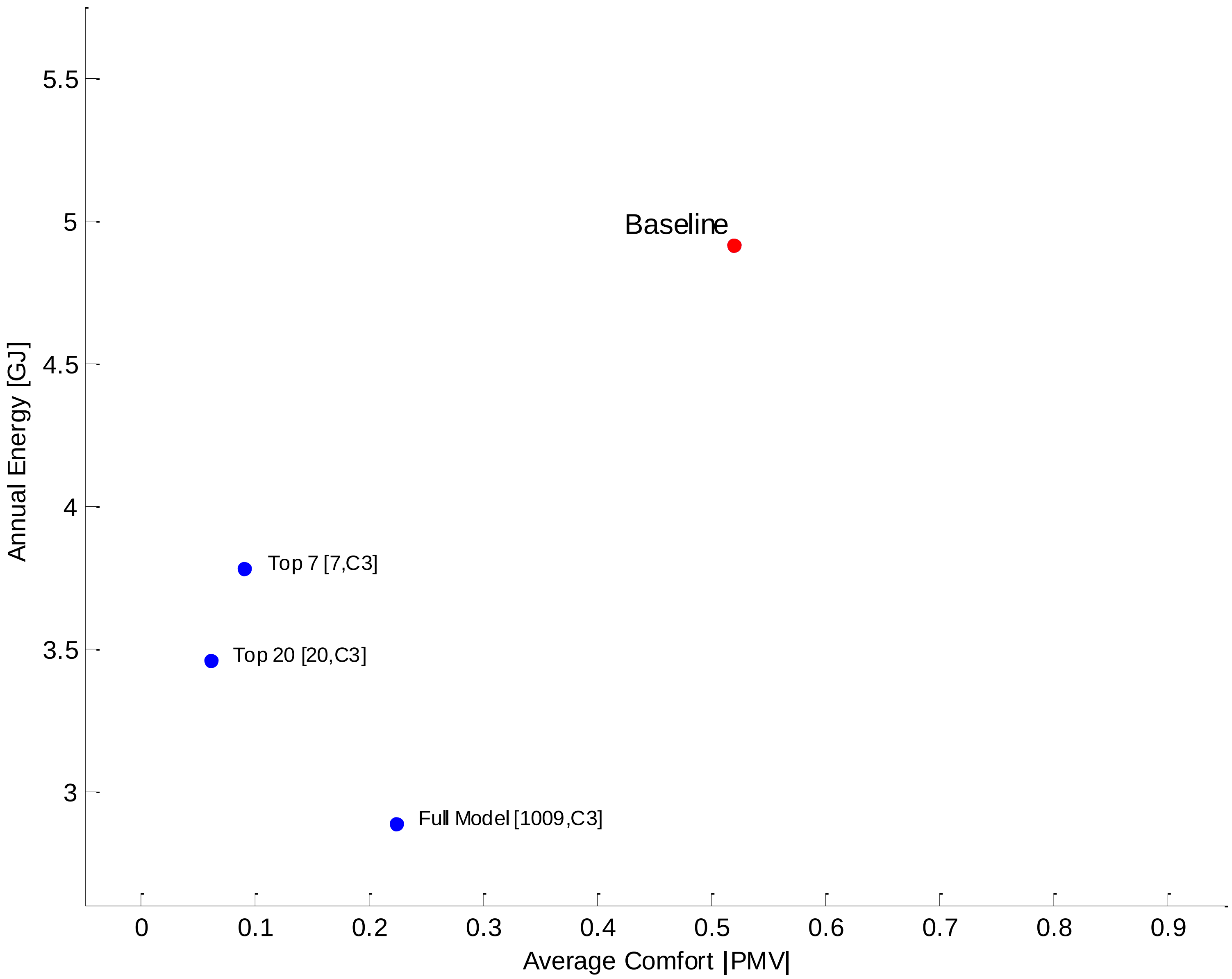

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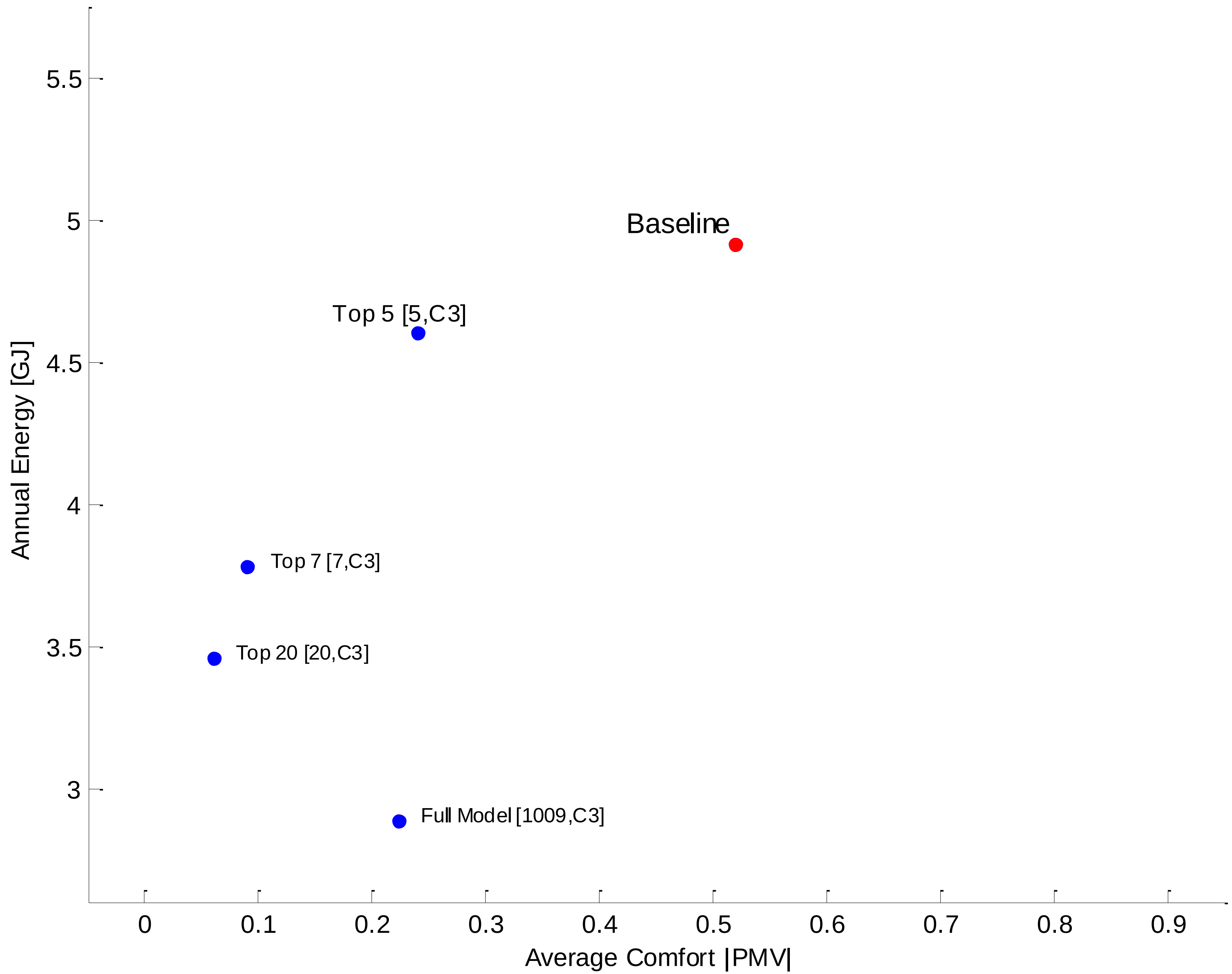

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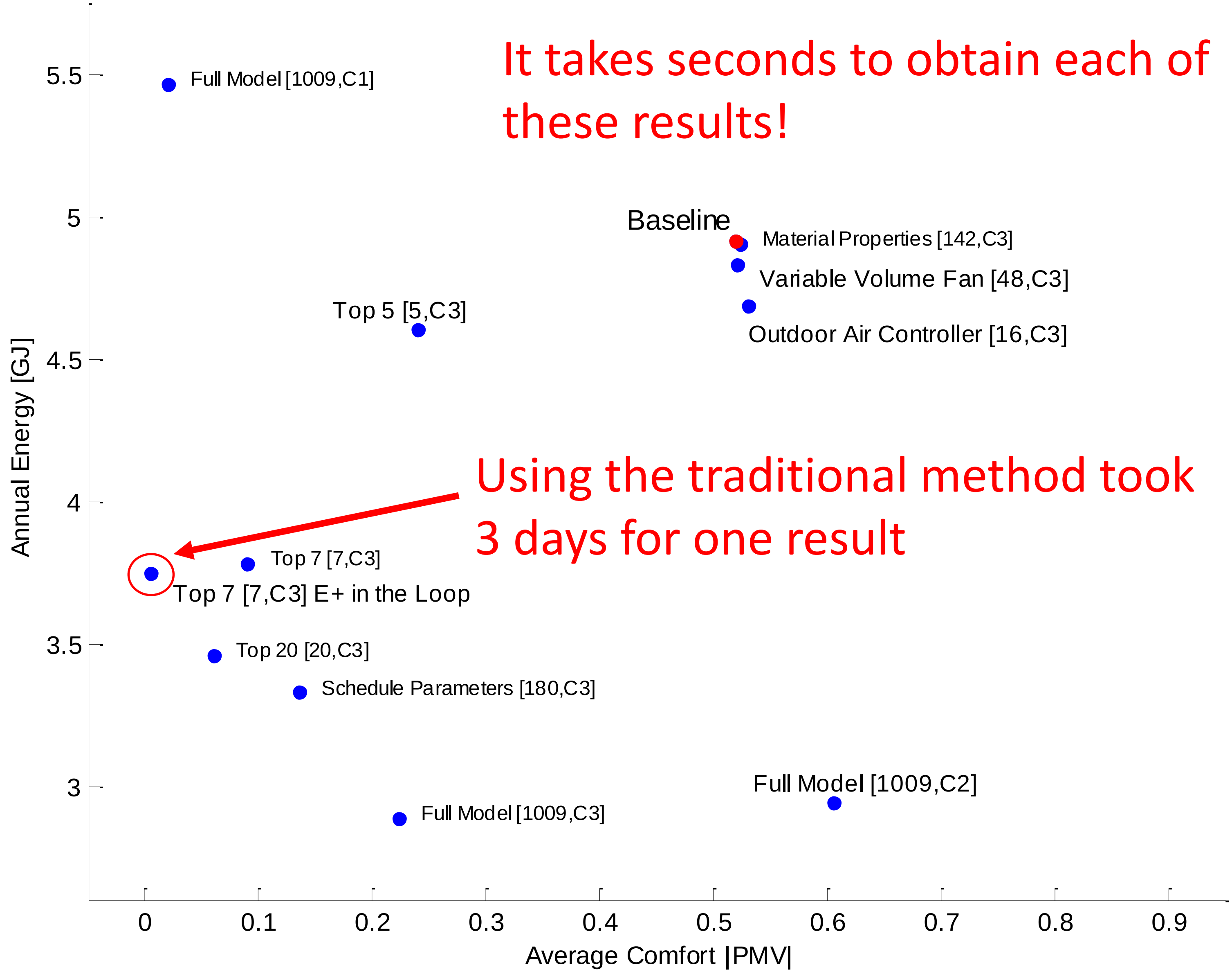

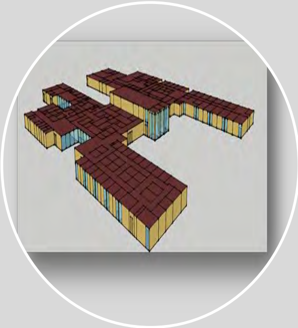

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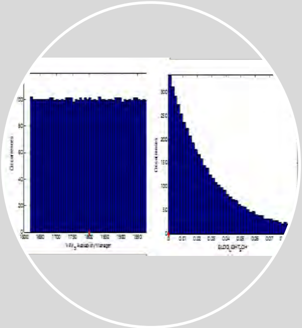

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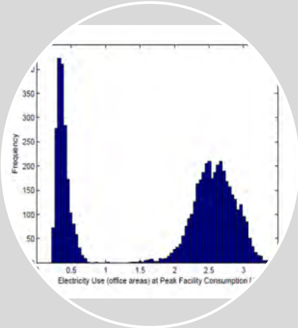

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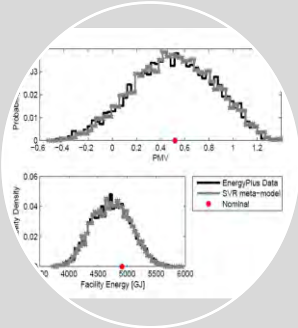
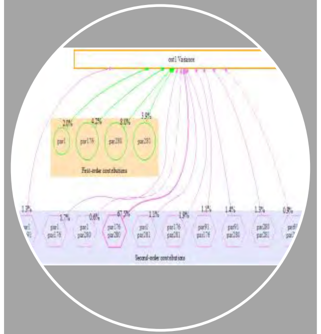


Calculate full order meta-model



Perform Sensitivity Analysis

- Model Reduction
- Optimization
- Calibration
- Failure Mode Effect Analysis

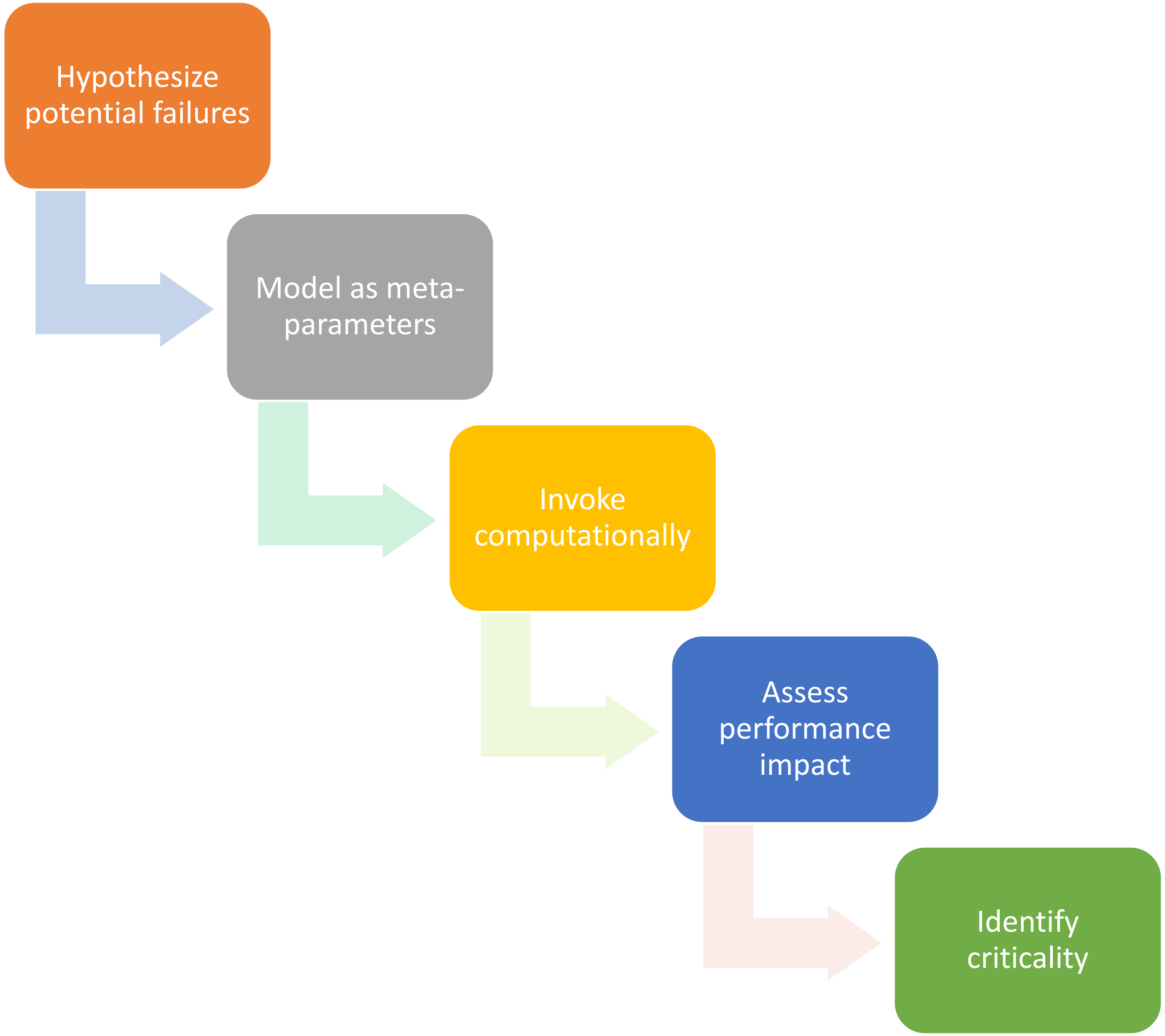
Analyzing Failures

Failures in buildings often lead to up 30% energy waste.

Katipamula, S. and M. R. Brambley (2005,2009)

A 47% reduction in buildings energy use will take ALL cars off the road!

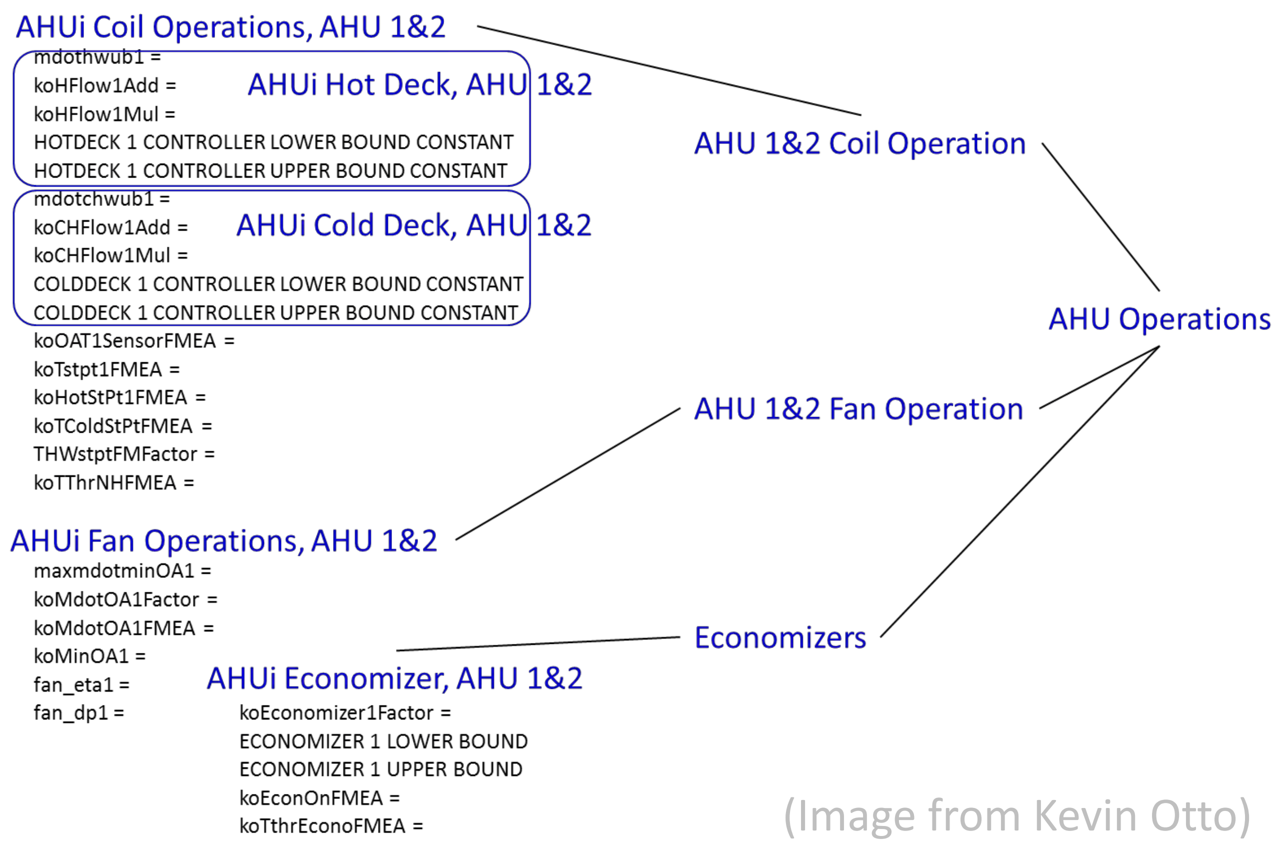
Analyzing Failures



Analyzing Failures

- **Hypothesize potential failures**
- Model as meta-parameters
- Invoke computationally
- Assess performance impact
- Identify criticality

- ❑ In a given system design, modeling and prediction of normal operation is challenging but typically straight forward
- ❑ For failure analysis, a different mindset is needed, hypothesizing what can break is not as straight forward
- ❑ Expert insight is often needed



(Image from Kevin Otto)

Analyzing Failures

Hypothesize potential failures

Model as meta-parameters

Invoke computationally

Assess performance impact

Identify criticality

Most industrial software modeling packages are derived for *normal* operation

Many aren't accurate when extremely far from design conditions

Wrappers / insight needed to appropriately map system-wide failures into standard simulations

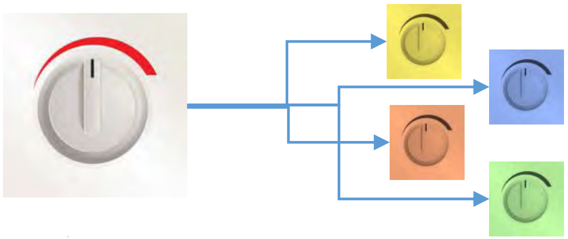
Mis-calibrated sensing:
Additive, multiplicative bias?
Noise? Correlated?

Broken actuation:
Constant or functional performance degradation?

Erratic user behavior:
Extreme input disturbance, stochastic?

Pump Impeller Broken:
Change in delta P, change in flow, change in efficiency

Failure Mode [0-1]



Many physical parameters[x-y]

Analyzing Failures

Hypothesize potential failures

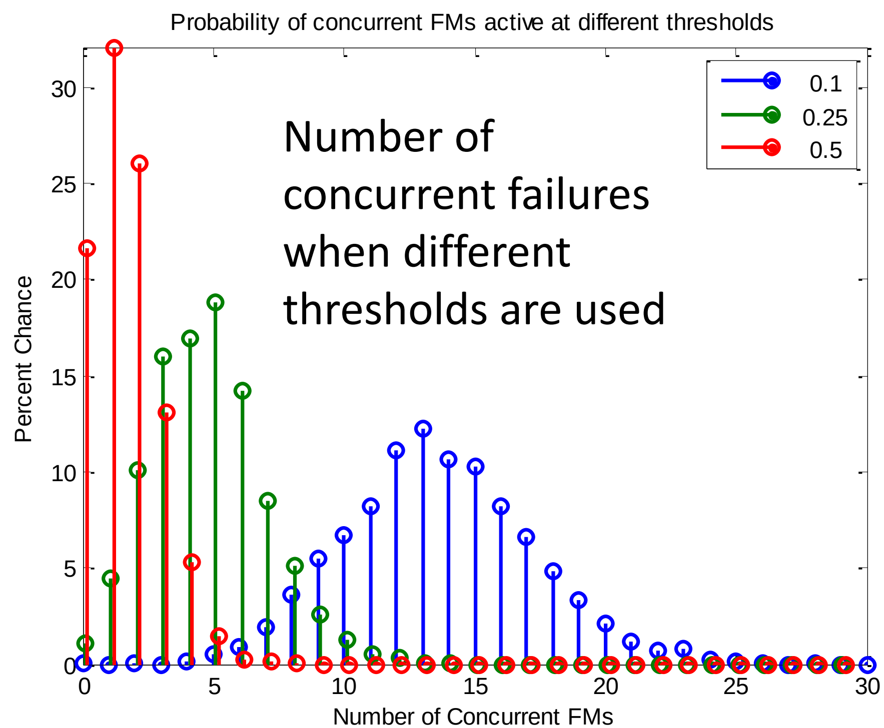
Model as meta-parameters

Invoke computationally

Assess performance impact

Identify criticality

- ❑ Failures must be assessed combinatorially
- ❑ Sampling and parameter implementation is *variable* (not binary)
- ❑ Function needs to be created on provides a mapping from a uniform distribution to a long tail distribution (which is expected for failed state, un-failed state ~90% of the time)

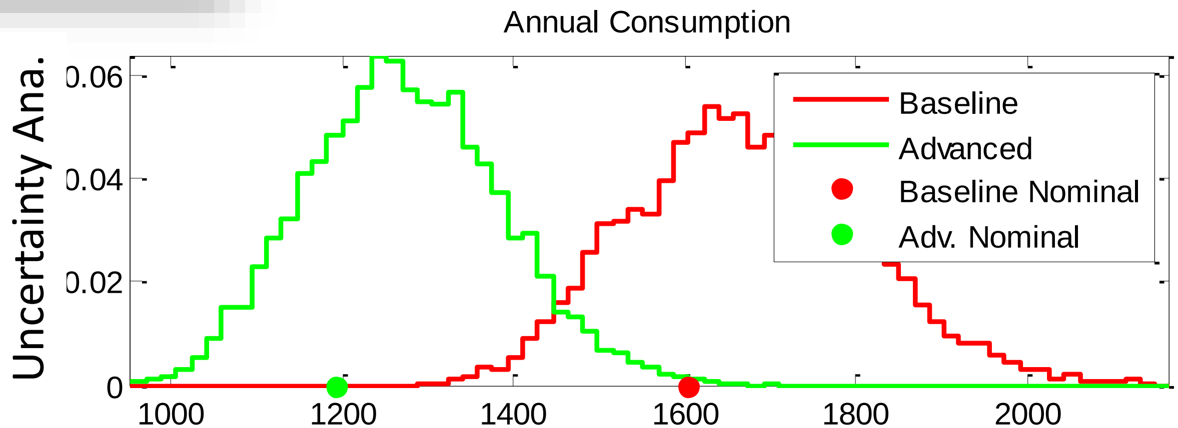


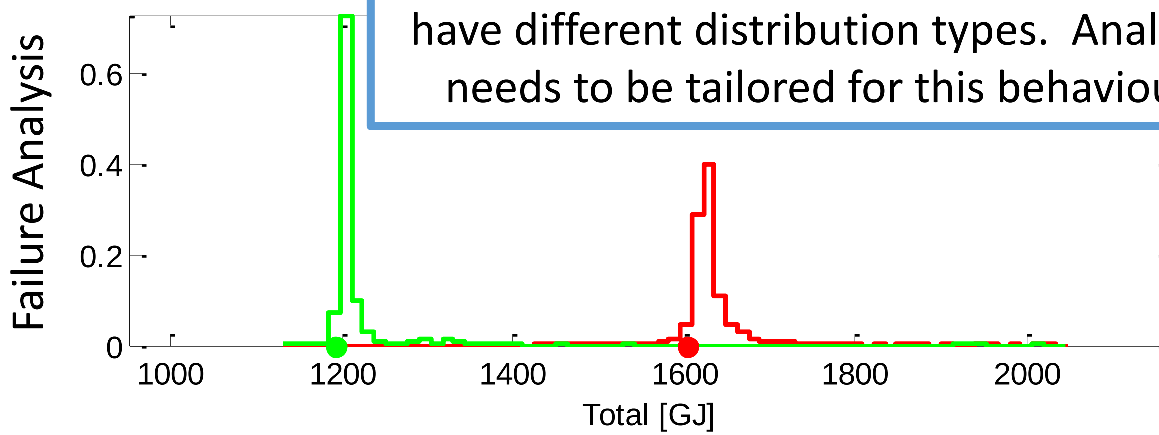
Analyzing Failures

- Hypothesize potential failures
- Model as meta-parameters
- Invoke computationally
- Assess performance impact
- Identify criticality

Case Study: DoD building

Energy model created → 533 individual component failures postulated → Failure modes mapped to real parameters → Sample simulations performed





Uncertainty analysis and failed analysis have different distribution types. Analysis needs to be tailored for this behaviour

Analyzing Failures

Hypothesize potential failures

Model as meta-parameters

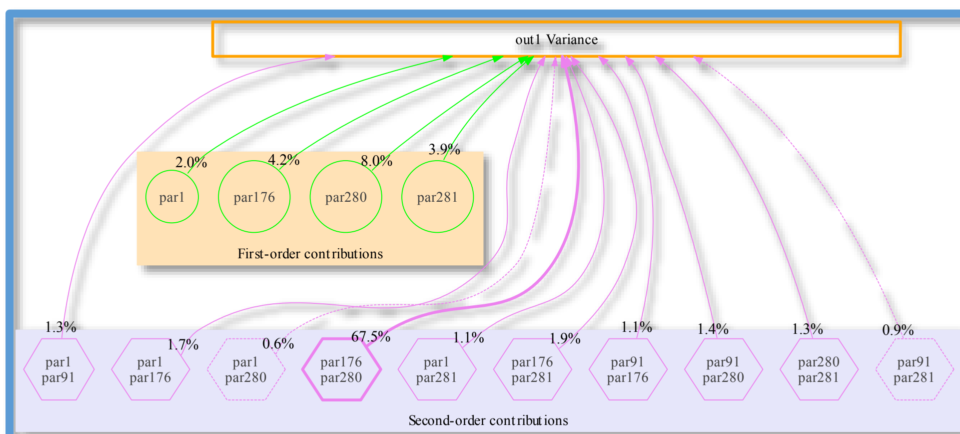
Invoke computationally

Assess performance impact

Identify criticality

- ❑ Sensitivity analysis performed between long tail distributions and failure mode parametric variation
- ❑ Second order effects (combinatorial) identified as most critical in many failed states

Output 9: Heating Annual Consumption					
	Boiler gas/air flow restricted/leaks	AHU2 Econ. OA damper fails open	Zone 7 T-stat improperly located	Nightsetpt temperature set incorrectly	Lighting not turned off at night
Total Sensitivity	0.09	0.05	0.81	0.84	0.12
First Order	0.02		0.04	0.08	0.04
Boiler gas/air flow restricted/leaks		0.01	0.02	0.01	0.01
AHU2 Economizer OA damper fails open			0.01	0.01	0.01
Zone 7 Thermostat improperly located				0.67	0.02
Nightsetpoint temperature set incorrectly					0.01
Lighting not turned off at night					



[Otto & Eisenhower, Simbuild 2012]

* GoSUM software

Summary Messages:

Model-based Design (MBD)
"Addressing design with computation"

- Time domain simulations rarely lead to design evolution
- More can be done with time domain simulations (wrappers)
- Dynamics matter!
- Continuity needed when modeling at different stages / fidelity
- Models need be appropriate for the intended use and user base
- Uncertainty analysis up front and throughout
- Critical parameter management at all levels
- The decomposability of a system cannot be ignored
- New curricula needed that addresses all of this
- …

We'll come back to these topics throughout the talk.

Open Opportunities

Software: Identification, creation, and standardization of industry-accepted models in other domains
- Airframe hardware, security systems, biological engineering, …
- Evolution of a design flow such as this on academic models is of only little use

Uncertainty Analysis: A sample-based approach was given, is this the best? Should the UA approach be problem specific, what are the key concerns in tool choice? Is there a single tool for all?

Expert Insight: The methods here are fairly automated but some expertise is needed (e.g. for setting up potential fault tables), what kind of automation can we get away with?

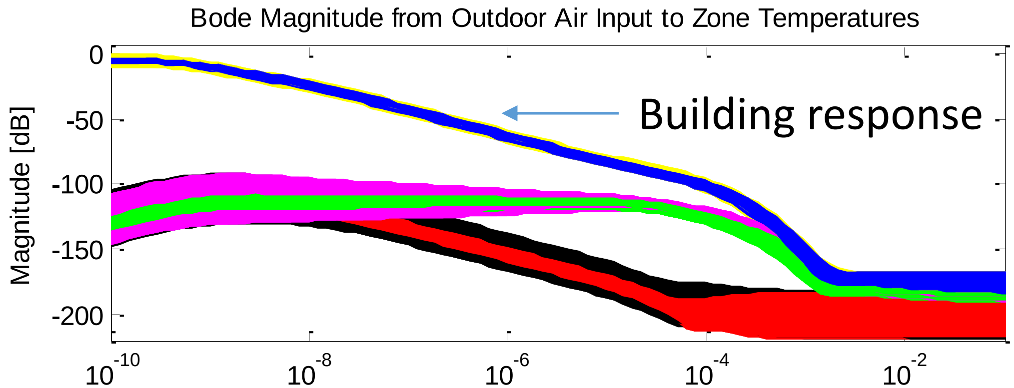
Curricula: Many industrial model-based design studies end with time simulations, Why? Curricula usually ends with time domain simulations. An expanded view is needed.

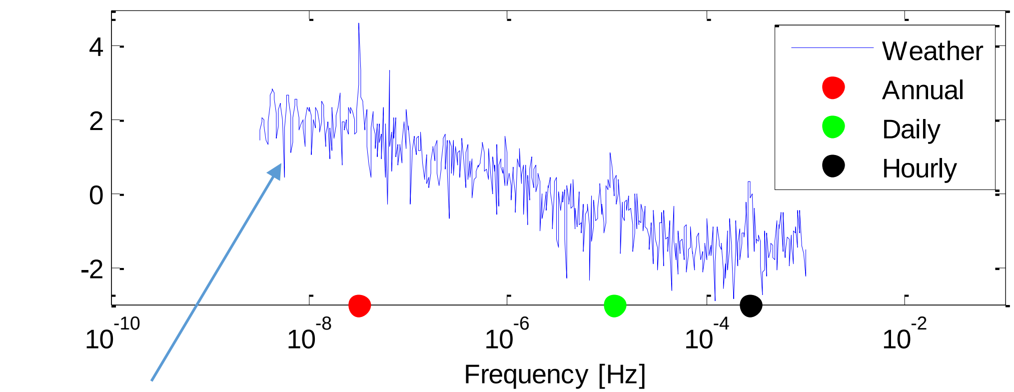
Sections

1. Motivation
2. Uncertainty Analysis / Critical parameter management
3. Analysis of dynamics
4. Verification
5. Decomposition
6. How its done

Dynamics Matter

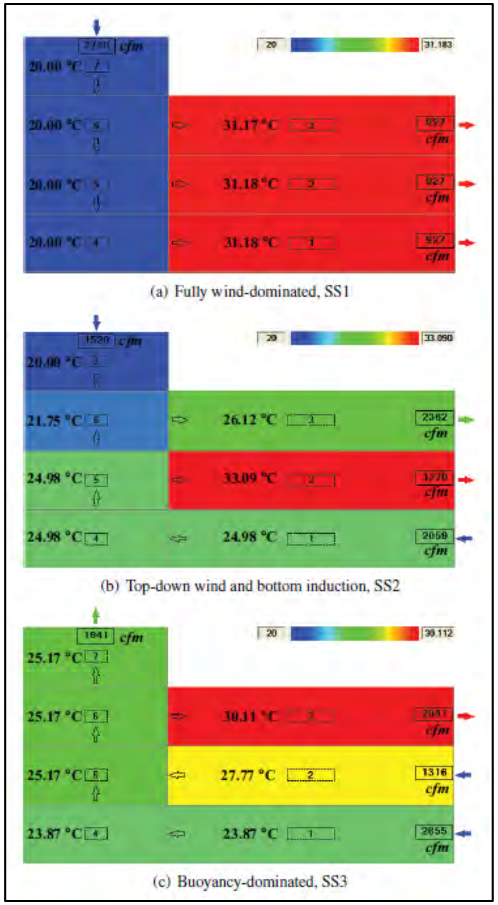
1) Overlapping timescales dynamics/disturbance





Spectrum of a decade of local weather

2) Multiple steady states



Flip between buoyancy and wind driven natural flows

Yuan 2010

CO_2 Heat Pump

COP ~ 1.0

1 unit electricity

~1 unit hot water

Electric

COP ~ 0.8

0.2 units waste heat

1 unit gas

0.8 units hot water

Gas

COP ~ 4.0

3 units heat (ambient air)

1 unit electricity

4 units hot water

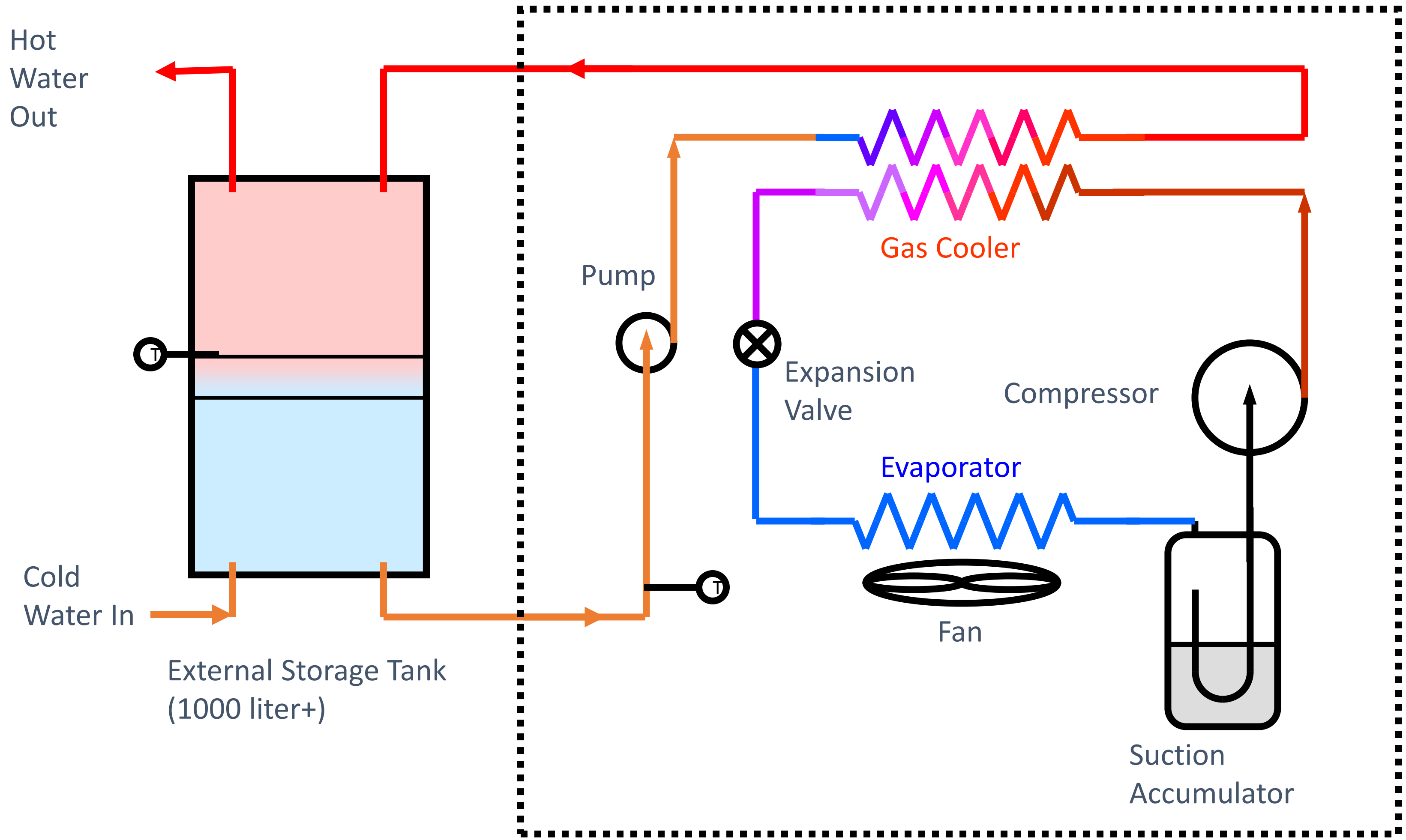
CO_2 heat pump

COP = Useful Energy Out / Costly Energy In

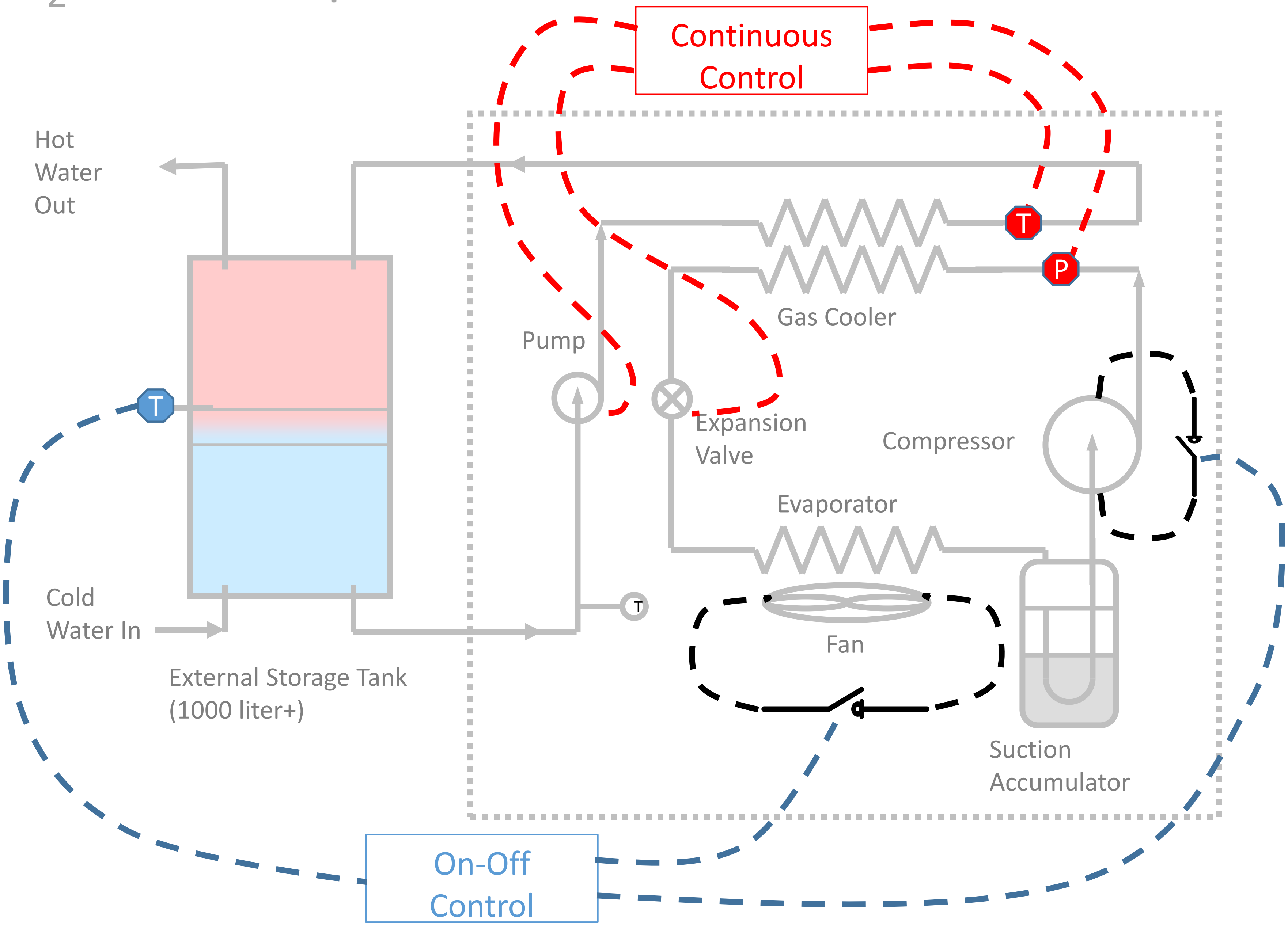
Opportunity:

4x improvement in efficiency relative to conventional systems

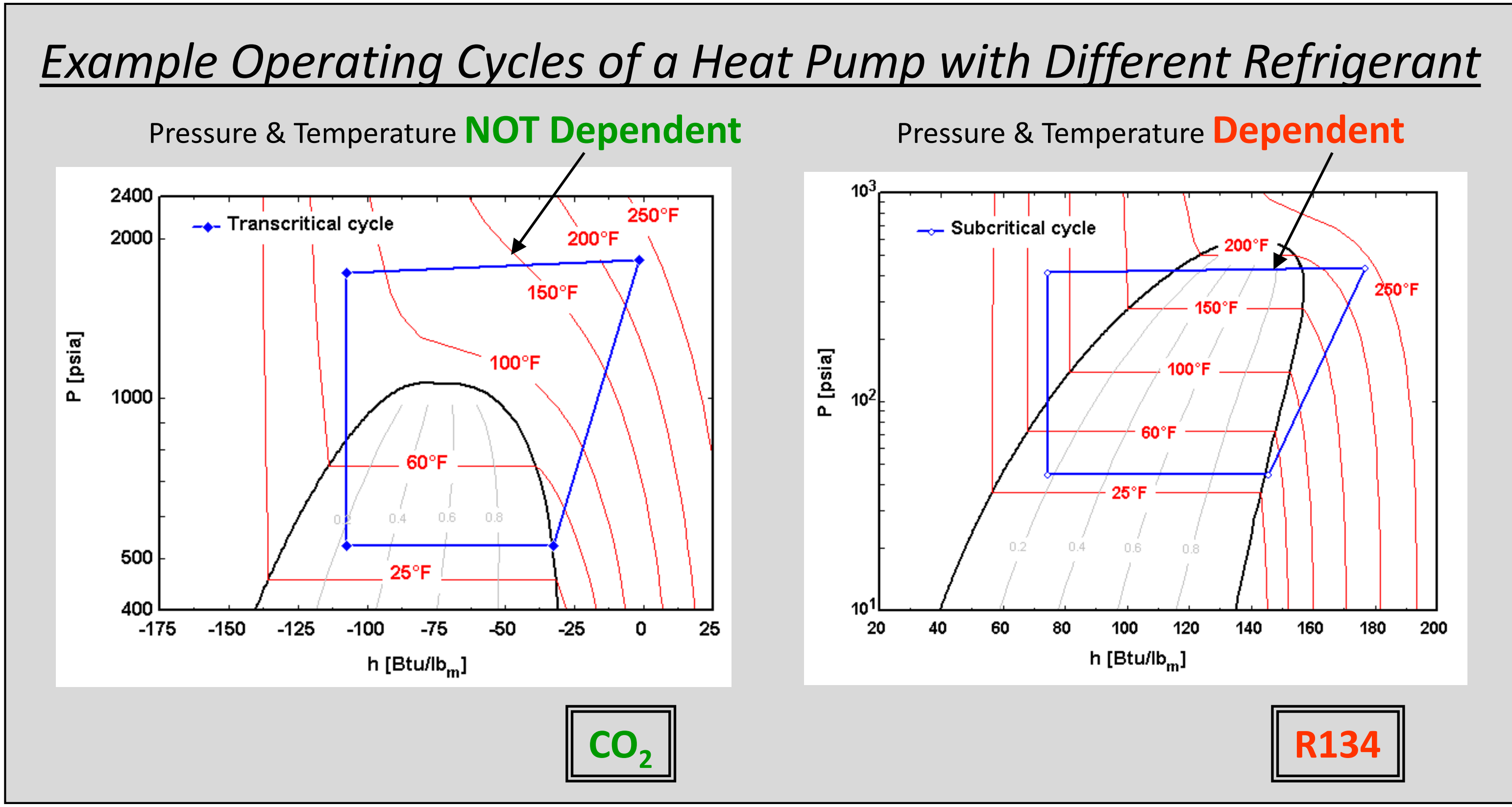
CO_2 Heat Pump & Hot Water Loop

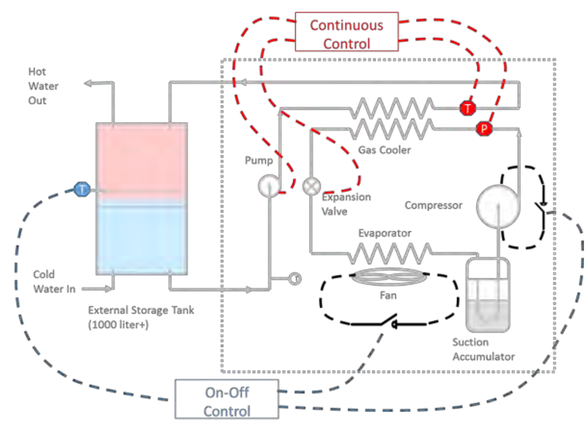


CO_2 Heat Pump - Control



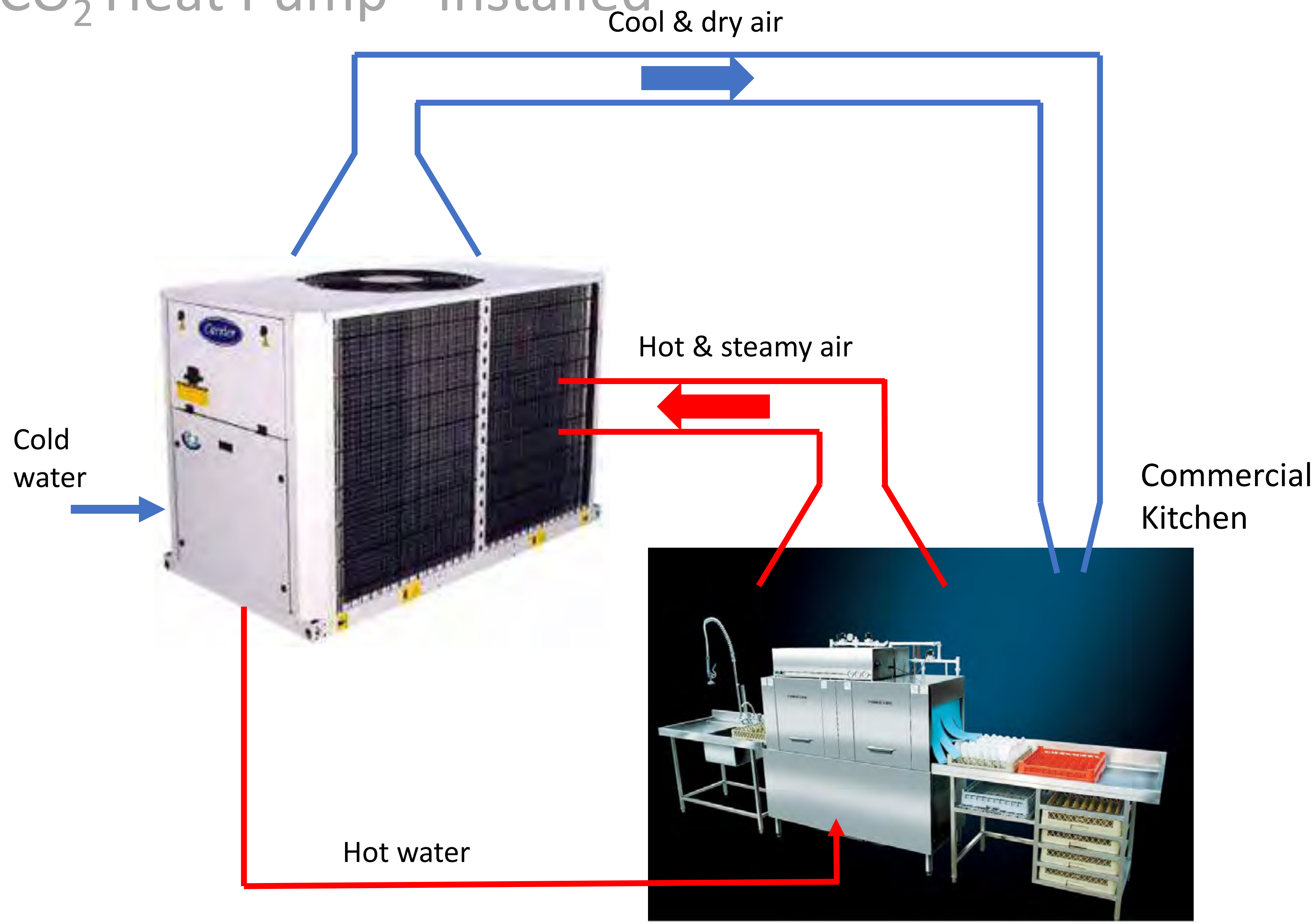
CO_2 Heat Pump – New Features





- ❑ Compressor load is strong function of *height* of the blue polygon
- ❑ Transcritical cycle provides a way to decouple desired output (temperature on top of polygon) with the height
- ❑ New degree of freedom for optimization is now available

CO_2 Heat Pump - Installed



http://www.made-in-china.com

CO_2 Heat Pump – Controlled Response

CO2 Heat pump transient dynamics (movie) in one case, the transient settles at an efficient equilibrium, in the other case, it settles at a very inefficient equilibrium. In both cases, the output control variable reaches the desired setpoint.

Sensed variable

Performance metric

*This is a movie

CO_2 Heat Pump - Modeling

Mass and Energy Balance for fluid in a walled-pipe

$$\boxed{\begin{aligned} \frac{\partial A\rho}{\partial t} + \frac{\partial \dot{m}}{\partial z} &= 0 \\ \frac{\partial (A\rho h - A\rho)}{\partial t} + \frac{\partial (\dot{m}h)}{\partial z} &= \pi D \alpha (T_w - T) \end{aligned}}$$

Under a few assumptions about the pressure drops, time scale separation in density and energy dynamics, ODE's can be developed

Evaporator Dynamics

$$\tau_{ef}\frac{d(\Delta h_e)}{dt} = -\dot{m}_f \Delta h_e + \overline{\alpha}_{ef}(T_{ew} - Tef)$$

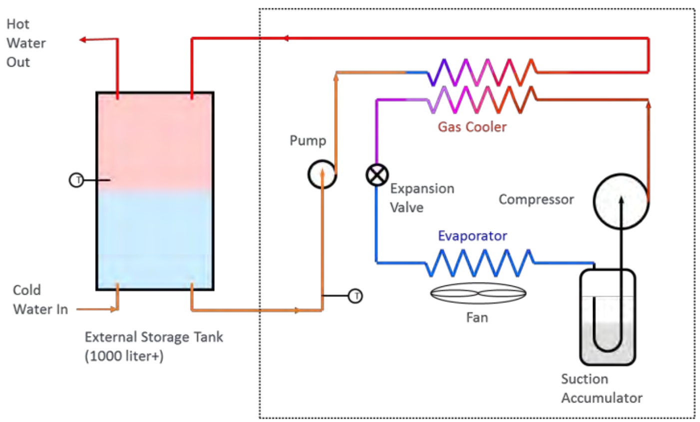
$$\tau_{ew}\frac{d(T_{ew})}{dt} = -\overline{\alpha}_{ef}(T_{ew} - Tef) + \alpha_a(T_{ai} - T_{ew})$$

Gas Cooler Dynamics

$$\tau_{wo}\frac{d(T_{wo})}{dt} = -\dot{m}_w c_{pw}(T_{wo} - Twi) - \alpha_{gw}(T_{wo} - T_{gw})$$

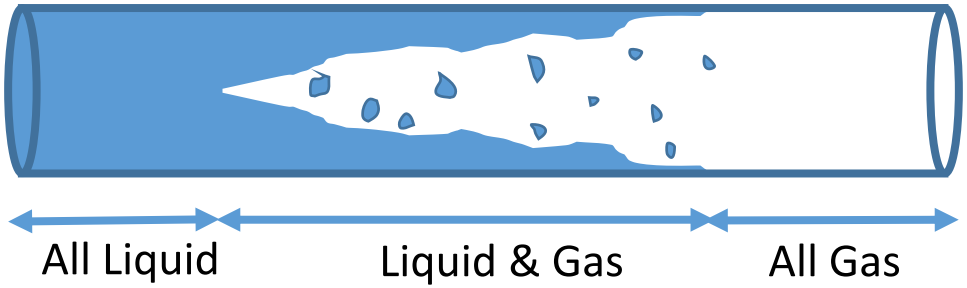
$$\tau_{gw}\frac{d(T_{gw})}{dt} = \alpha_{gw}(T_{wo} - T_{gw}) + \dot{m}_f(\Delta h_c + \Delta h\_e)$$

- ❑ Time constants become complex from spatial reduction
- ❑ Dynamics are coupled by:
  - Compressor statics (adds heat)
  - Expansion statics (adiabatic)
- ❑ α = Heat Transfer Coefficients



[Eisenhower '04, Eisenhower '09]

Heat Transfer Coefficient

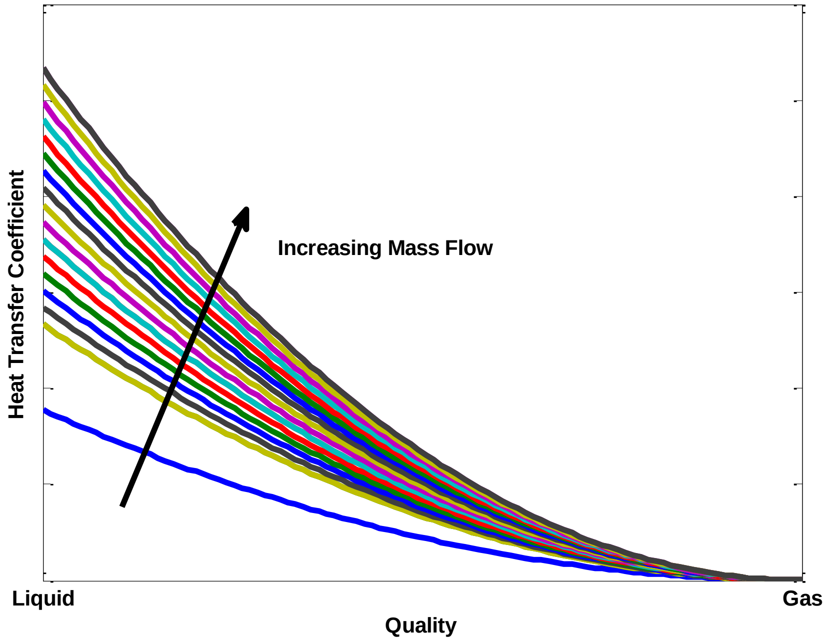


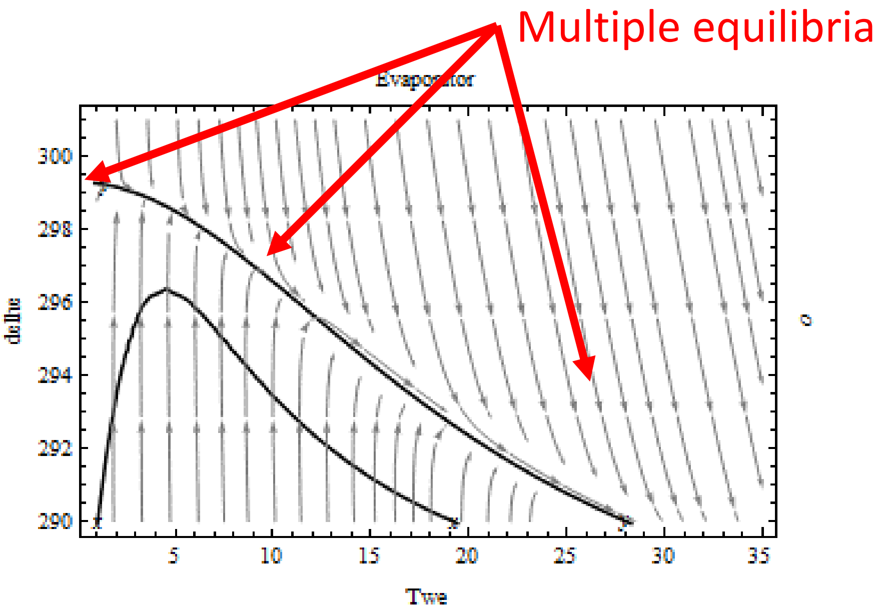
Modified Bennet-Chen relation

$$\overline{\alpha_{ef}} = \alpha_{lsat}(\dot{m}_f) + \psi(x_{in})\left(\alpha_{vsat}(\dot{m}_f) - \alpha_{lsat}(\dot{m}_f)\right)$$

<u>Evaporator Characteristic Equation</u>

$$\overline{\alpha_{ef}} = k_{\alpha_{ef}}\left(k_{vsat}\dot{m}_f + \Delta h_{ef}^2\left(\frac{k_{lvsat}\dot{m}_f}{h_{vlsat}^2}\right)\right)$$



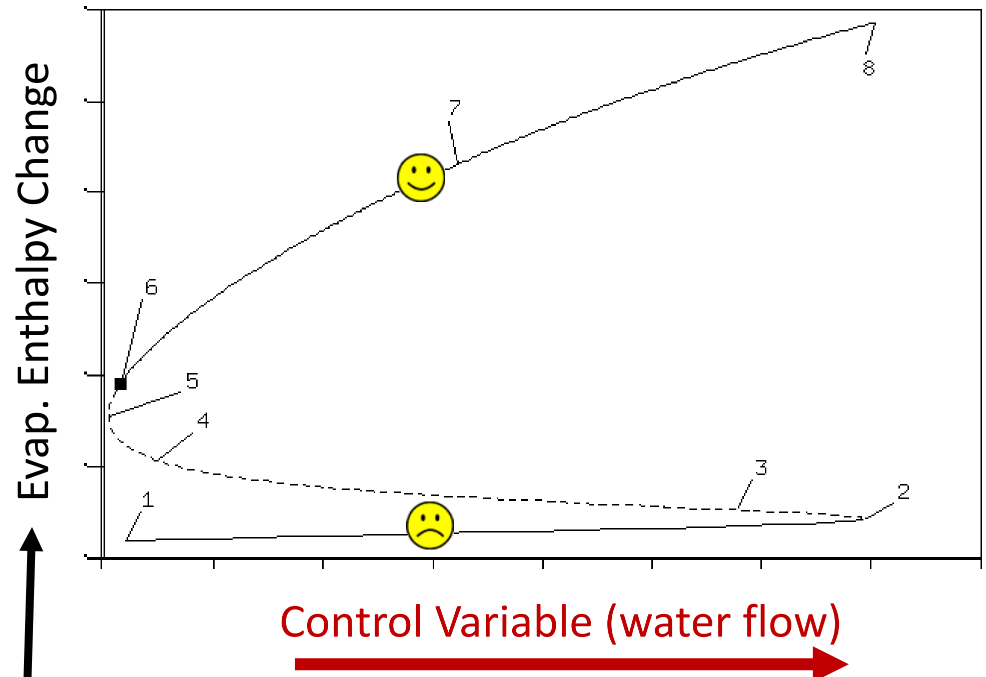


Bifurcation Analysis

Physic-based modeling

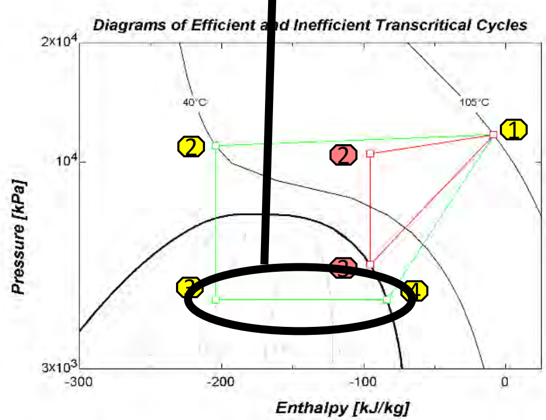
$$\frac{\partial A\rho}{\partial t}+\frac{\partial \dot{m}}{\partial z}=0$$

$$\frac{\partial(A\rho h\ -A\rho)}{\partial t}+\frac{\partial(\dot{m}h)}{\partial z}=\pi D\alpha(T_w-T)$$



Branch Descriptions
1-2) Stable Branch
2-6) Unstable Branch
6-8) Stable Branch

Solution Points
2) Fold
5) Fold
6) Hopf Point



Insight into a nonlinear controller that provides robust efficient operation obtained from model and tested on prototype

[US 6,813,895, US 7,171,820, US 7,127,905, US 7,010,925, US 7,225,629, US 6,993,921 Eisenhower 2005, 2007, 2009]

Summary Messages:

Model-based Design (MBD)
"Addressing design with computation"

- Time domain simulations rarely lead to design evolution
- More can be done with time domain simulations (wrappers)
- Dynamics matter!
- Continuity needed when modeling at different stages / fidelity
- Models need be appropriate for the intended use and user base
- Uncertainty analysis up front and throughout
- Critical parameter management at all levels
- The decomposability of a system cannot be ignored
- New curricula needed that addresses all of this
- …

- Dynamics matter! Without analysis of dynamics unfortunate steady state's may have been found too late
- Time domain simulation would not have led to the amount of insight gained from bifurcation analysis with the CO2 problem
- With proper wrappers, time domain simulation can be used to gather information regarding uncertain dynamics
- Abstraction of industry problems leads to collaboration and scientific discovery

Open Opportunities

- Which products get a deeper analytical treatment of their dynamics? When is excel engineering enough?

- Continuation methods on detailed models are getting old, what else is there?

- Curricula past introductory dynamics – industrial dynamics?

Sections

1. Motivation
2. Uncertainty Analysis / Critical parameter management
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4. Verification
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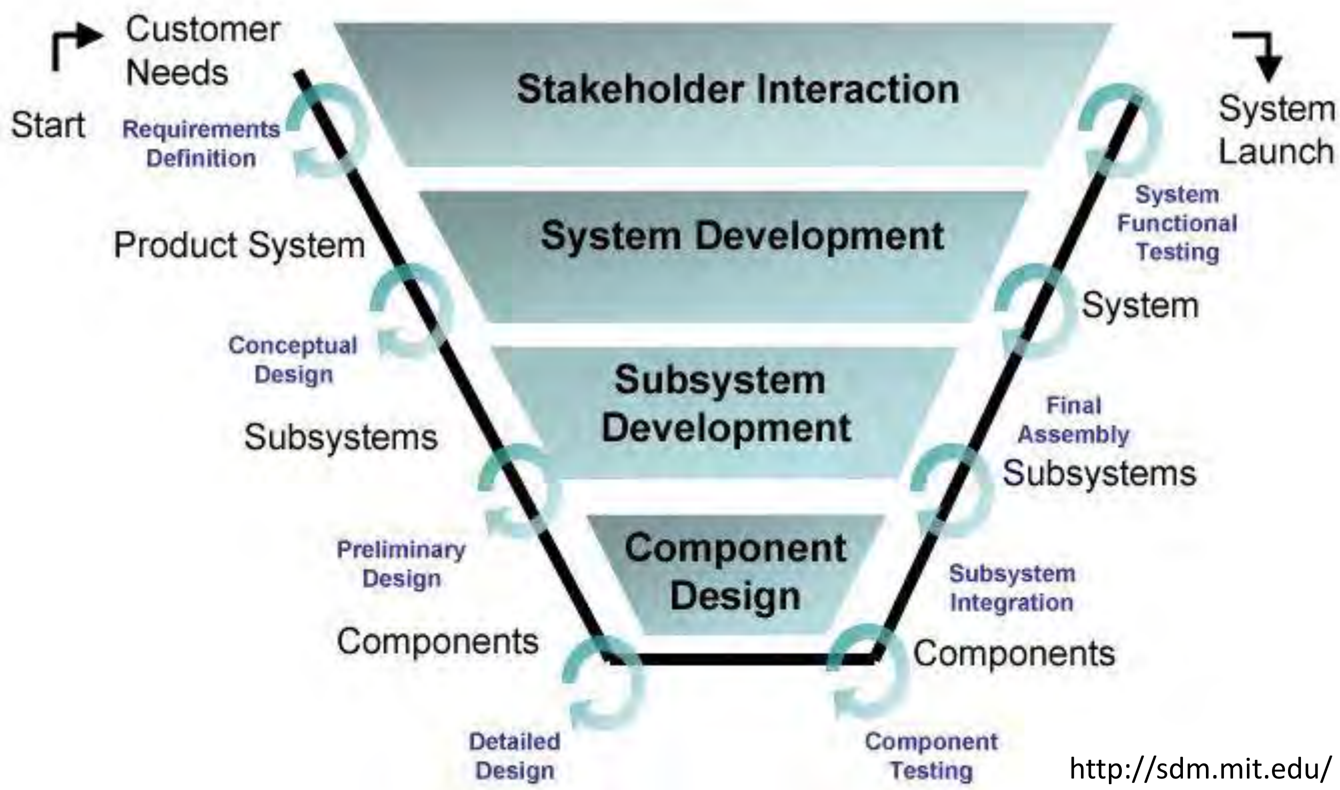
6. How its done

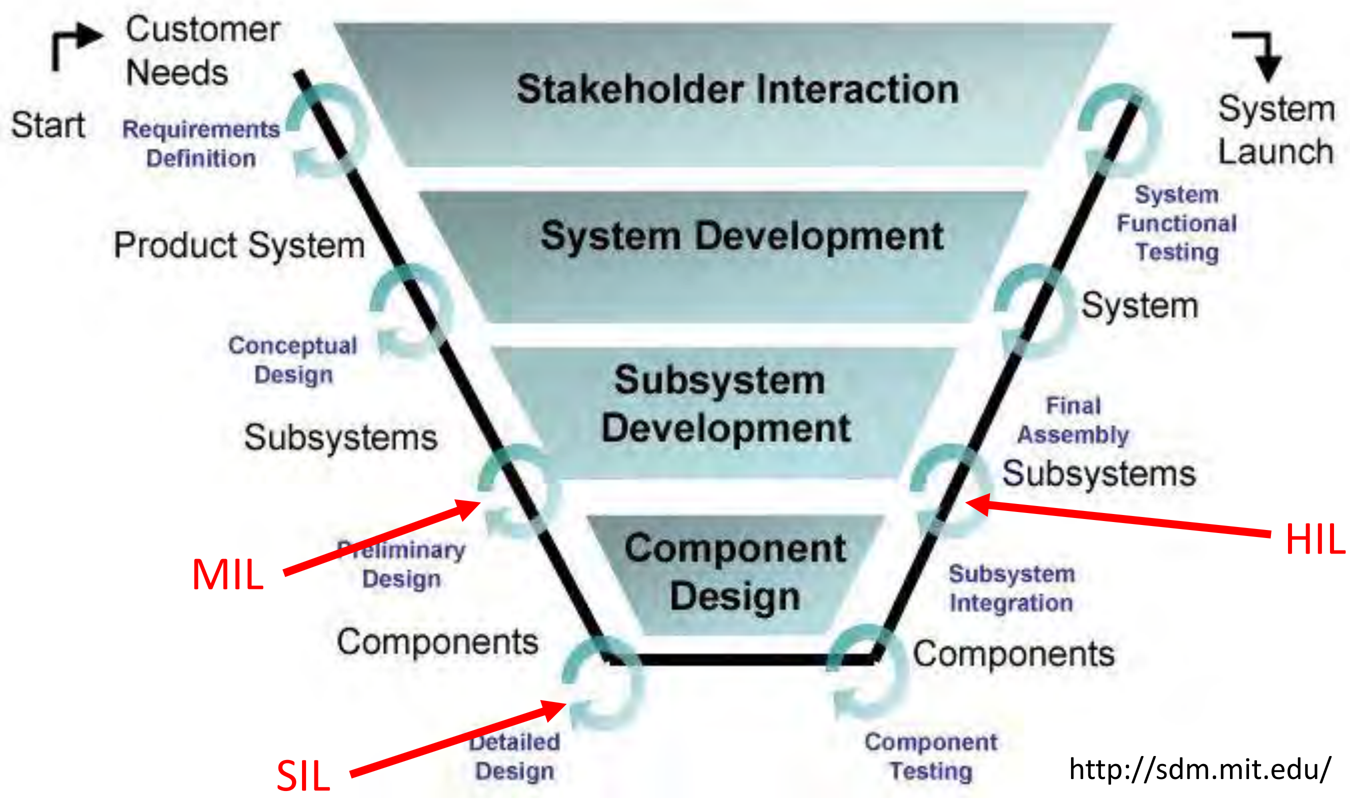
Design Flow



http://sdm.mit.edu/

Design Flow

Model-based design tools

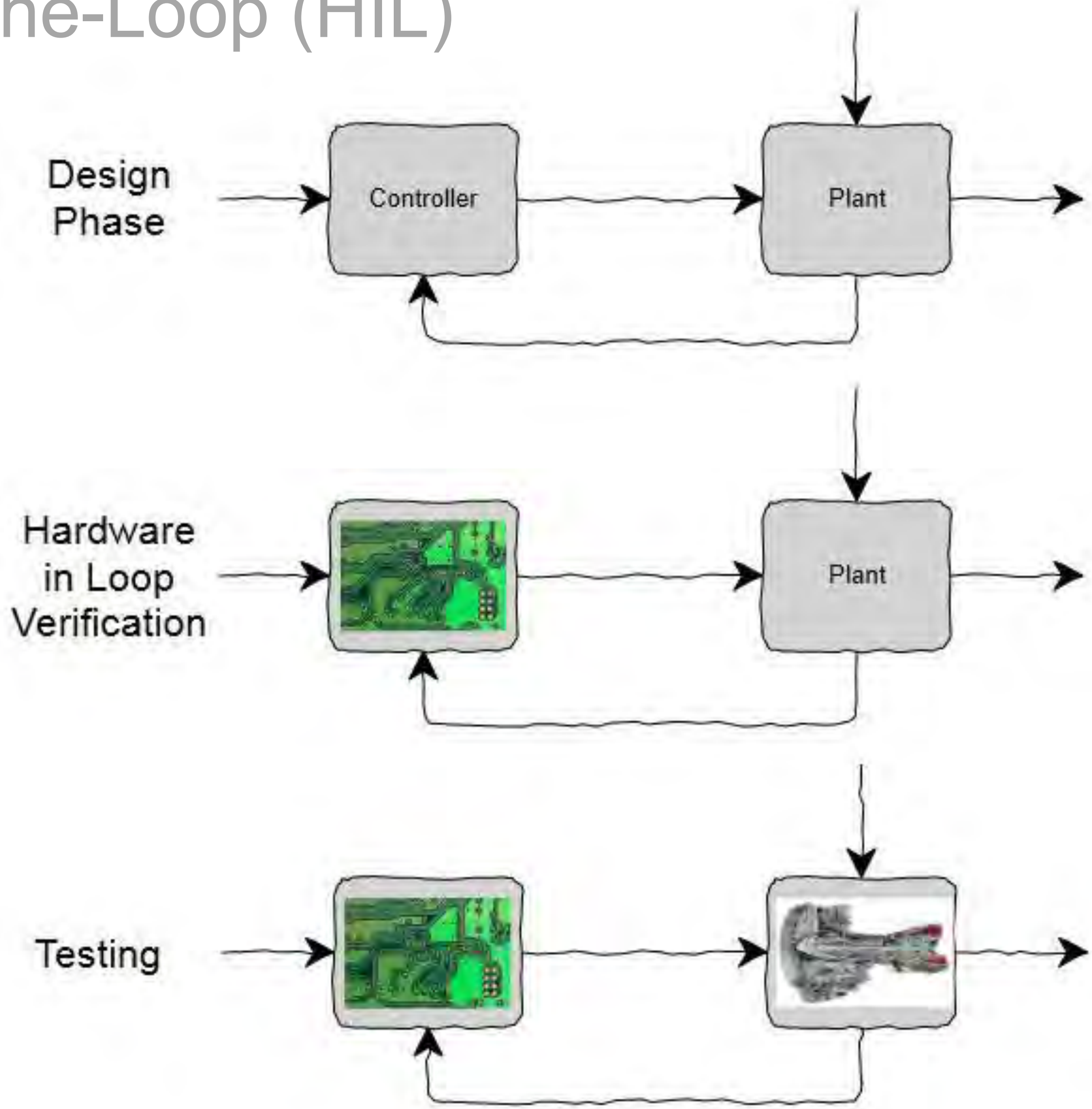


http://sdm.mit.edu/

Hardware-in-the-Loop (HIL)

Hardware in the Loop is a methodology for verifying controlled systems prior to full blown system testing

By testing the software and its implementation on the control hardware implementation issues and surprises can be assessed



UTC PureComfort™ CHP System

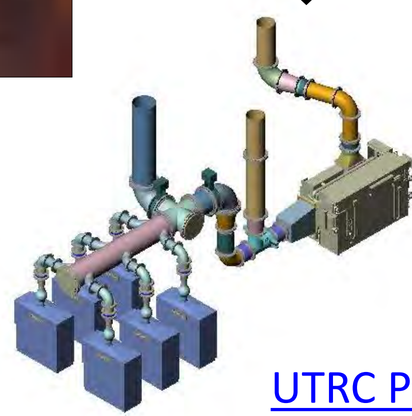
…Two different control systems, one common function

Carrier Chiller
Gas fired burner -> Cold / hot water
Carrier control system

Capstone MicroTurbines
Gas -> Electricity and hot exhaust
Capstone control system

Carrier
Controller

Capstone
Controller



UTRC PureComfort CHP

Goal: Modify *Carrier* controller for supervisory needs

Necessary Controller Changes

Adjust to operation of chiller to different heat source:

1. Micro-turbines at full power all 4 micro-turbines on
2. Micro-turbines load following
   a) All 4 micro-turbines running with power fluctuations below 60kW
   b) 1-2 micro-turbines turned on/off with power fluctuations greater than 60kW
   c) All 4 micro-turbines shut down
3. Include Damper Valve Model
4. Start/Stop Procedures
   a) Chiller does not start if all 4 micro-turbines are turned off
   b) Chiller shuts down safely if all 4
   c) micro-turbines are shut down
5. Refine Protective Limits and Alarms

…necessary changes take many months to implement, many more to test/certify

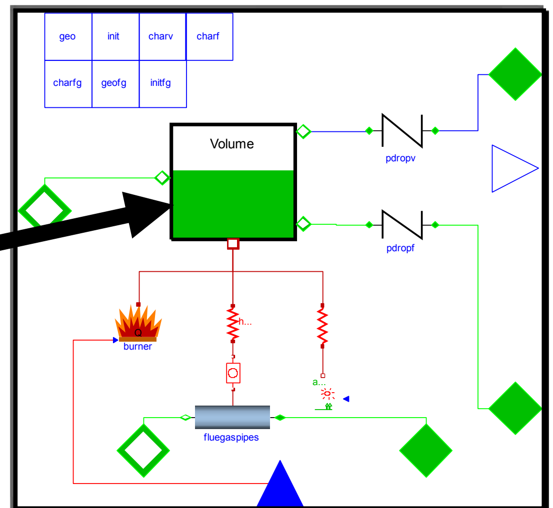
Modelica Modeling for H-I-L

LiBr Modelica component libraries built in collaboration with SJTU

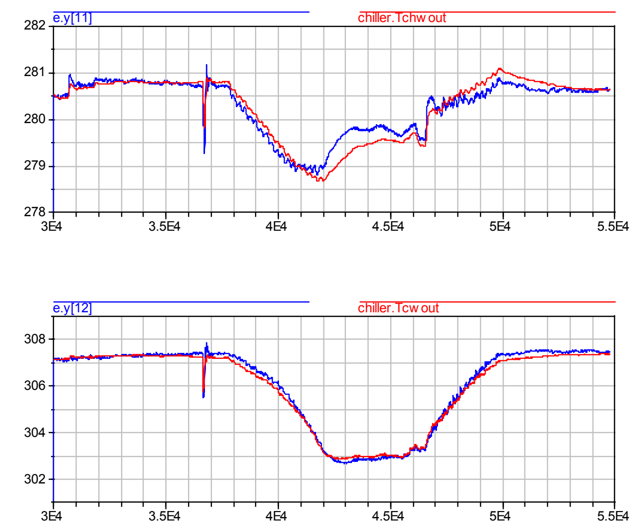
Conservation Equations

```
//Dynamic Mass Balance
M_x = transposex*M;
for i in 1:nspecies loop
   derM_x[nspecies] = summdot_x[:, nspecies]
end if;
//Dynamic Energy Balance
U = M*h - p*Vt;
derU = sumqdot + sumheat.Q_s + sumheat.W_loss;
// Volume conservation
M[1] = d[1]*V[1];
```

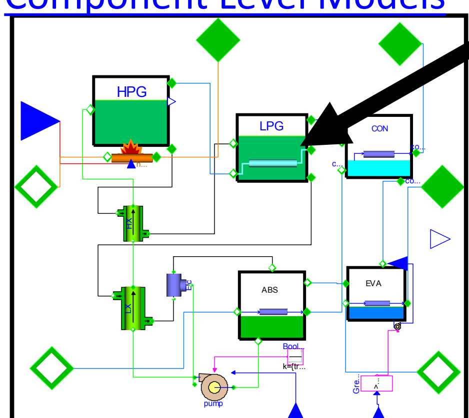
Subcomponent Level Models



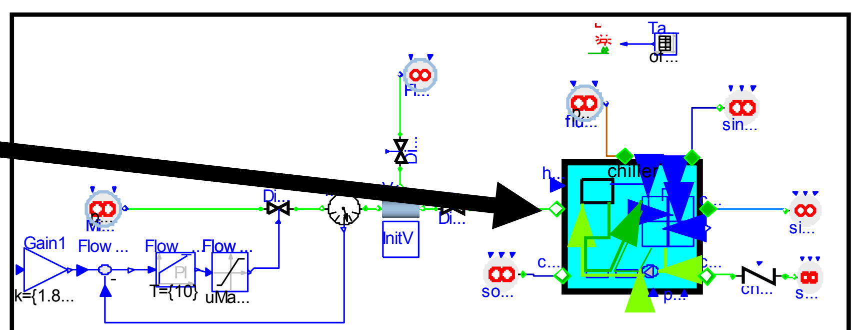
Sensor to model validation



Component Level Models

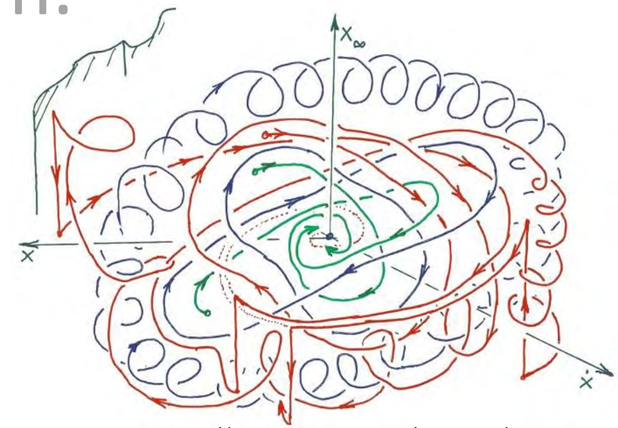


System Level Model

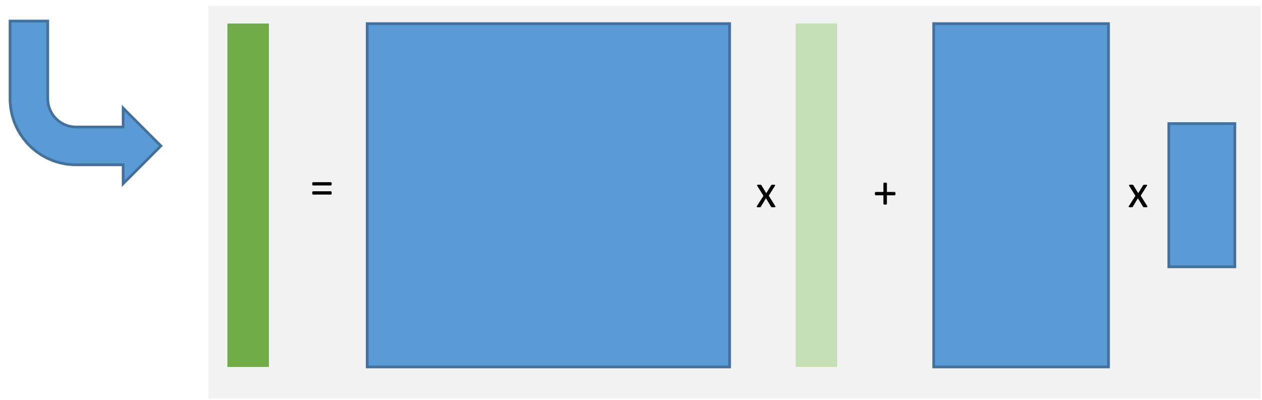


Modeling and Reduction for RT sim.

$$\dot{x} = f(x, p, u, \varepsilon)$$



http://www.mm.bme.hu/IDEAS14/logo.jpg

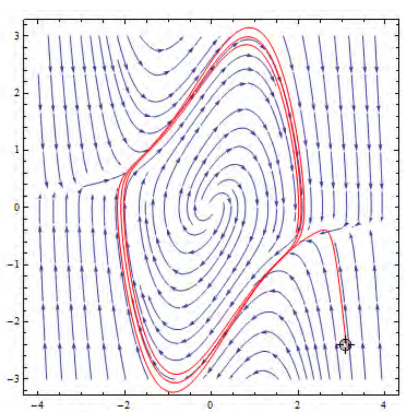


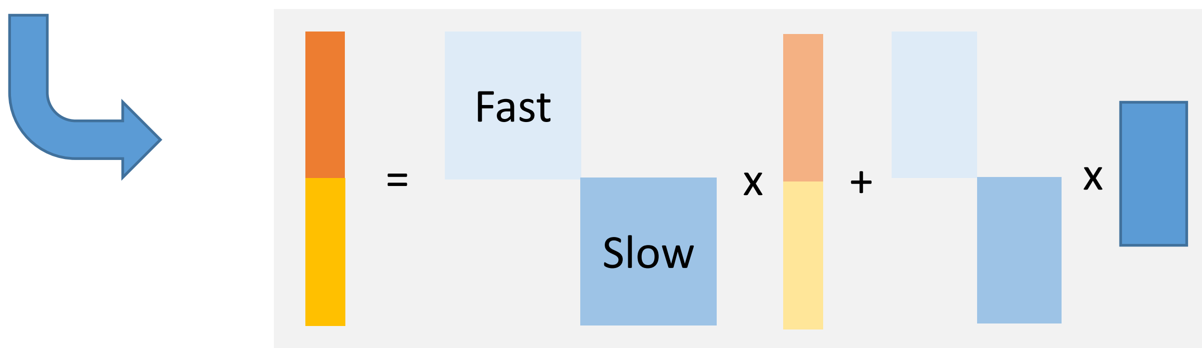
<u>Efficiency:</u>

Analytical
 (modeling paradigms)

Numerical
 (localization)

Computational
 (solvers)





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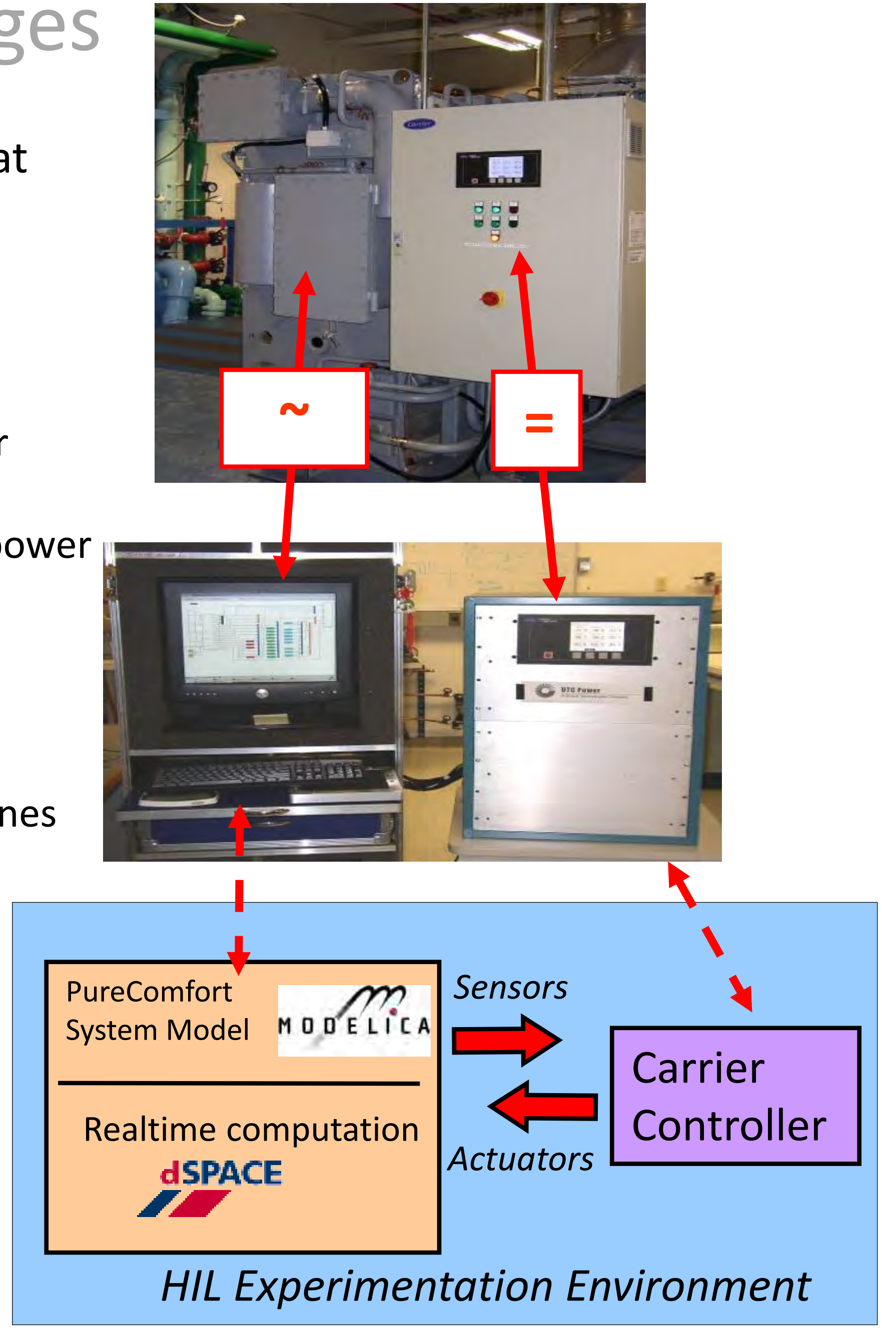

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- Critical parameter management at all levels
- The decomposability of a system cannot be ignored
- New curricula needed that addresses all of this
- …

- Verification needed to accelerate product development through by adding feedback and robustness to the design process
    - Identify unexpected behavior, track alignment with requirements, test matrix outside of lab conditions
- Common semantics and well defined interfaces are needed for models as it is likely they will be a collaborative effort
- To avoid surprises, re-work, and other discontinuities, use of one model platform is useful – model reduction, abstractions or other methods are used to preserves design flow

Open Opportunities

- Automation: From industrial design tools to real time simulation is often a big step. Some wrappers and numerical routines have been established more efforts in co-simulation and applied model reduction are needed (e.g. to low level audiences).

- Common semantics and well defined interfaces are needed for models as it is likely they will be a collaborative effort

- To avoid surprises, re-work, and other discontinuities, use of one model platform is useful – model reduction, abstractions or other methods are used to preserves design flow

- Accessibility to non experts

Sections

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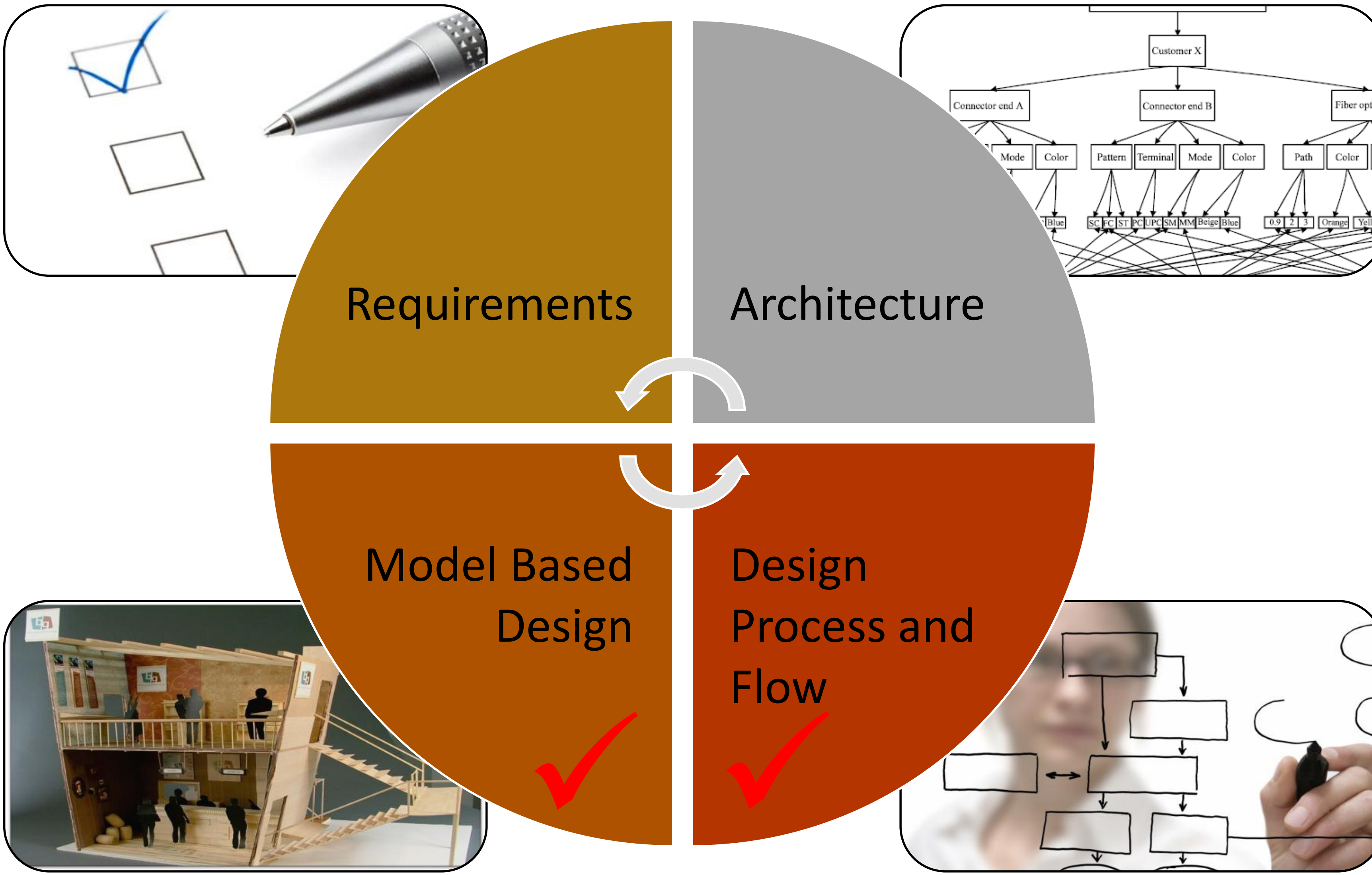
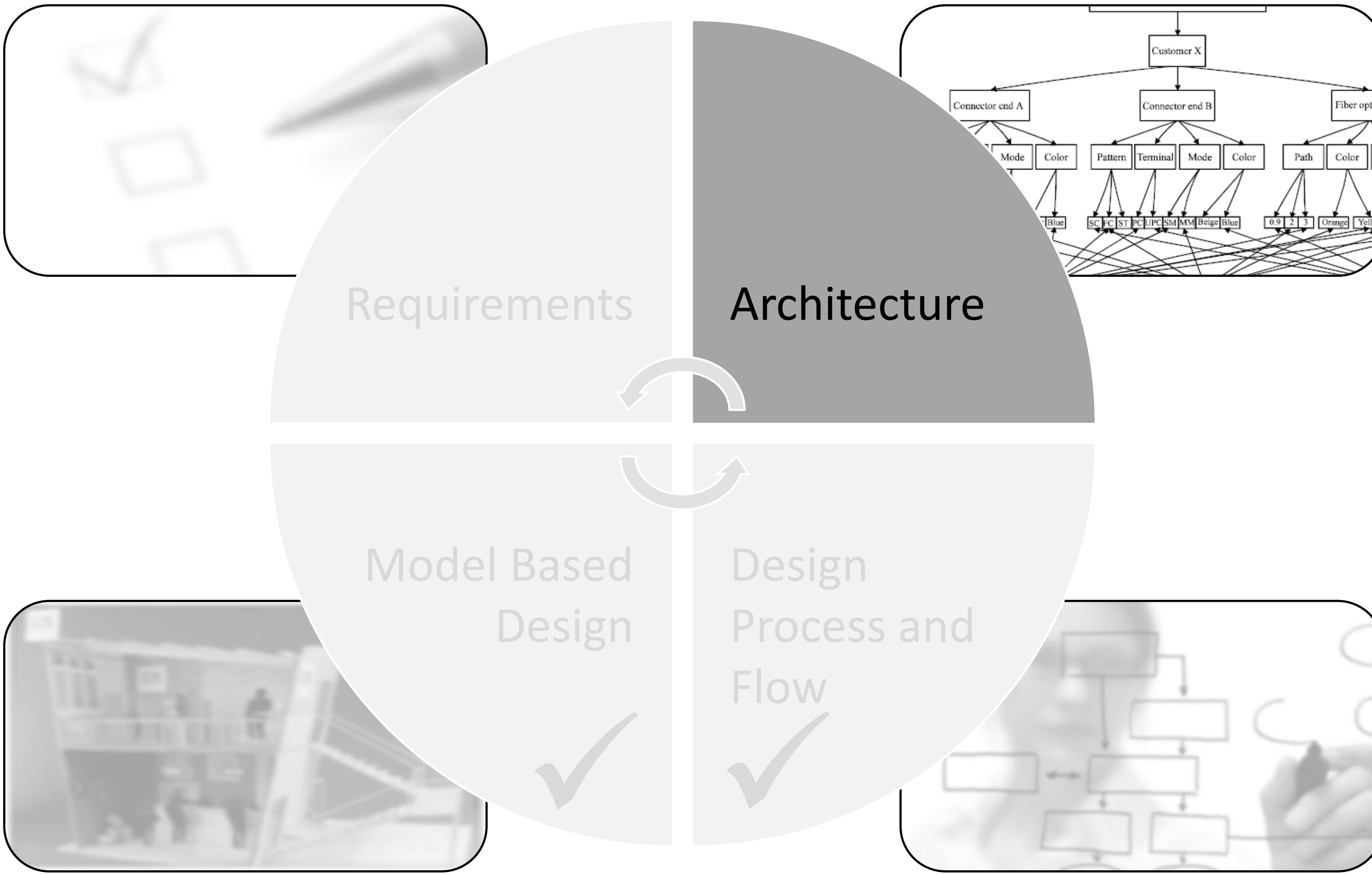
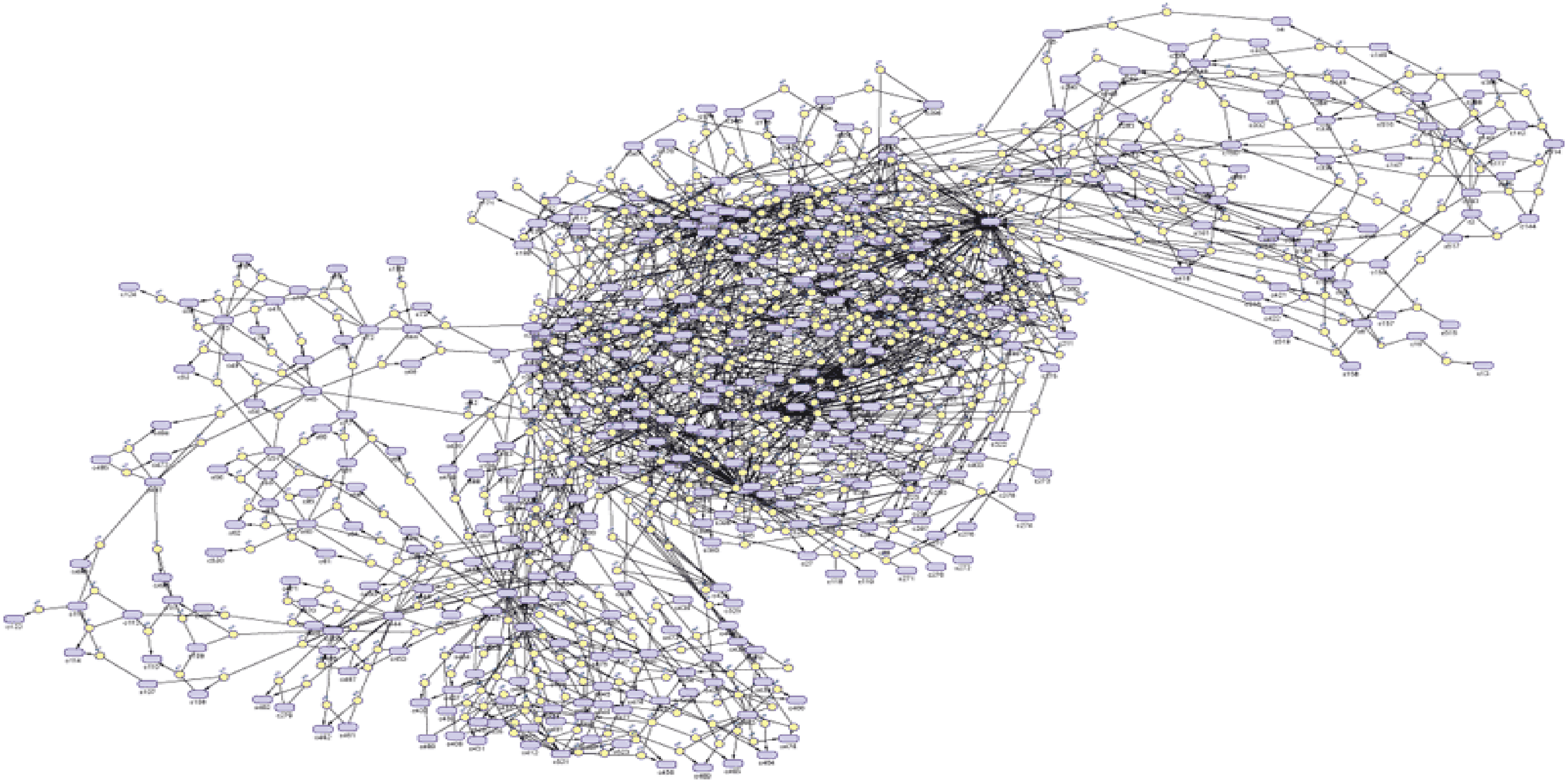
Elements of Systems Engineering



Elements of Systems Engineering





Recent research areas: Big Data, complexity, graph analysis, interconnectivity, …

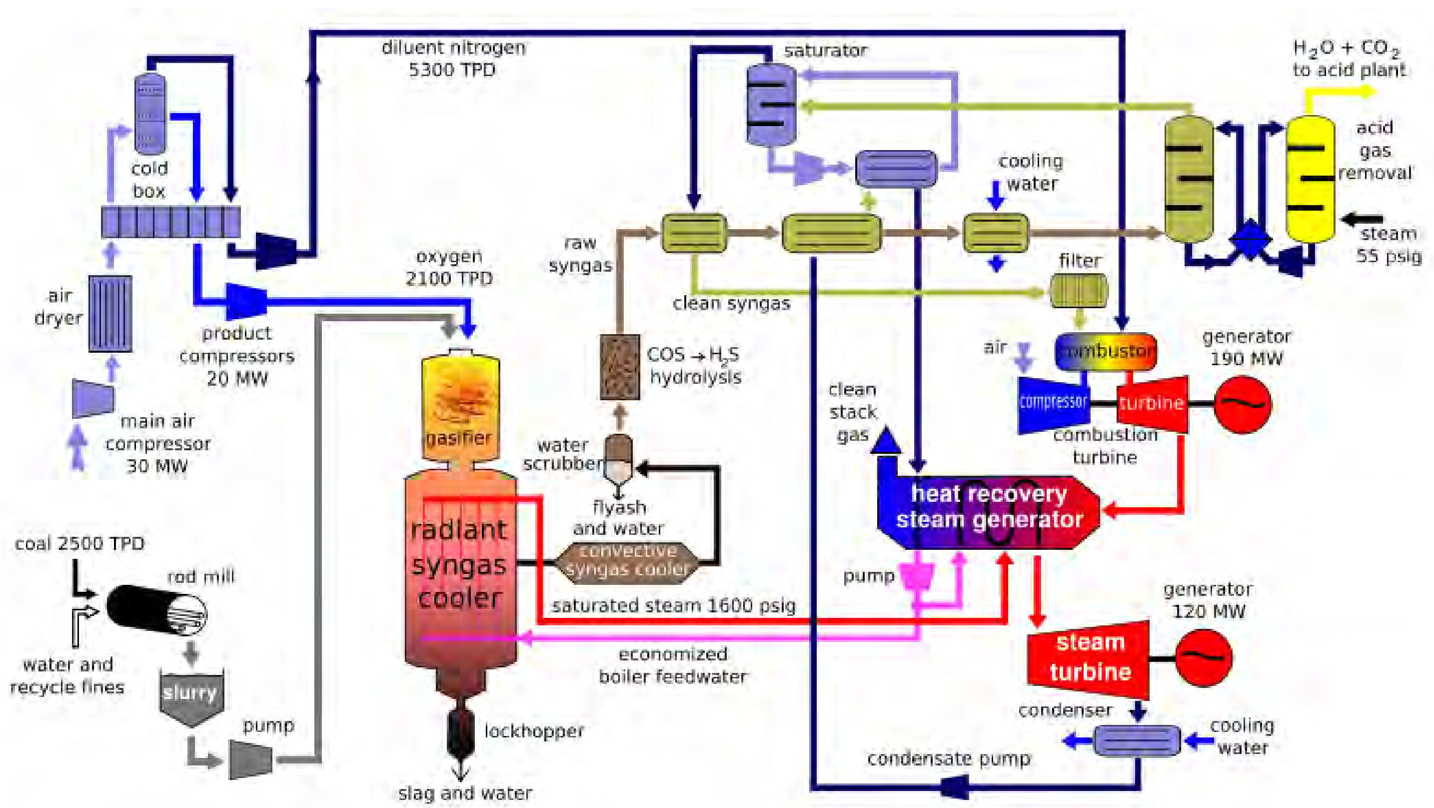
Driven by ease in manufacturing, higher efficiencies, greater robustness …

Defn: If a system is complex – it is decomposable. If this is fact is not used in design, optimization, computation, analysis you are ignoring something very important

Clustering essential dynamics

"A generic complex system"

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

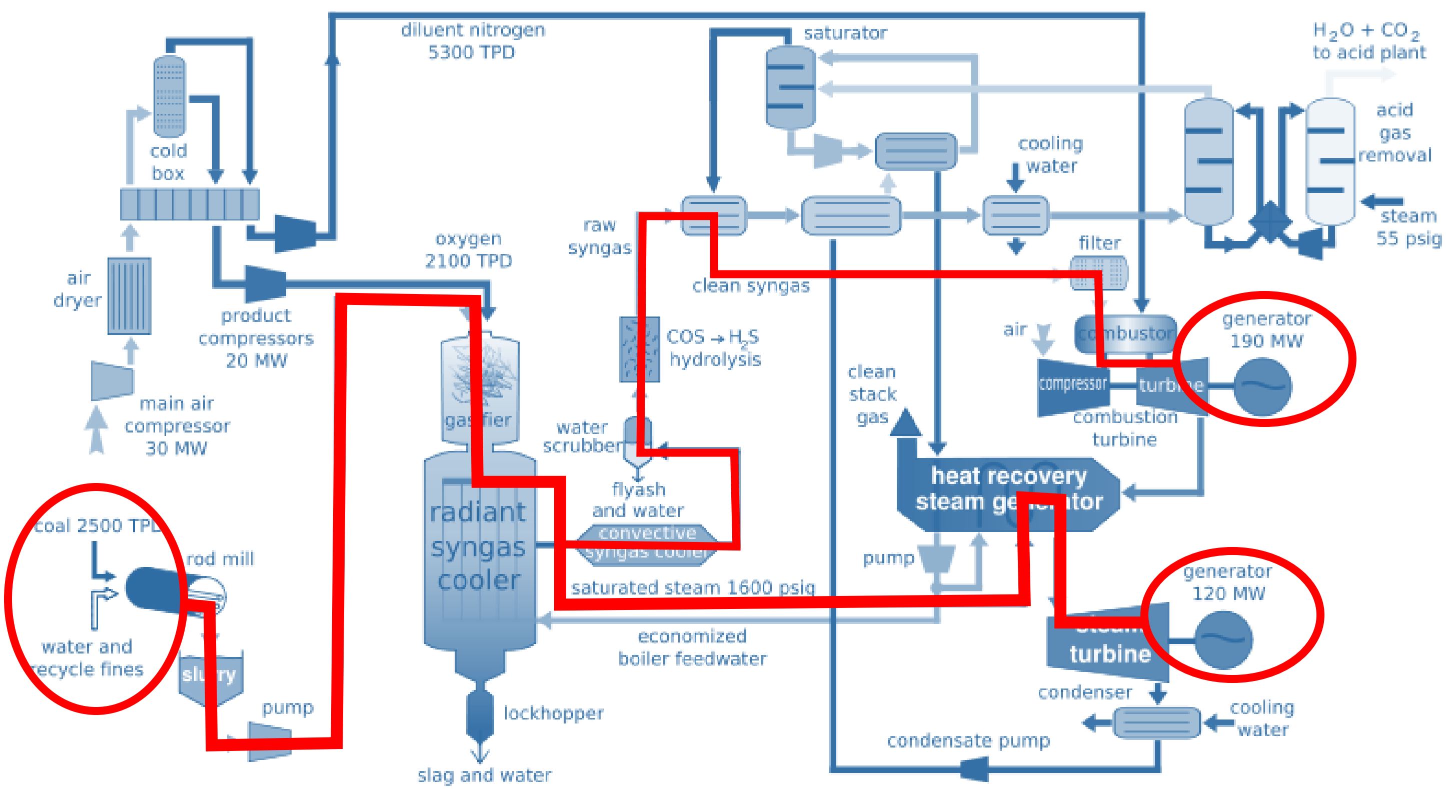


Clustering essential dynamics

"A generic complex system"

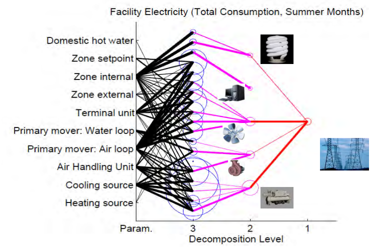
Critical path, without this nothing can happen – everything else is safety and regulation/control of process efficiencies

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

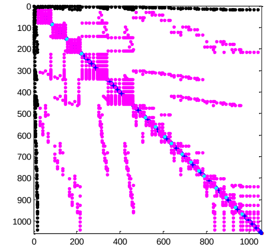


Decomposition Studies:

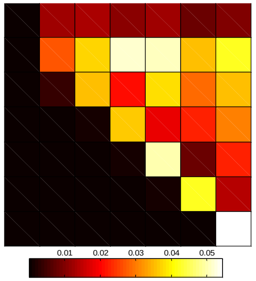
1. Identifying critical uncertainty flows



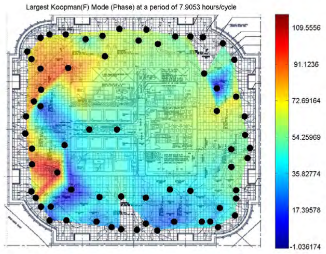
2. Partitioning state dynamics

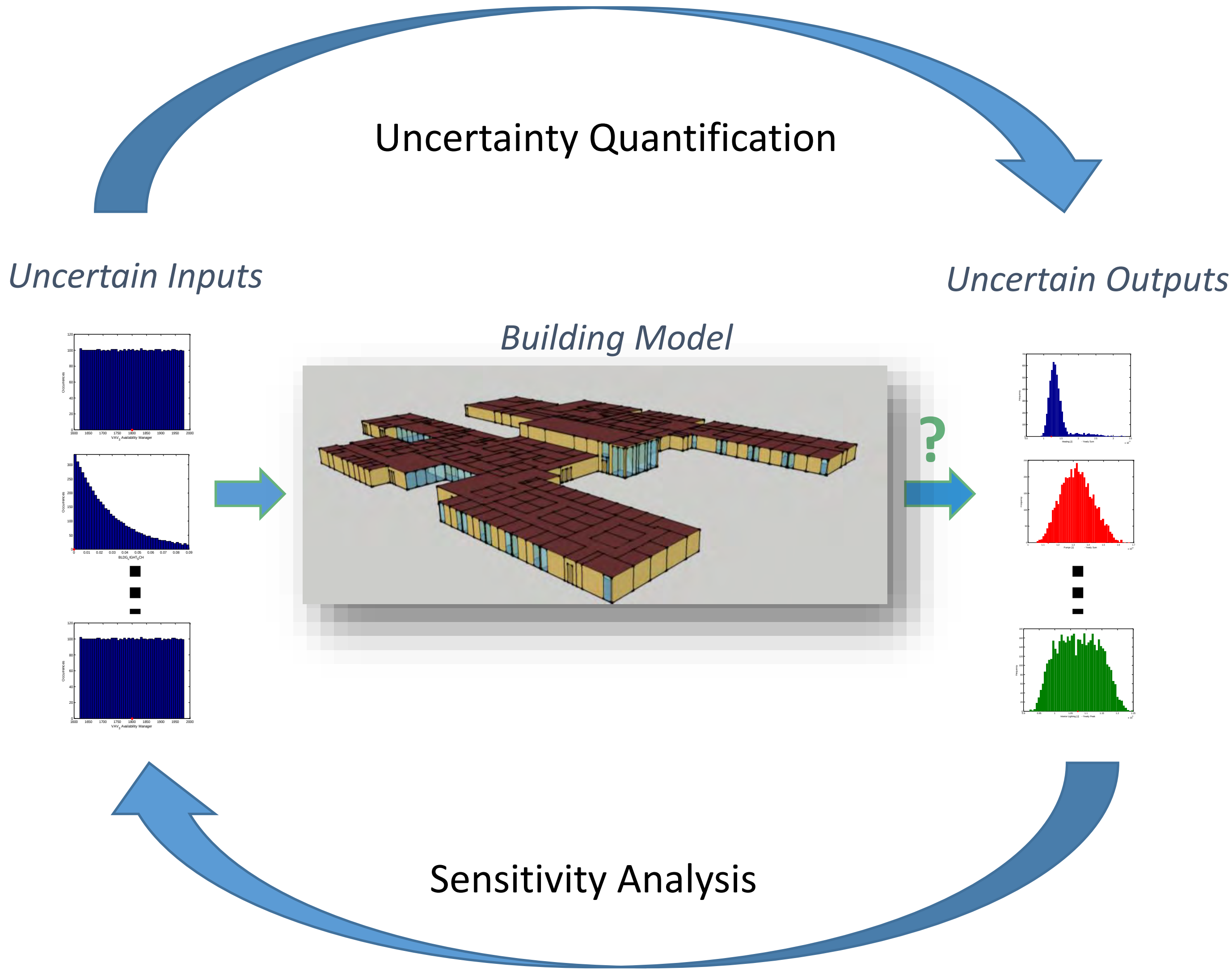


3. Modal design



4. Modal extraction from data



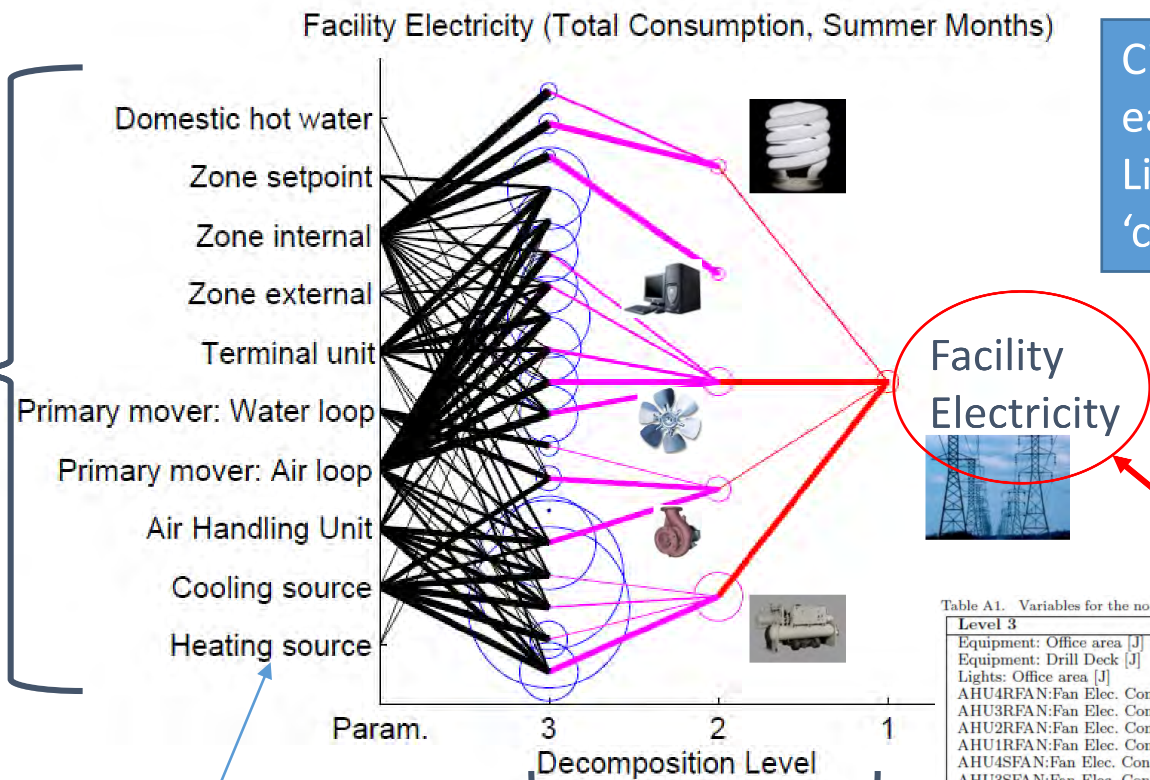

Uncertainty Quantification
Uncertain Inputs
Building Model
Uncertain Outputs
?
Sensitivity Analysis

Clustering Essential statics

Nodes are subsystems. Circle around each node is its uncertainty in energy consumption. Edges are weighted by sensitivity.

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

Input Parameter Types



Intermediate Consumption Variables

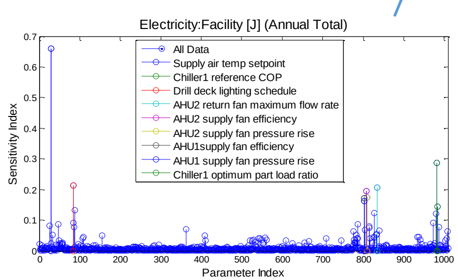


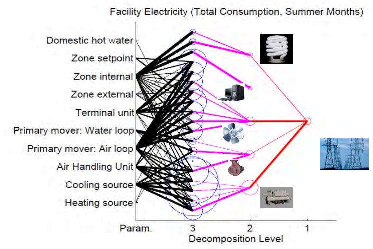
Table A1. Variables for the nodes of the sensitivity decomposition of Facility Electricity (Figure 7).

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]		

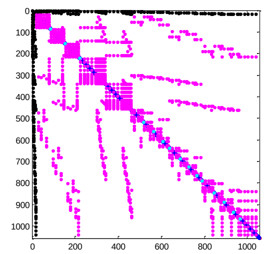
[Eisenhower, JBPS 2010]

Decomposition Studies:

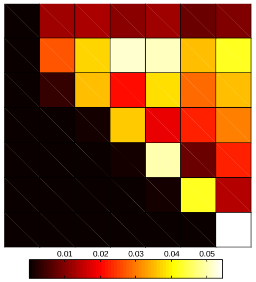
1. Identifying critical uncertainty flows



2. Partitioning state dynamics



3. Modal design



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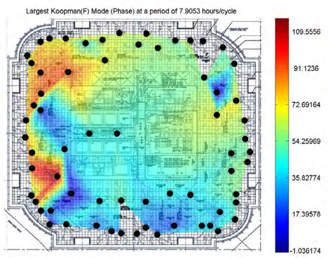
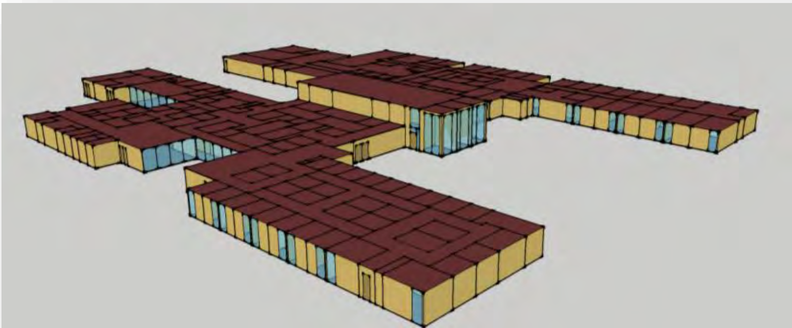


Sorting Essential Dynamics



Detailed Whole-Building Model

Detailed Energy Software

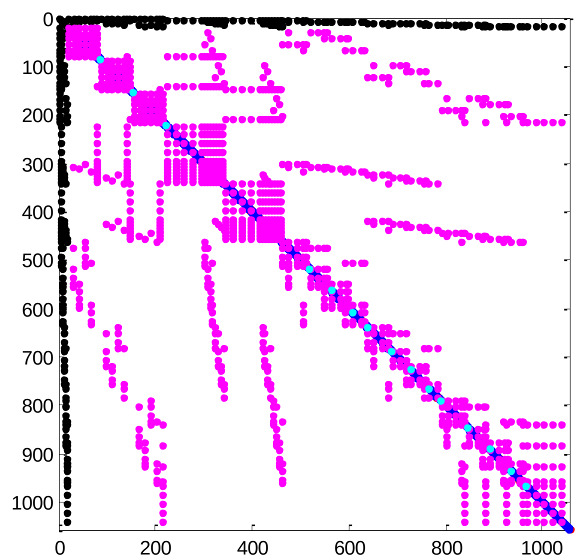
EnergyPlus

$$C_z \frac{dT_z}{dt} = \sum_{i=1}^{N_{surfaces}} \dot{Q}_{conv_i} + \sum_{i=1}^{N_{zones}} \dot{Q}_{mixing_i} + \sum_{i=1}^{N_{sl}} \dot{Q}_{sl_i} + \dot{Q}_{inf_z} + \dot{Q}_{HVAC_z}, \quad (1)$$

State-space dynamics

$$\dot{x} = A(x_0, p)x + B_u(x_0)u + B_w(x_0, p)w$$
$$y = Cx$$

Unsorted *A*-matrix interconnections



Information about how ~1000 differential equations is *hidden* in this matrix

Clustering

Spectral clustering used to map interconnectedness of the dynamics

$$\dot{x} = Ax + Bu$$
$$y = Cx + Du$$

T_{zones}(x18)

Internal States (x1056)

$T_{outdoors}$
T_{ground}
$T_{HVACsupply}$
$T_{window\ surface}$

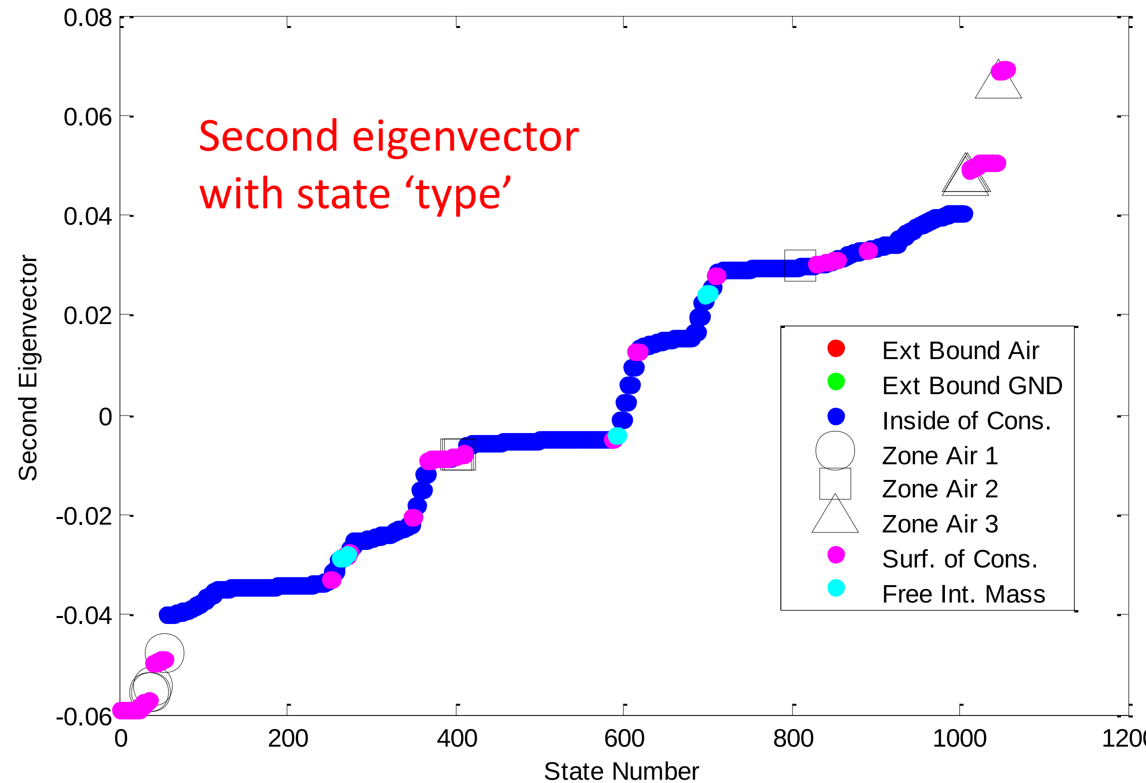
Test case:
Medium office building, 53 kft^2, 18 zones

Binary adjacency matrix defined from analytic linearized form of full EnergyPlus model:

$$\tilde{A} = \frac{1}{2}(A + A^T)$$

$$W_{Bin} = \begin{cases} 1 \ if \ A \neq 0 \\ 0 \ if \ A = 0 \end{cases}$$

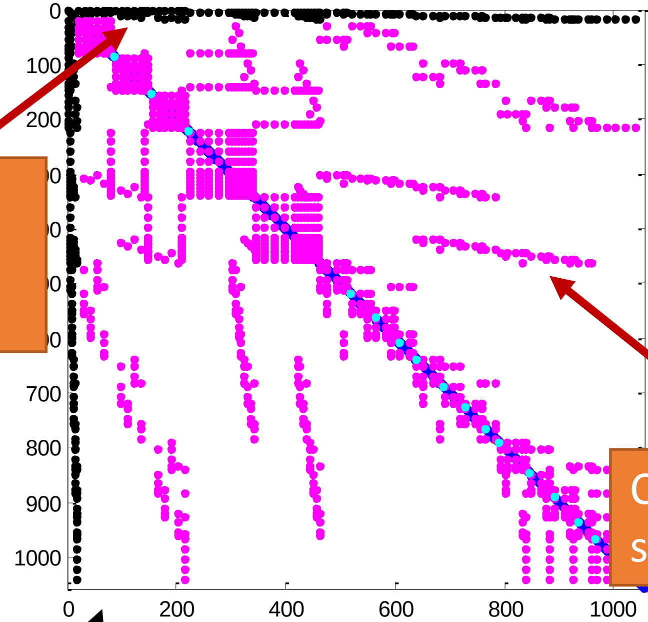
$$L = \deg(W) - W$$



Clustering

Clustering leads to: parallelization of analysis / computation / control / diagnostics

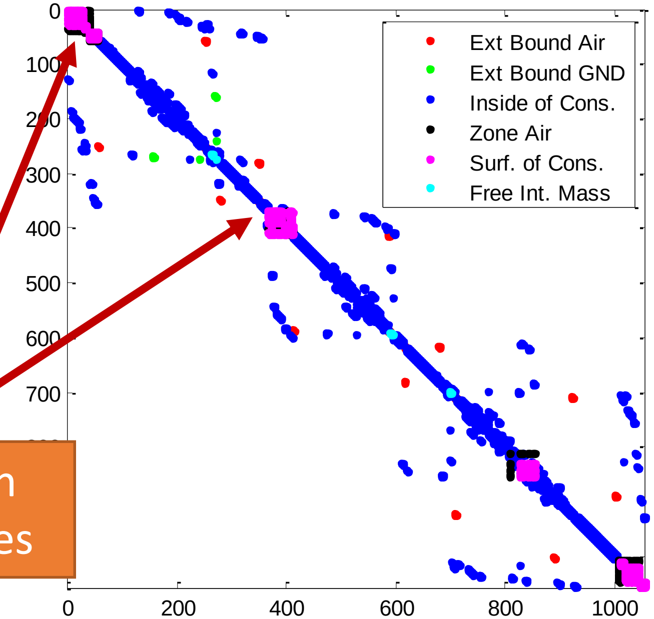
Unsorted *A* matrix interconnections



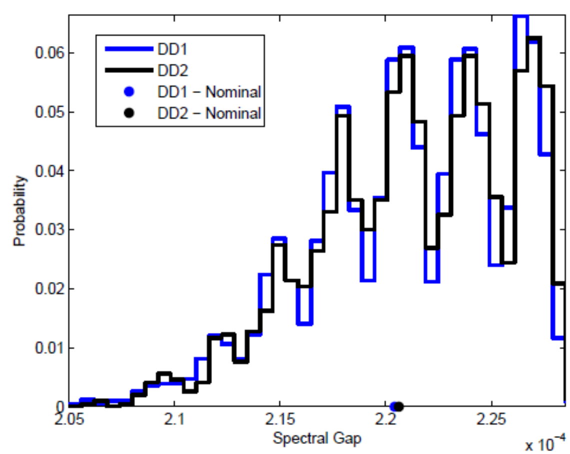
Zone air states

Construction surface states

Sorted based on interconnection matrices



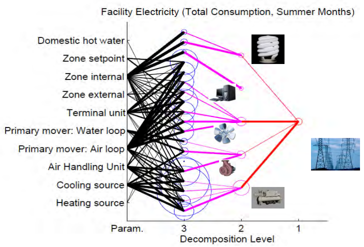
A matrix of Dynamics in an EnergyPlus model



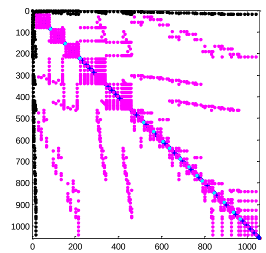
Uncertainty in spectral gap of the graph Laplacian illustrates robustness of interconnectivity of energy dynamics

Decomposition Studies:

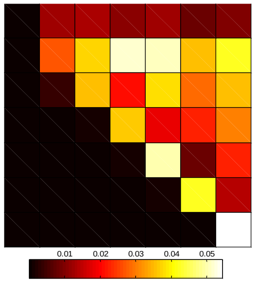
1. Identifying critical uncertainty flows



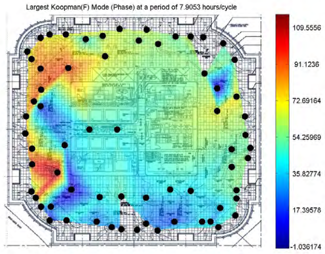
2. Partitioning state dynamics



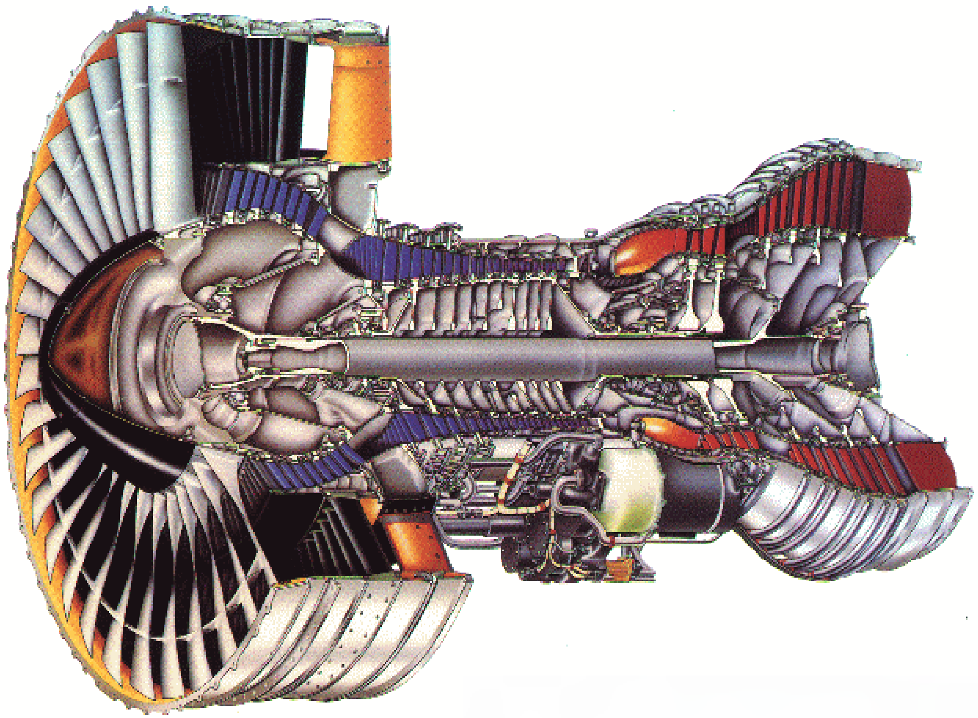
3. Modal design

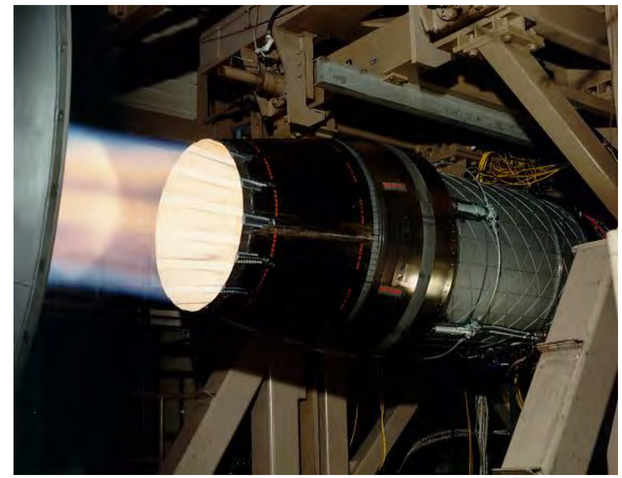


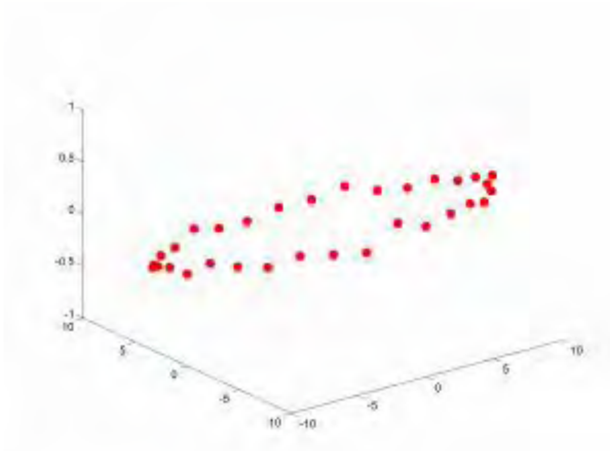
4. Modal extraction from data



Effect of Symmetry







Normal operation leads to instability observed by rotating acoustic waves

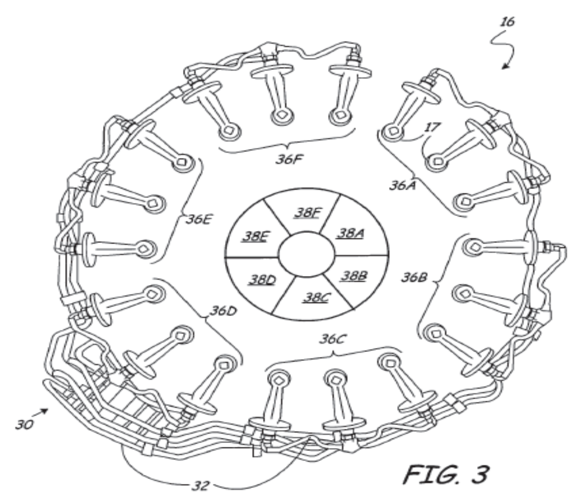
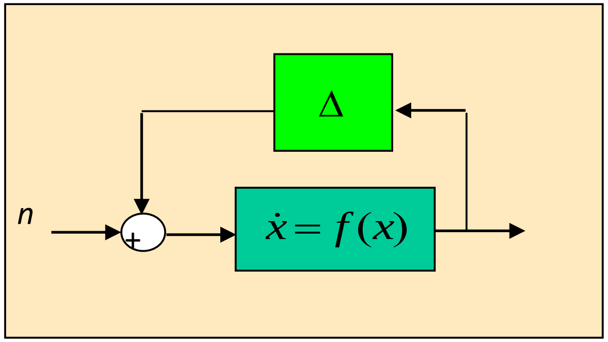


FIG. 3

Rotating Combustion Instability: Analysis

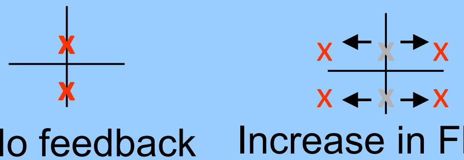
The heat release (flame) causes a coupling which de-stabilizes the system causing noise....but the flame is needed for the engine to run



The 1-D transport equations couple pressure, velocity, and heat release

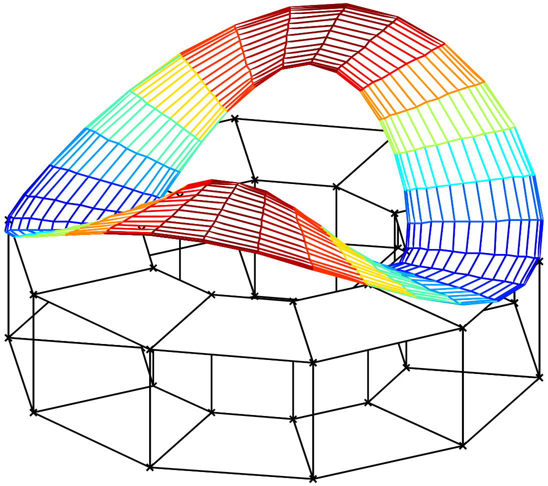
$$\frac{\partial u_\Theta}{\partial t} = -a^2 \frac{\partial p}{\partial \Theta}$$
$$\frac{\partial p}{\partial t} + \frac{\partial u_\Theta}{\partial \Theta} = -\zeta p + q,$$

Eigenvalues vs. Coupling (flame)



Always detrimental!

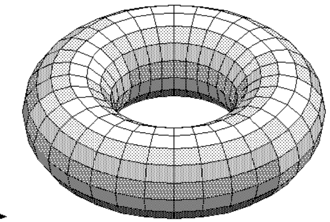
Optimal Wavespeed Pattern



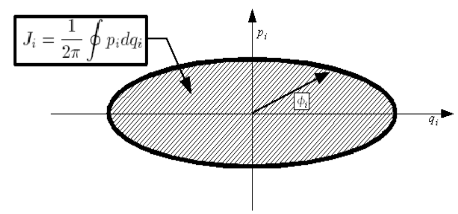
Decomposition Methods - Cascade

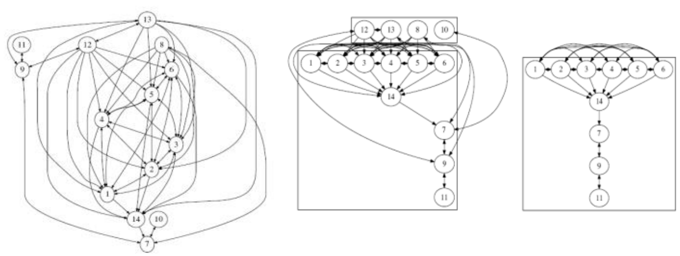
Analysis of energy coordinates (Action-Angle) highlights *funneling* of energy to specific low order modes in the system

System dynamics is *right* coordinates make a difference

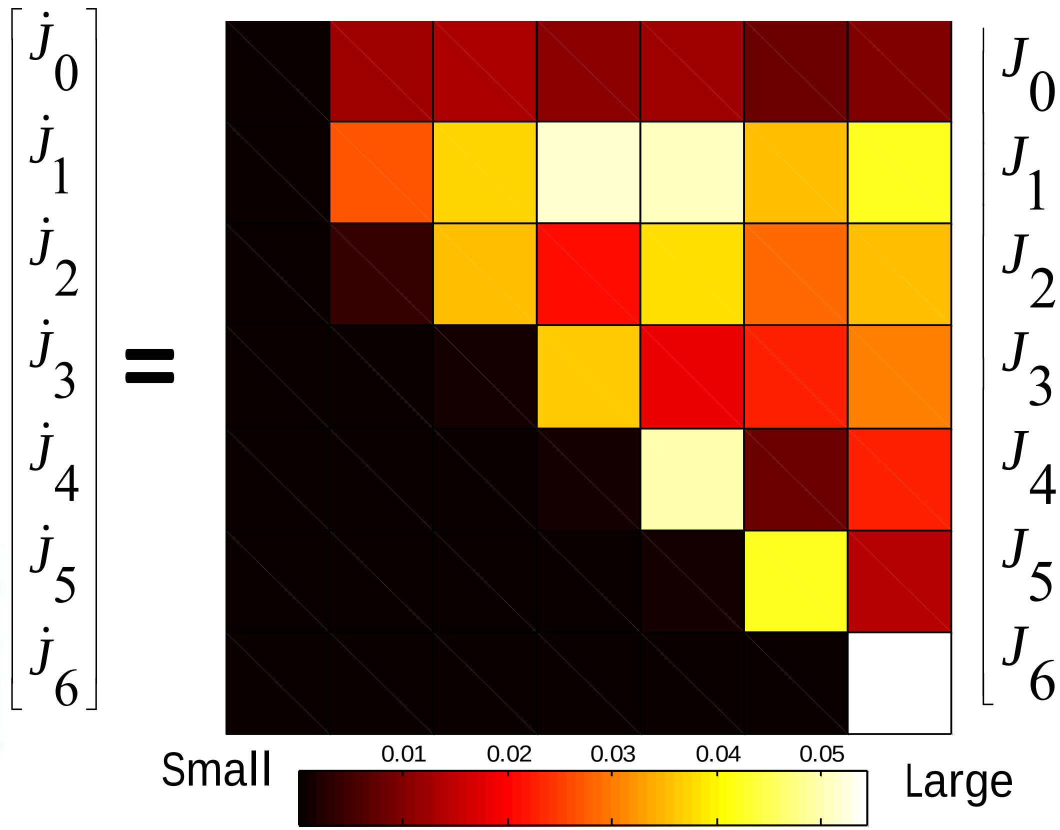


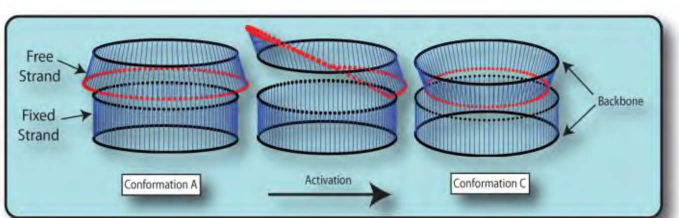
Complex stability analysis of jet engine noise abstracted to nonlinear analysis of a few modes





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





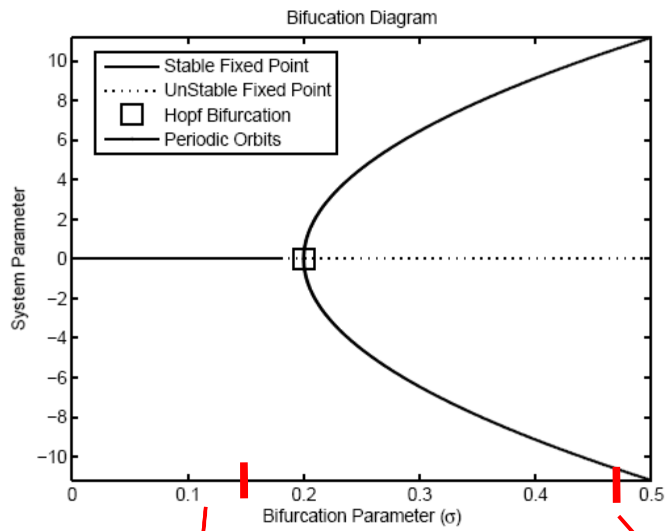
[Eisenhower and I. Mezic *Physical Review E, 2010]*

Rotating Combustion Instability: Fix

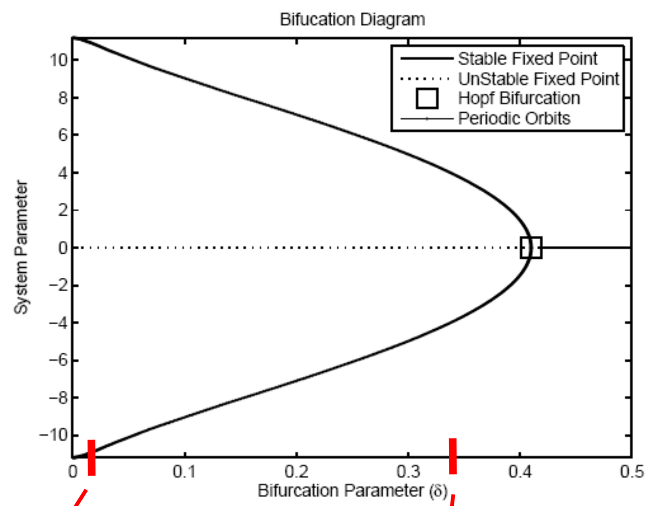
Transport equations projected onto first Fourier Modes

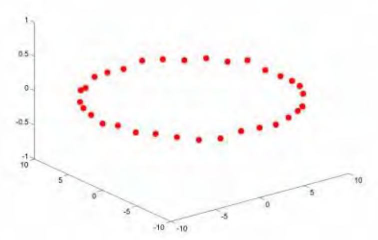
$$x_1'' + \zeta x_1' + (a_0^2 - \delta)x_1 = x_2(a_0^2 - \delta)\left(\sigma - \alpha\left(\frac{3\sqrt{\pi}}{4}(x_1^2 + x_2^2)\right)\right)$$
$$x_2'' + \zeta x_2' + (a_0^2 + \delta)x_2 = -x_1(a_0^2 + \delta)\left(\sigma + \alpha\left(\frac{3\sqrt{\pi}}{4}(x_1^2 + x_2^2)\right)\right)$$

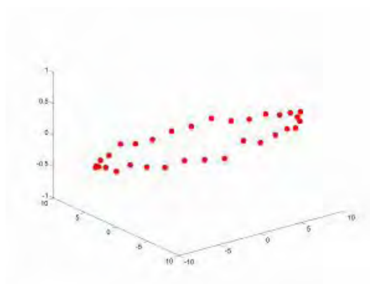
Destabilize by Necessity

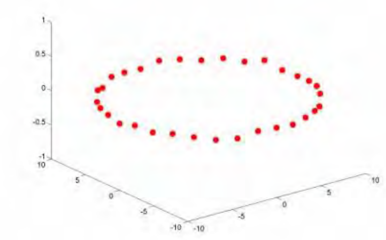


Restabilize by Design





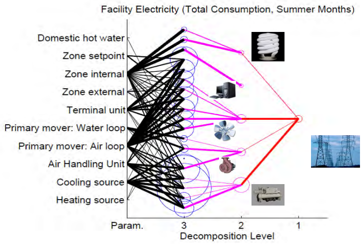




[Eisenhower, Hagen, Banaszuk and Mezic Journal of Applied Mechanics Jan. 2009]
[US 8037688 B2]

Decomposition Studies:

1. Identifying critical uncertainty flows



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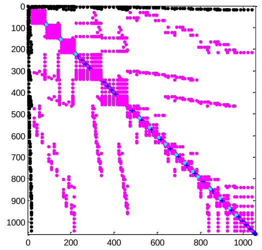
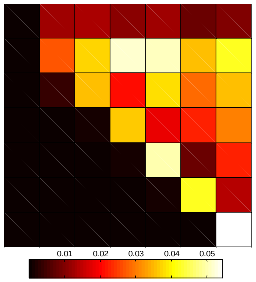
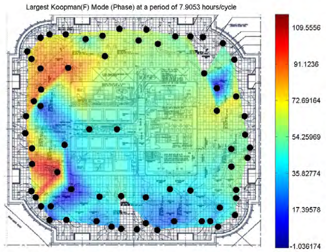


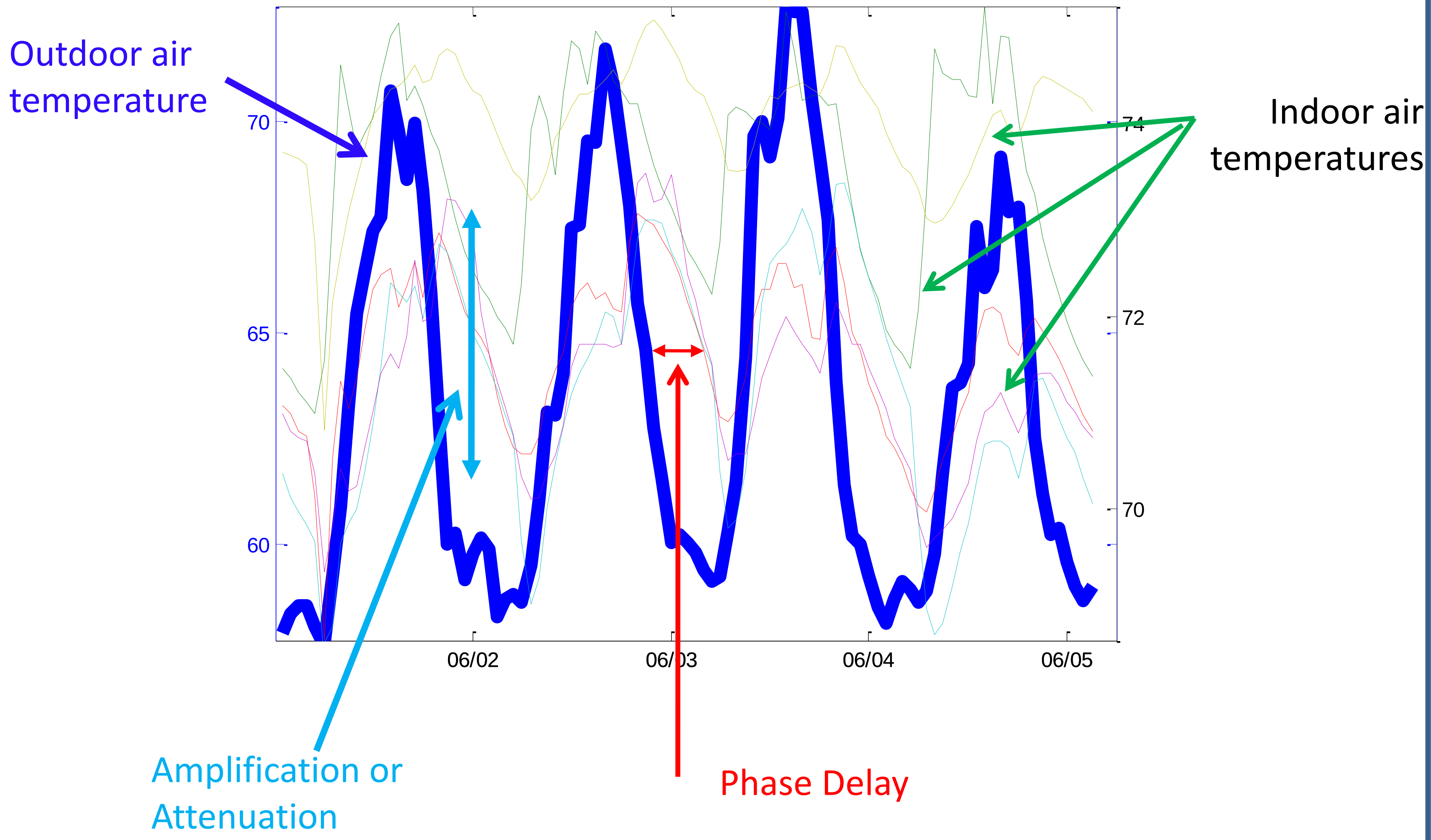
3. Modal design



4. Modal extraction from data



Typical Building Response



Mathematical Preliminaries

Model or Data

$$x_{i+1} = f x_i$$

Begin with an arbitrary finite dimensional nonlinear function/system/model (f)

where $i \in \mathbb{Z},\ x \in M$

M is an arbitrary manifold

g is a sensing/sampling function

$$g : M \to \mathbb{R}^N$$

Actual sensed variables

for say N sensors.

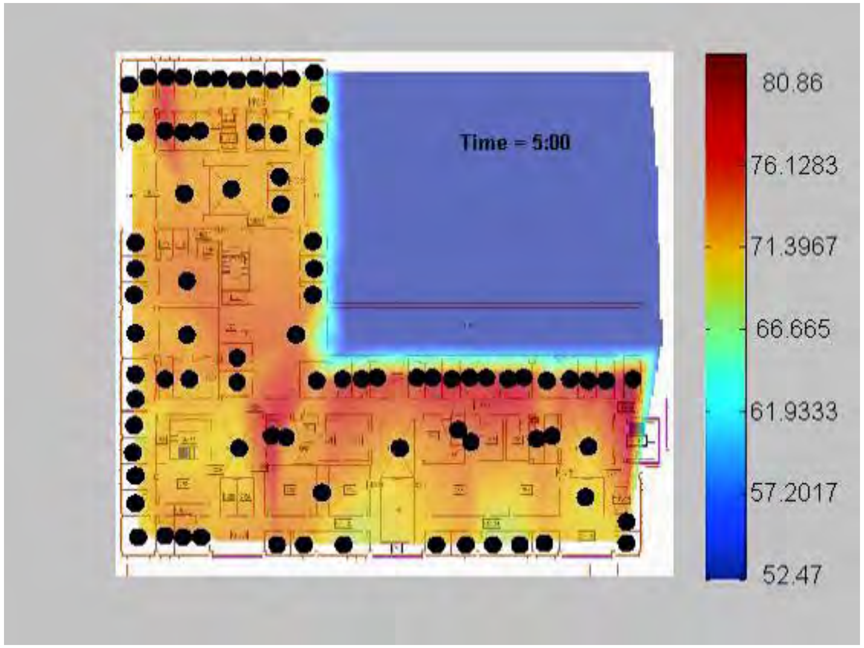
The Koopman operator U is an infinite dimensional operator that maps g to Ug

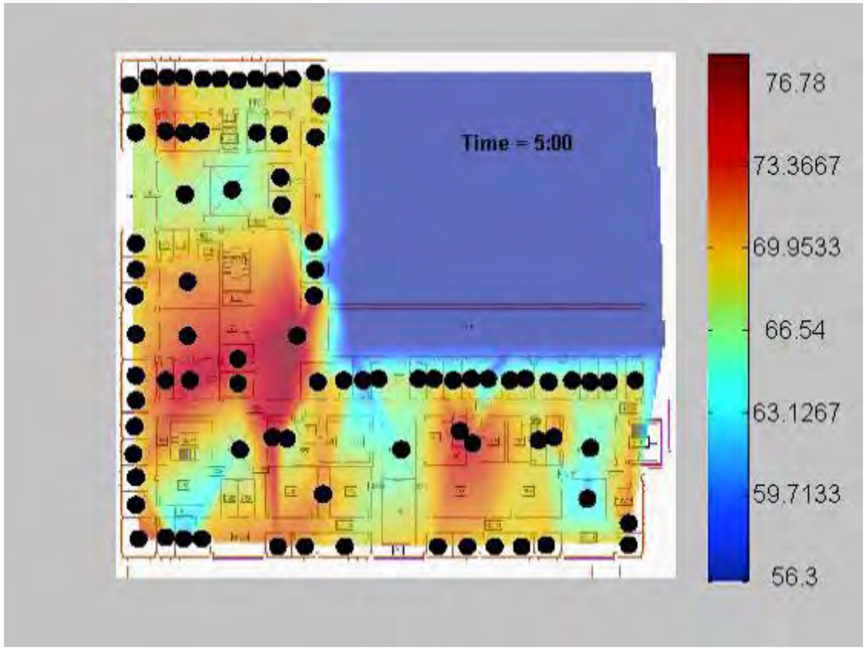
$$Ug(x) = g(f(x))$$

The goal is to find the dynamical properties (spectral content, orthonormal basis, etc.) of the operator Ug

[*Mezic 2005, Nonlinear Dynamics*]

Typical Building Response





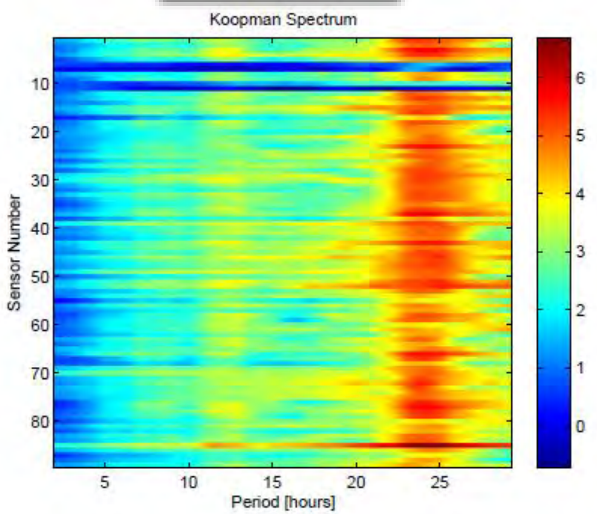
Model Tuning

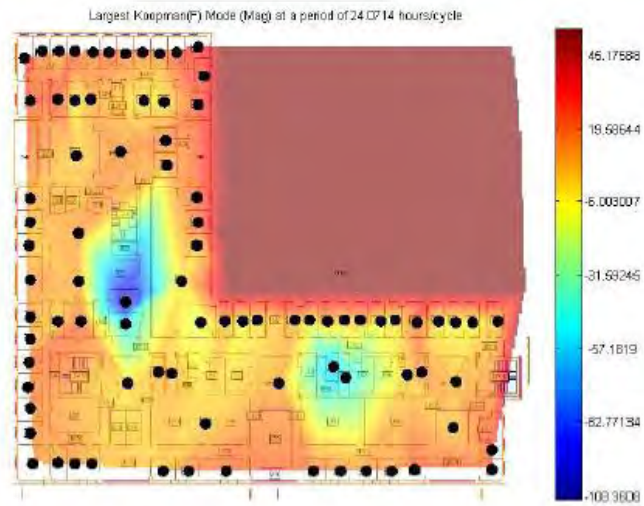
Comparison between extensive EnergyPlus model and data

Spectrum

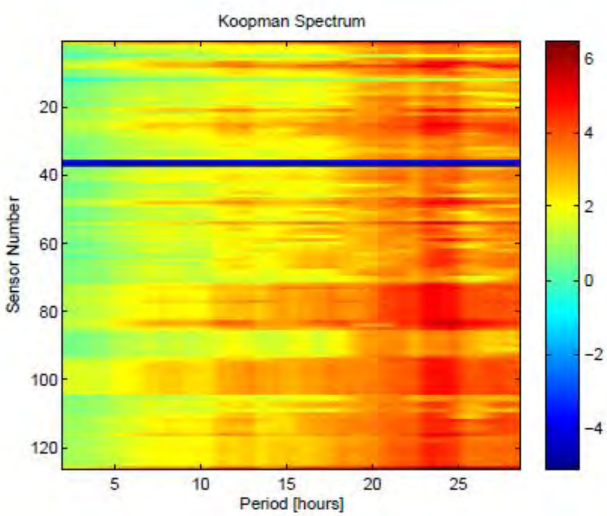
Magnitude

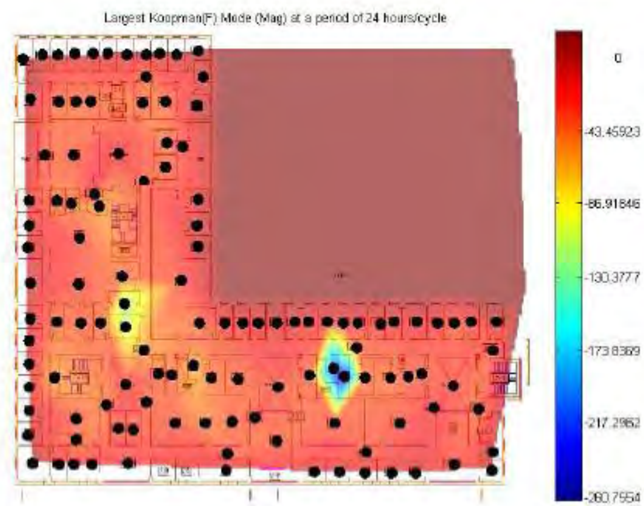
Data





Model

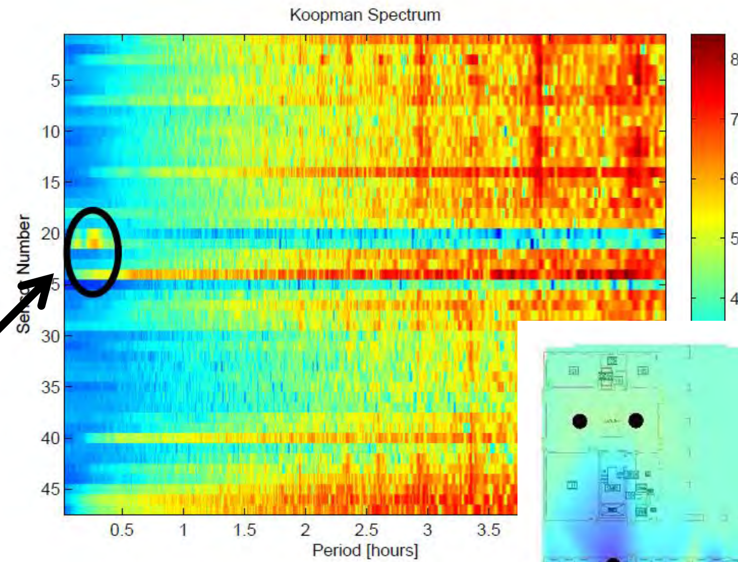




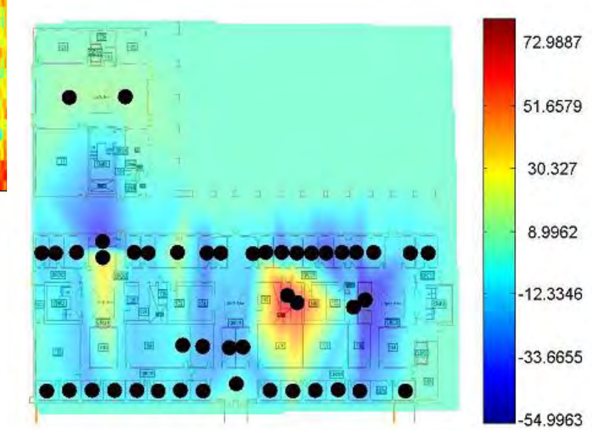
[Eisenhower, Simbuild 2010]

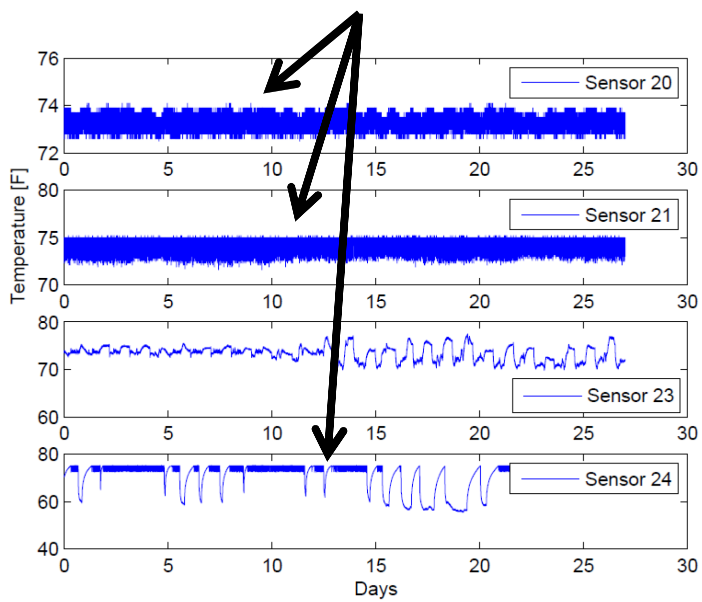
Spectral Approach

- ❑ Method quickly isolates sensor / control issues



Energy at unexpected frequencies



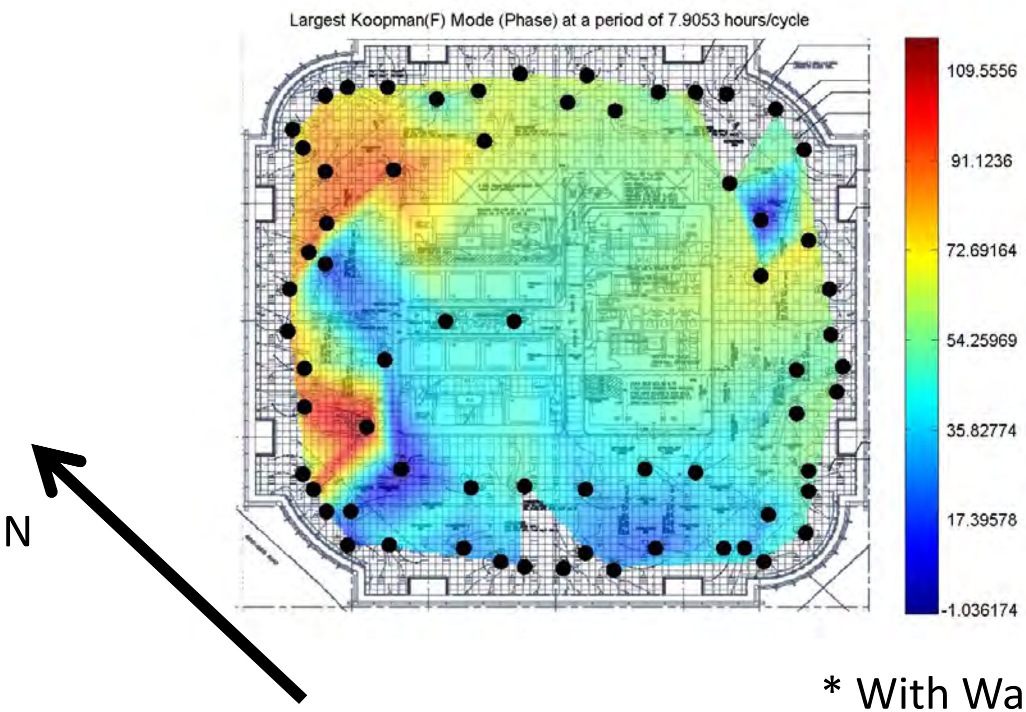


- ❑ Cycling found in control system
- ❑ System retuned to reduce cycling

Hong Kong Diagnostics

- One Island East – Westlands Rd. Hong Kong
  - 70 story sky-scraper
  - Data: 11/1/2009 – 11/15/2009

- Out-of-phase controller response one heating, one cooling is usually indicative of inefficient operation



* With Walter Yuen, Hong Kong Poly. Univ.

Summary Messages:

Model-based Design (MBD)
"Addressing design with computation"

- Time domain simulations rarely lead to design evolution
- More can be done with time domain simulations (wrappers)
- Dynamics matter!
- Continuity needed when modeling at different stages / fidelity
- Models need be appropriate for the intended use and user base
- Uncertainty analysis up front and throughout
- Critical parameter management at all levels
- The decomposability of a system cannot be ignored
- New curricula needed that addresses all of this
- …

- Decomposition can be performed on industry standard models that engineers are comfortable with to assess:
  - common architectures, fragility of the architecture dynamics, optimized design or control
- Analytical study (combustion) leads to new science and deeper understanding
- Data based analysis is helpful for diagnostics and post design analysis

Open Opportunities

- Automation: From industrial design tools to decomposed physics is a big step. Modeling techniques and analysis tools to drive commonality are needed

- More tools for transforming mathematical interconnectedness to product architecture is needed

- Curricula (outside CS departments) needed for system decomposition methods, interconnectedness needs to be taught not just let to happen

Sections

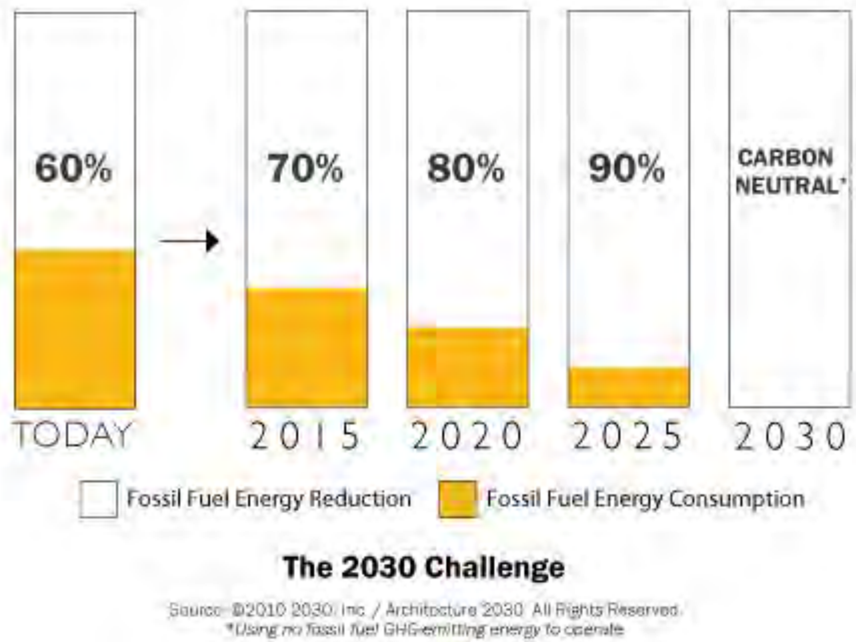
1. Motivation
2. Uncertainty Analysis / Critical parameter management
3. Analysis of dynamics
4. Verification
5. Decomposition
6. How its done

How it is done

1. Initiatives
2. Funding
3. Policy
4. Field engagement
5. Curricula

Initiatives (Energy)

Ed Mazria's challenge to get companies, govt, product manufactures to make Carbon Neutral Buildings by 2030



US: $25 Billion funding for energy efficiency (not solely buildings)
2009

Initiatives

Federal:

NSF FY 2014 Priorities:

$300 Million - Cyber-enabled Materials, Manufacturing, and Smart Systems

… transform static systems, processes, and edifices into adaptive, pervasive "smart" systems with embedded computational intelligence that can sense, adapt, and react

$155 Million - Cyber-infrastructure framework for 21st Century Science, Eng. and Edu

$25 Million - NSF Innovation corps

$63 Million - Integrated NSF support promoting Interdisciplinary R&Edu

$223 Million - Science, Engineering, and Education for Sustainability (SEES)

… SEES uses a systems-based approach to understanding, predicting, and reacting to change in the linked natural, social, and built environment and addresses challenges in environmental and energy research and education

$110 Million - Secure and trustworthy cyberspace

Darpa FY 2014:

$72 Million CCS-02: MATH AND COMPUTER SCIENCES

in new computational models and mechanisms for reasoning and communication in complex, interconnected systems.

$106 Million IT-02: HIGH PRODUCTIVITY, HIGH-PERFORMANCE RESPONSIVE ARCHITECTURES

ability to design complex defense and aerospace systems that are correct-by-construction.

$86 Million TT-13: *NETWORK CENTRIC ENABLING TECHNOLOGY*

Technical challenges include the need to process huge volumes of diverse, incomplete, and uncertain data streams in tactically-relevant timeframes

Initiatives

Federal:

DOE FY 2014:

$169 Million Electricity Delivery and Energy Reliability

electric grid modernization and resiliency in the energy infrastructure while working to enable innovation across the energy sector. Improved modeling and self healing / reliable systems

$379 Million Advanced Research Projects Agency – Energy (ARPA-E)

Transformational technologies with clear commercialization path

$2.775 Billion Energy Efficiency and Renewable Energy

… technologies, tools, and approaches that overcome grid integration barriers   …timely, affordable access to physical and virtual tools, and to demonstrate new materials and critical processes to advance the use of clean energy manufacturing technologies for industry.

Initiatives

State (just two):

<u>New York State Energy Research and Development Authority (NYSERDA)</u>

FY 2014: $424 Million (57%) in energy efficiency programs

The 2014 Draft State Energy Plan envisions and drives toward an energy system that is more clean, flexible, affordable, resilient, and reliable.

- Not all of this money is allocated for systems engineering R&D, however:

Advanced Buildings Consortium ($7.5 Million over 5 years)

The Advanced Buildings Consortium (ABC) will have a central technology theme in which to focus its efforts for improving energy efficiency and "resiliency, recoverability, and adaptability" (hereafter resiliency) of buildings to infrastructure disruptions.

<u>California Energy Commission (CEC)</u>

1996-2012 CA Energy Commission supported $884 Million ($1.4 Billion after matching) in innovative and clean energy R&D

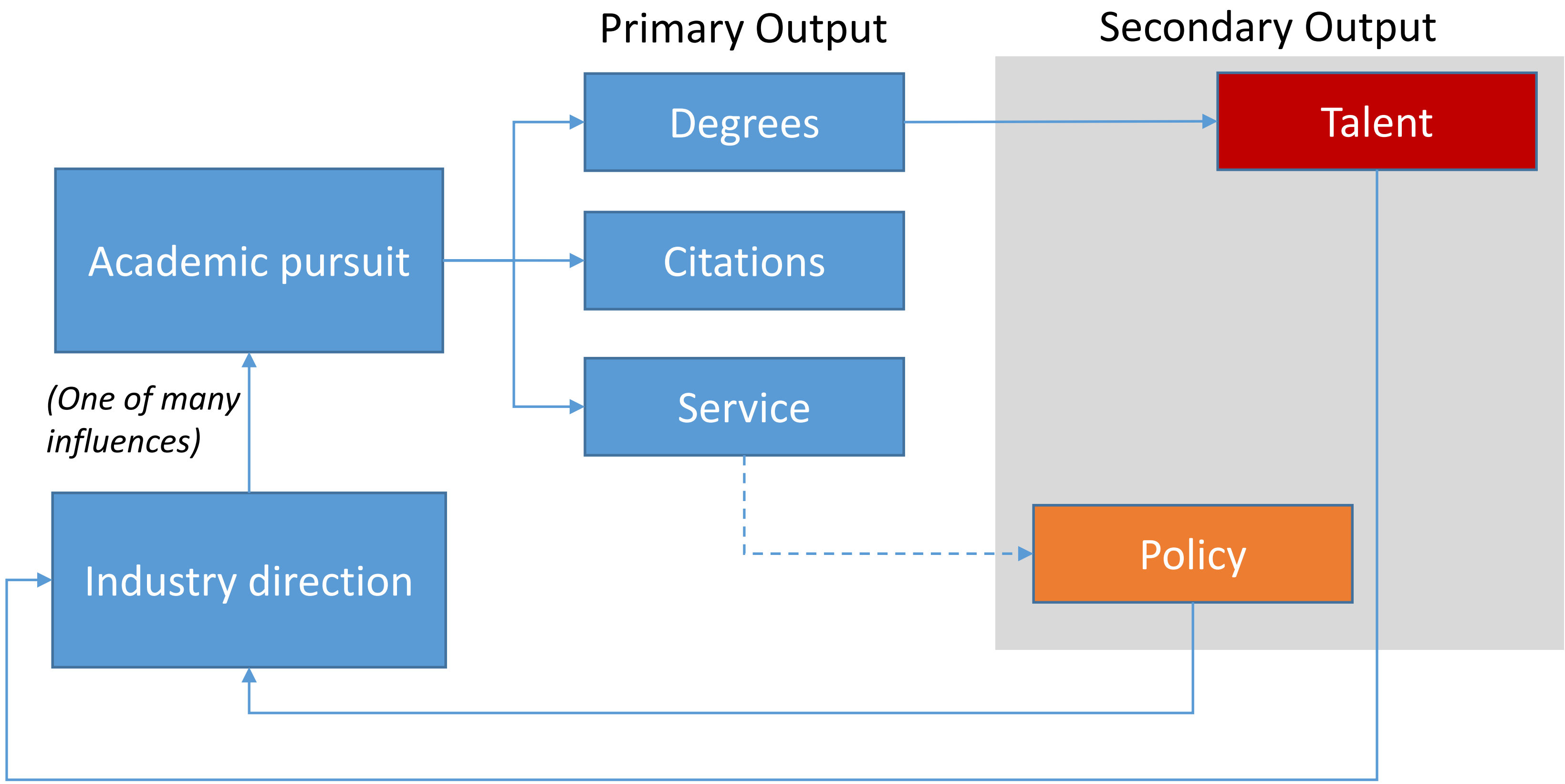
The California Public Utilities Commission approved a total of $162 million annually beginning January 1, 2013, and continuing through December 31, 2020 (20% managed by IOU's)

2015-2017: $152 million Applied R&D, $145 million Technology demonstration & deployment, $53 million in market facilitation

Applied R&D Topics 1) EE & Demand Response, 2) Clean generation, 3) Smart Grid 4) Cross cutting

Funds allocated to in-state institutions while supporting out-of-state collaboration

Policy



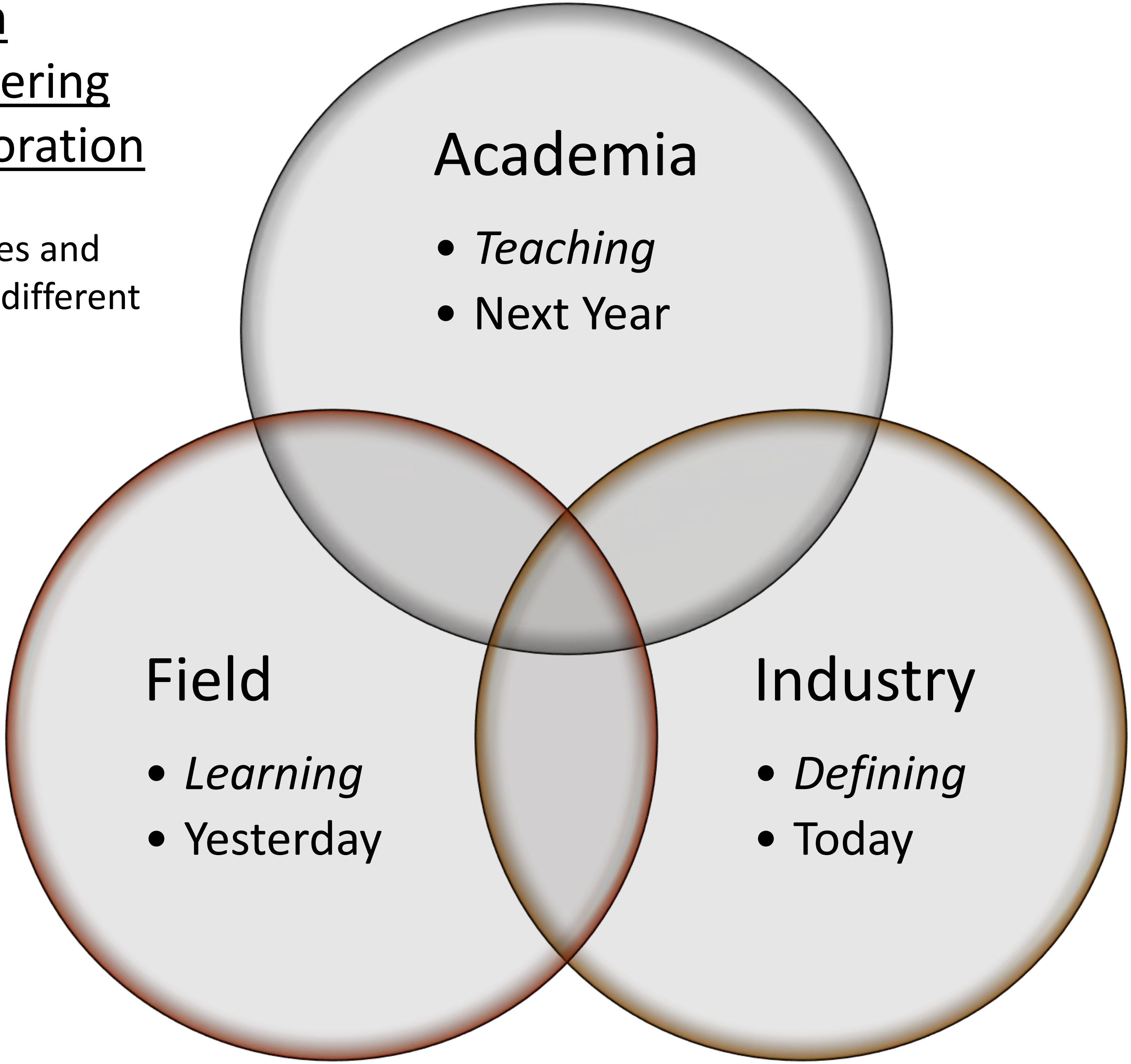
Opportunity to shape policy exists through government (state/fed) & industry collaboration

How it is done

1. Initiatives
2. Funding
3. Policy
4. Field engagement
5. Curricula

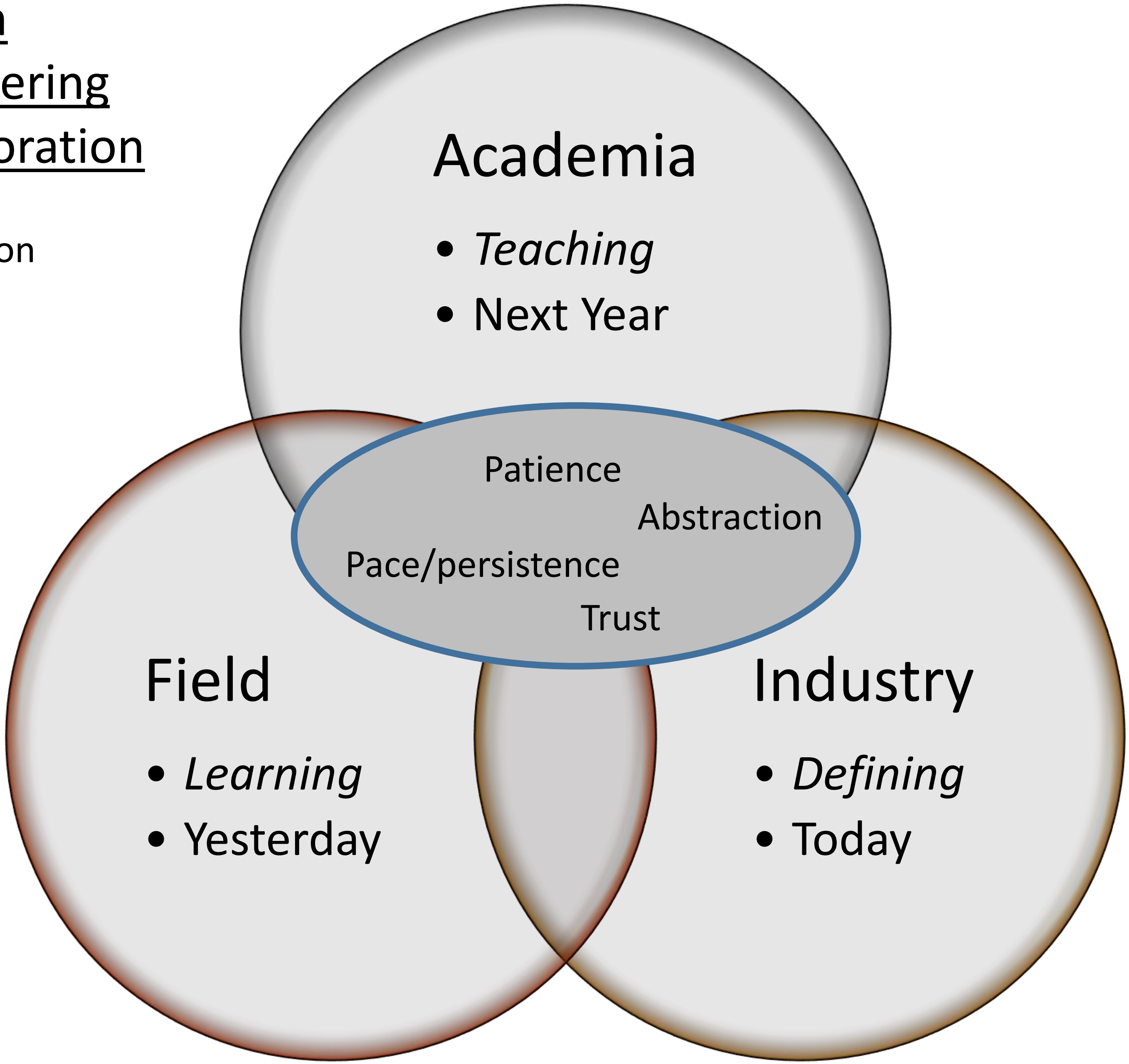
System Engineering Collaboration

Timescales and focus on different outcome



System
Engineering
Collaboration

Lubrication



Living Laboratories

<u>Student Resources Building:</u>
44% hot water reduction
16.5% total building energy savings
Occupant outreach on operations

<u>Student Health:</u>
$75K saved in equipment replacement
$36K savings/year in operation
Comfort complaints are gone

<u>Pollack Theater:</u>
Model-based control tuning
20F oscillations mitigated
Better occupant comfort

<u>Engineering Sciences Building:</u>
Clean room operation assessed
Natural ventilation control strategies

Living Laboratories

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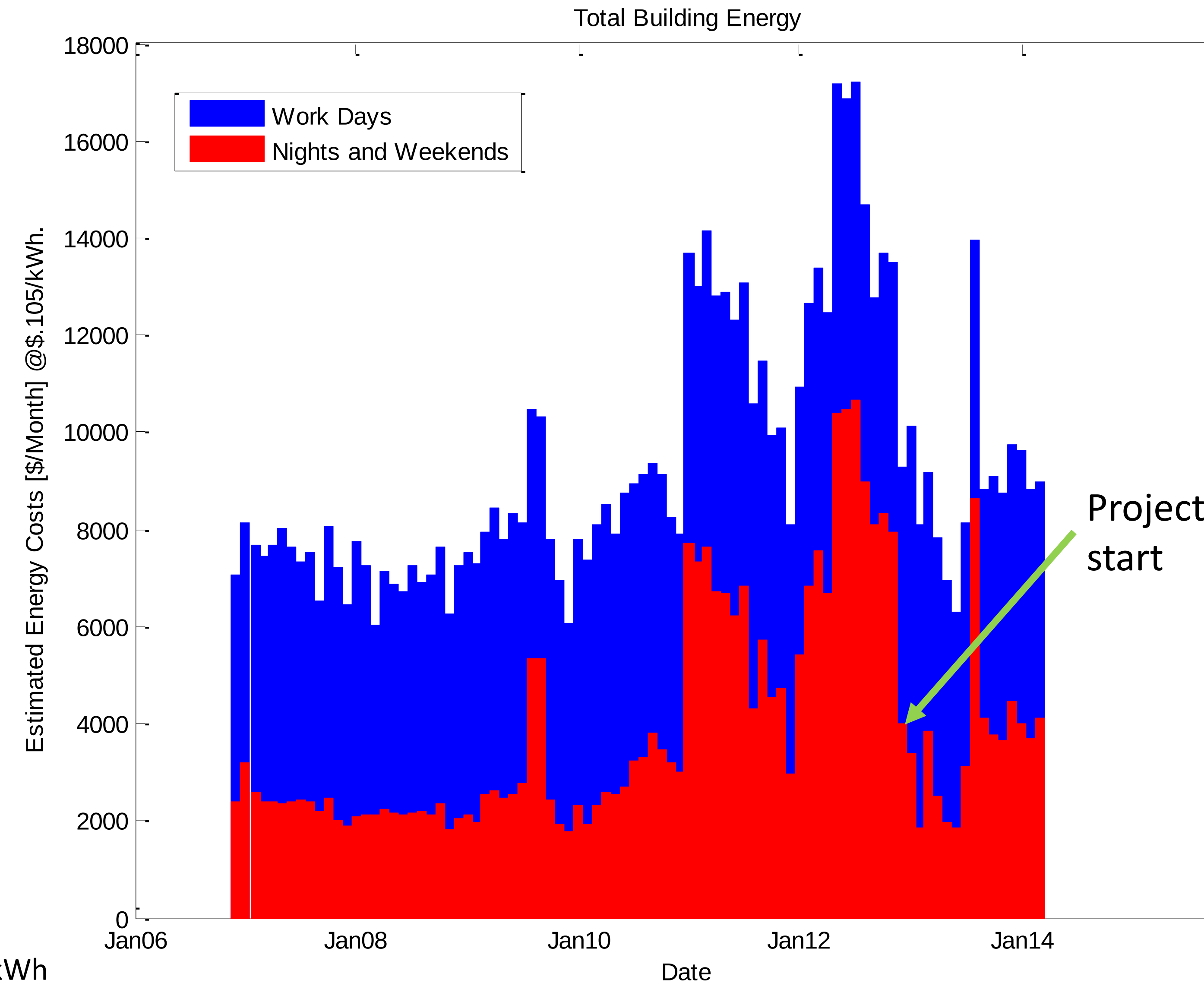
Energy Costs

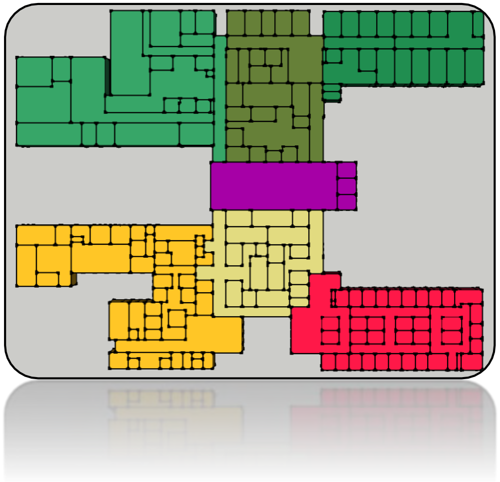


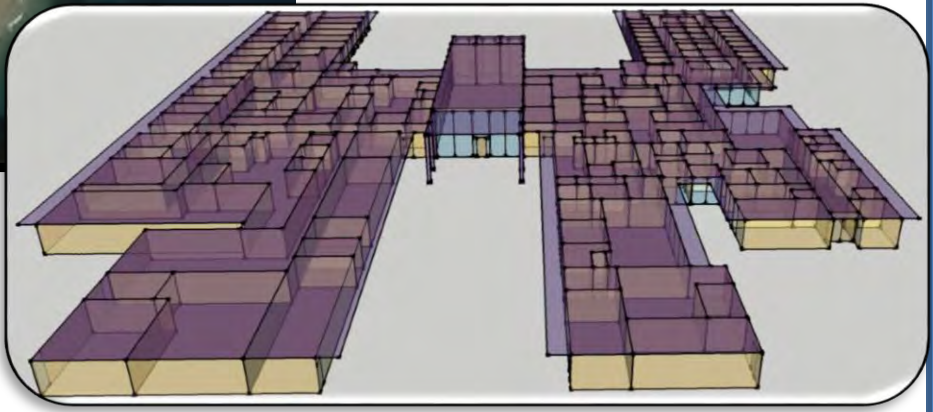
$0.105/kWh
$0.7/therm

UCSB Student Health Center

38K ft^2 (3500 m^2) Outpatient facility built in the early 1970’s

Building location and climate





Initial Conditions

Energy

Of *Student Affairs* buildings, the student health building had the largest consumption per square foot

Boiler systems were not delivering enough capacity, new boiler slated to be purchased

Comfort

Medication inside an indoor refrigerator had to be thrown away at times because of high temperatures

Many space heaters used, general complaints about poor temperature regulation

Operations

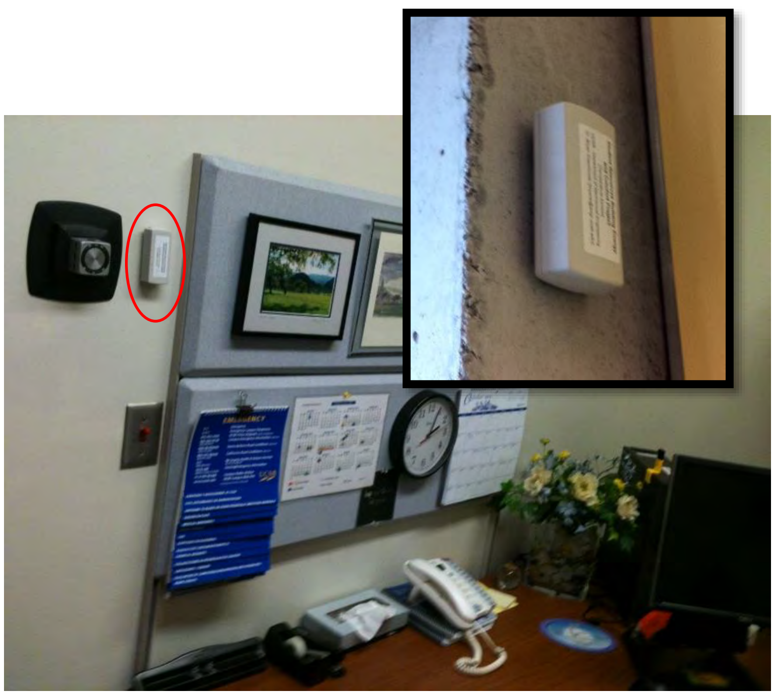
The building 'can not be turned off'. Turning the HVAC system down at night would result in discomfort up until mid-day the next day. It is unoccupied 19:00-07:00.

Lack of Data

Because of age, there were no comfort measurements (pneumatic systems)

Primary systems are sensed but not saved

82 Wireless temperatures added to gather comfort data from the building



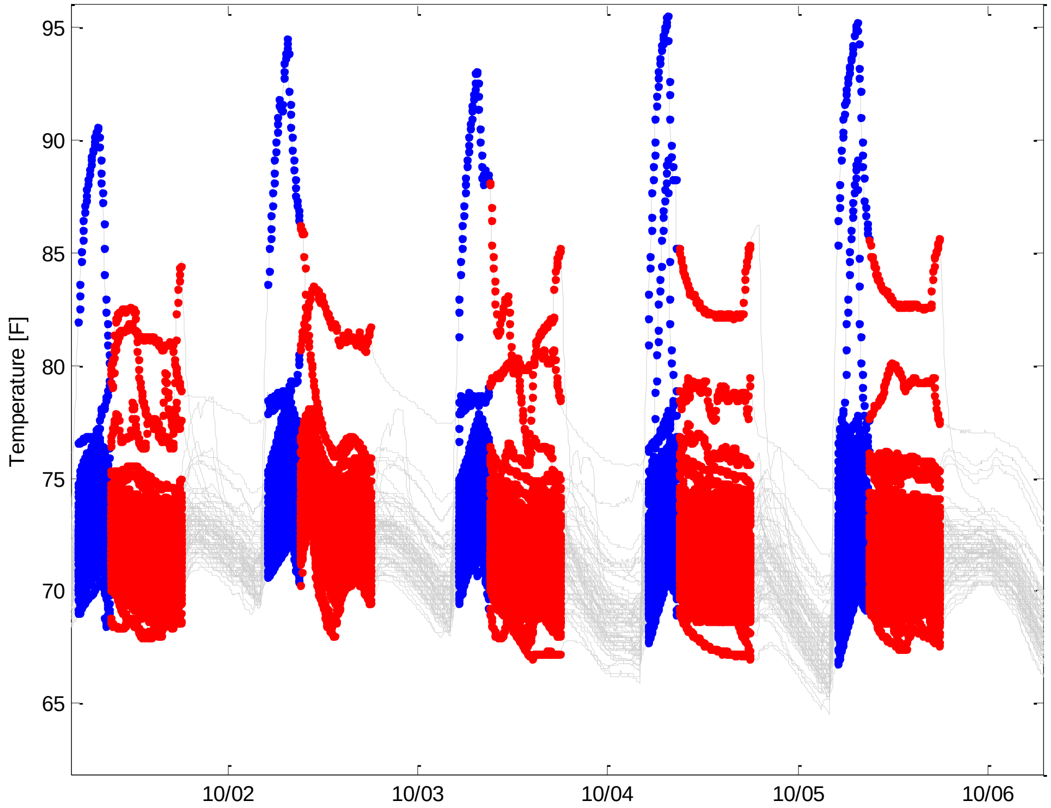
Black: no sensor added

Wireless Data

Wireless data confirms issues with comfort management

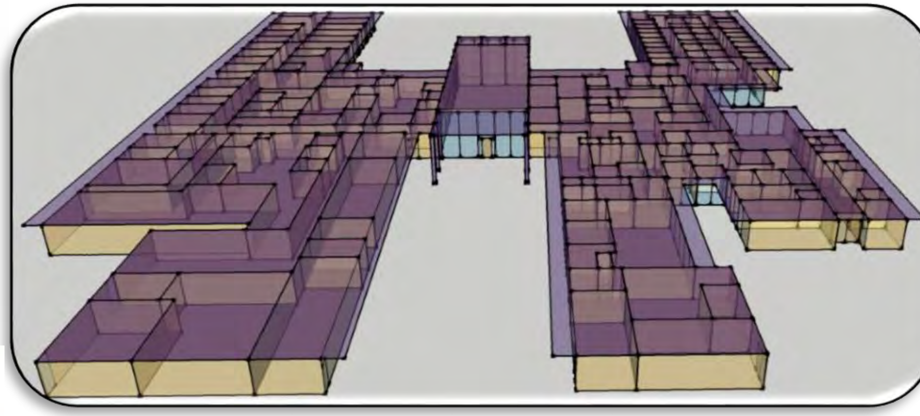
82 wireless temperatures sensors

~5days data

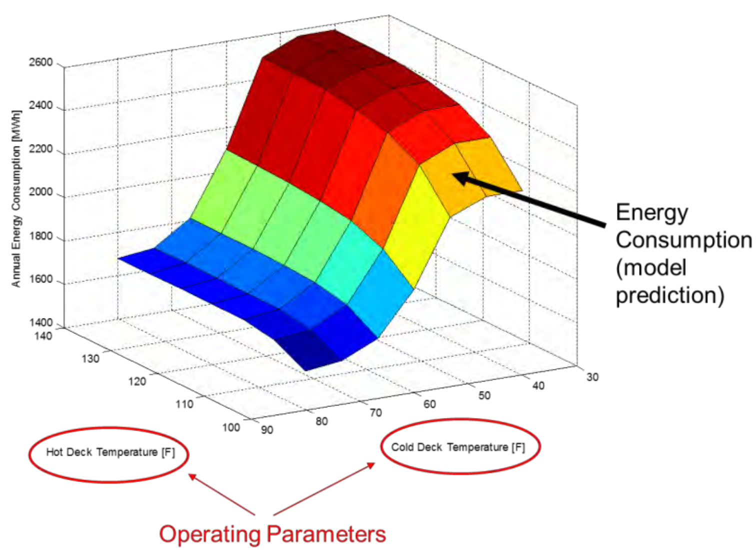


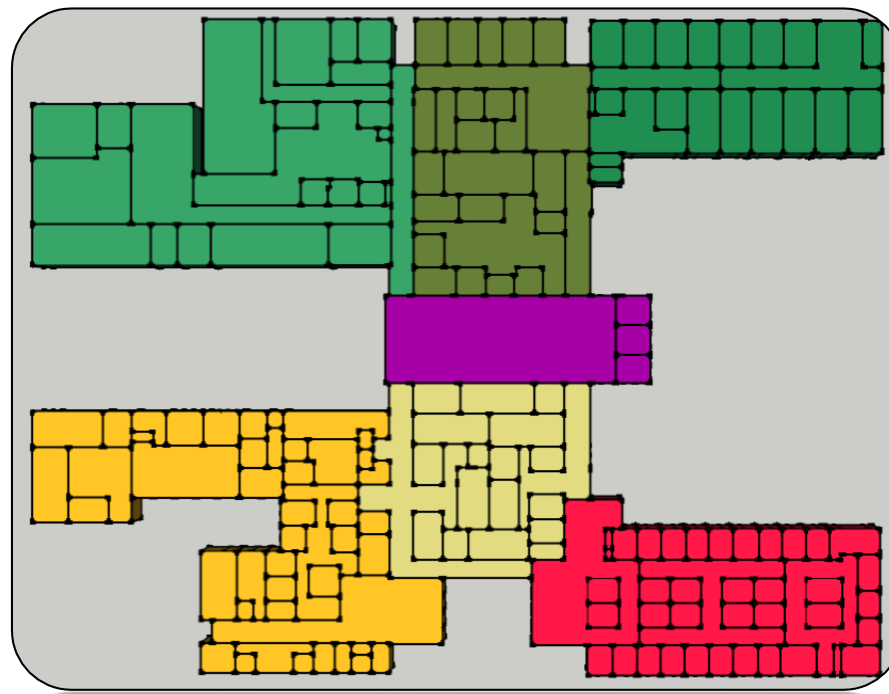
Blue = 05:00-09:00
Red = 09:00 – 17:00 M-F

Modeling



Modeled by
'untrained' experts

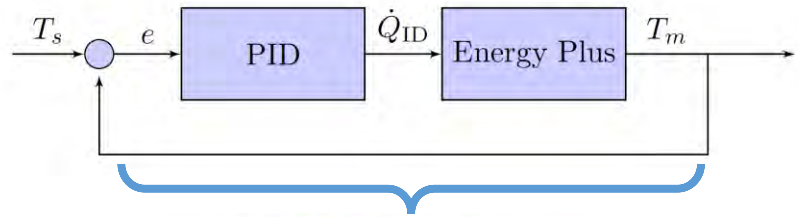


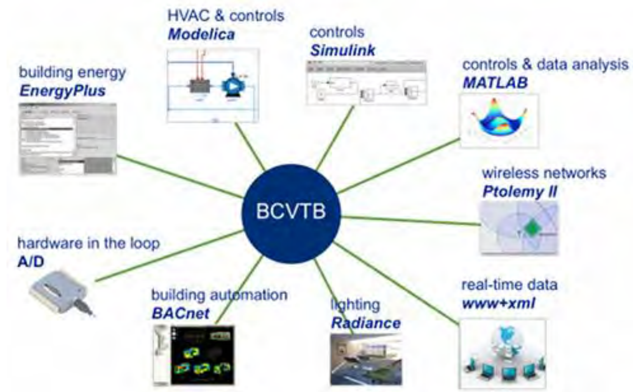


Model Assimilation

85 wireless sensors

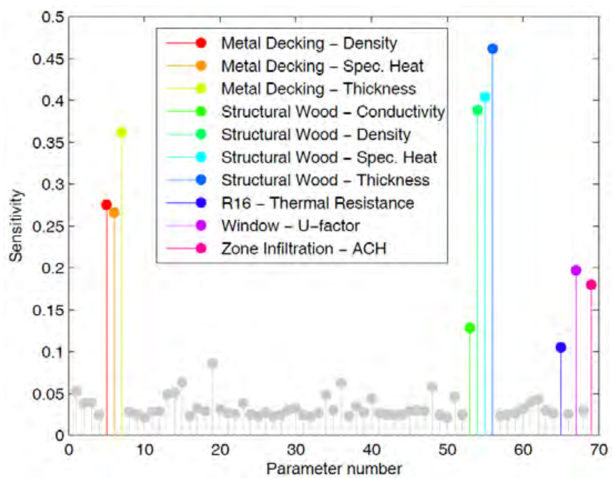
85 model zones

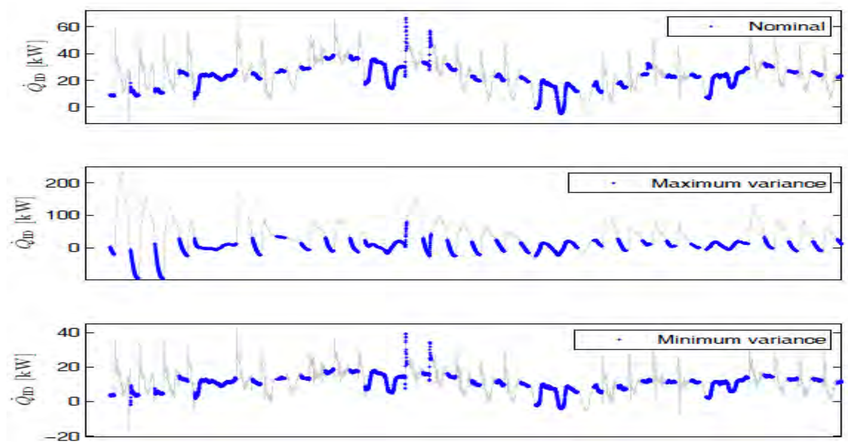




Rigorous model tuning

- Co-simulation
- Uncertainty / sensitivity
- Stochastic

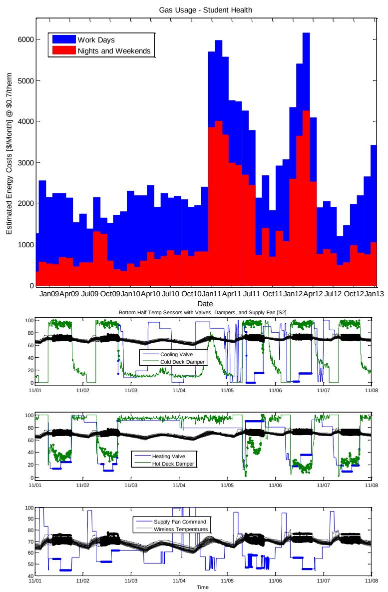


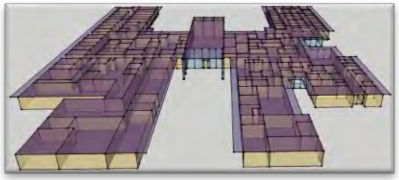


[Bhamornsiri & Eisenhower, 2013]

Results

New Data





Diverse Team

Diagnostics / Solution

1. R&R Boilers, increase energy efficiency saving the need to replace / upgrade

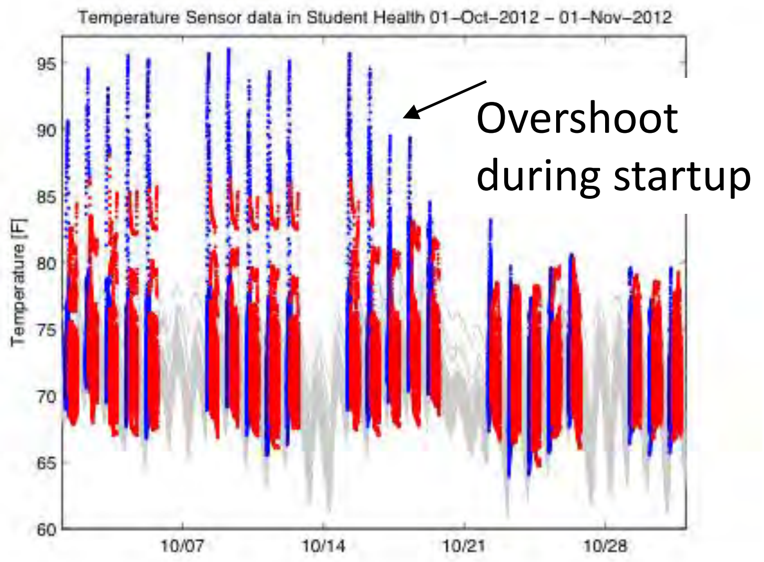
2. Set unoccupied times at night for systems

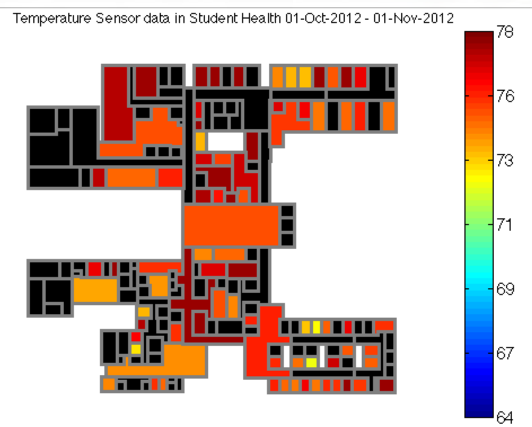
3. Optimize start / stop times

Immediate savings: $50K
Annual savings: $50K
ROI (before project end)

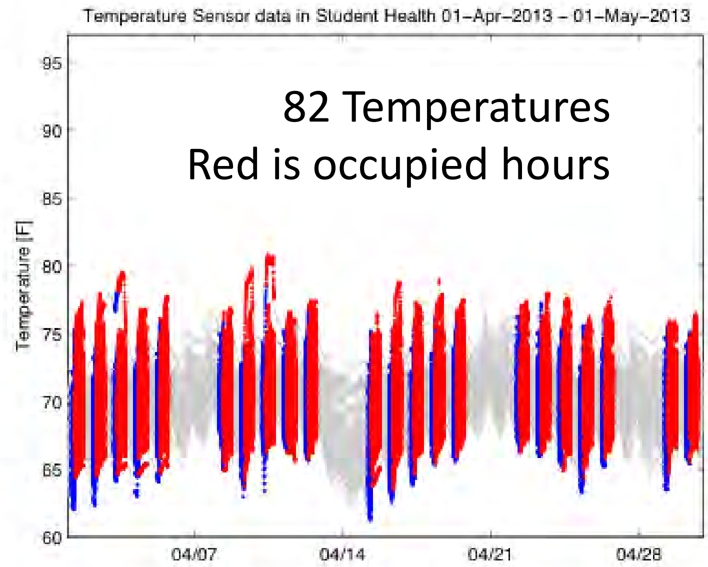
Results

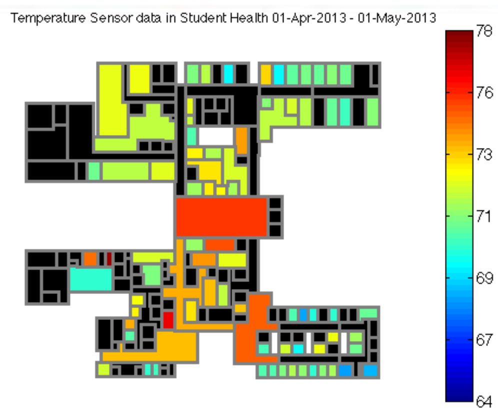
Before





After Re-commissioning





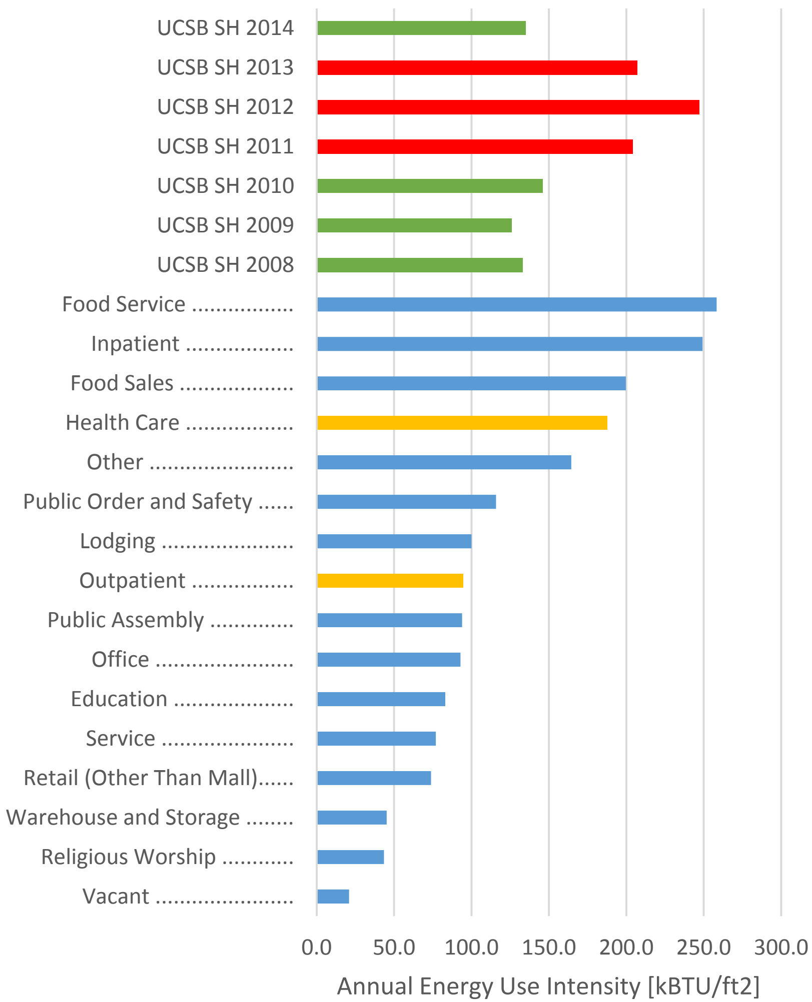
82 wireless sensors measure comfort in various rooms in the building

During October there were periods of extreme overheating because of startup procedures, these are fixed now

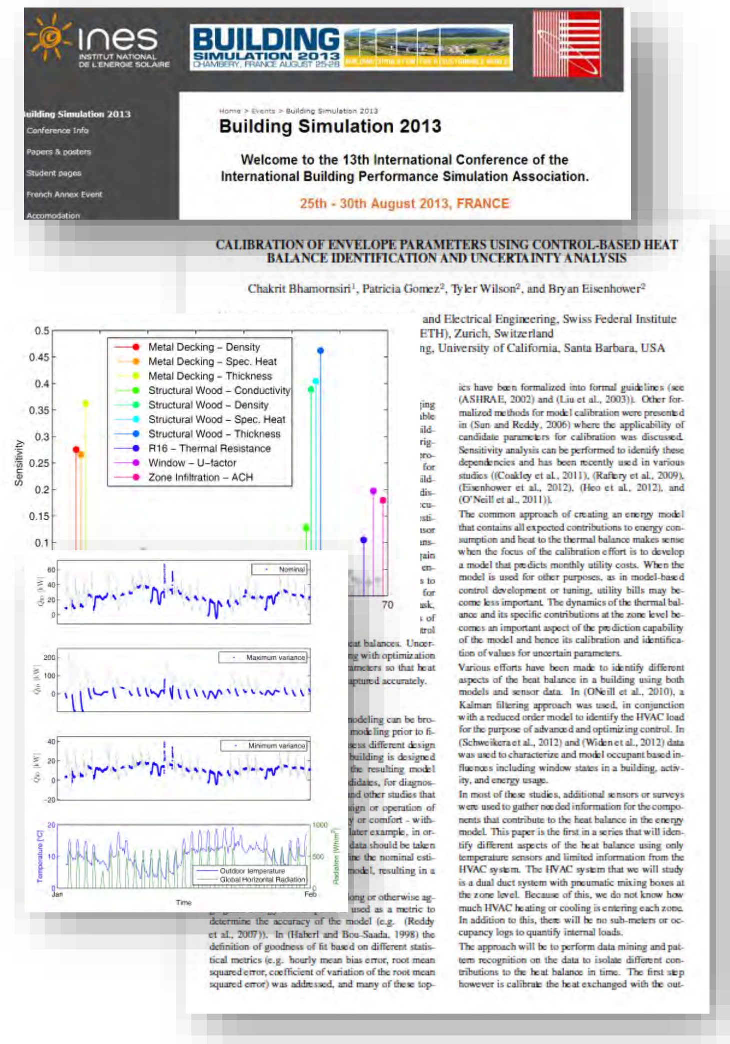
Output

Energy Savings

2003 Commercial Building Energy Consumption Survey
vs. UCSB Student Health



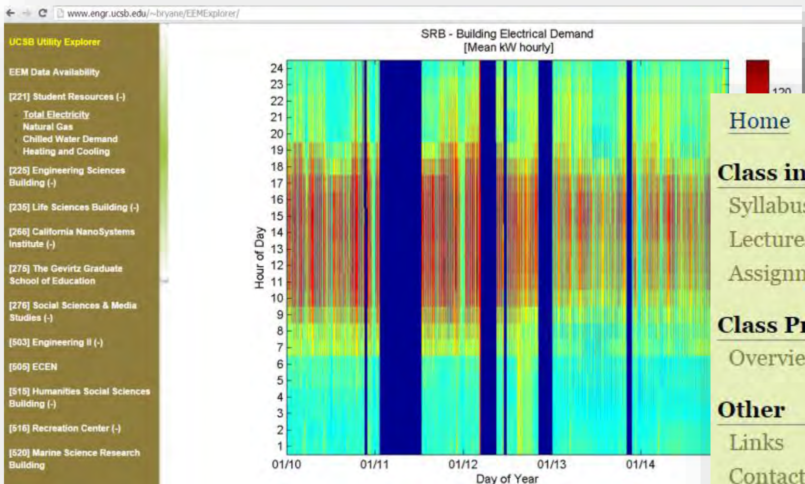
Research



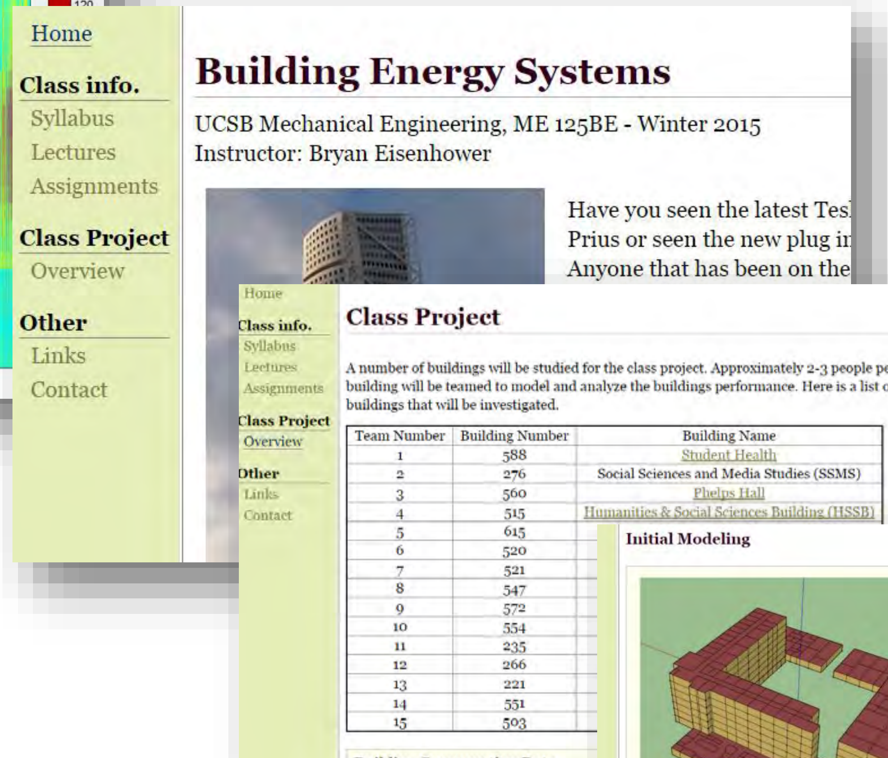
Scaling / Codification

Scaled initiative driven by field collaborators after pilot!

More Data ~ 100 utility pts.



More Buildings (15 at once)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Building Energy Systems

UCSB Mechanical Engineering, ME 125BE - Winter 2015
Instructor: Bryan Eisenhower

Have you seen the latest Tes
Prius or seen the new plug in
Anyone that has been on the

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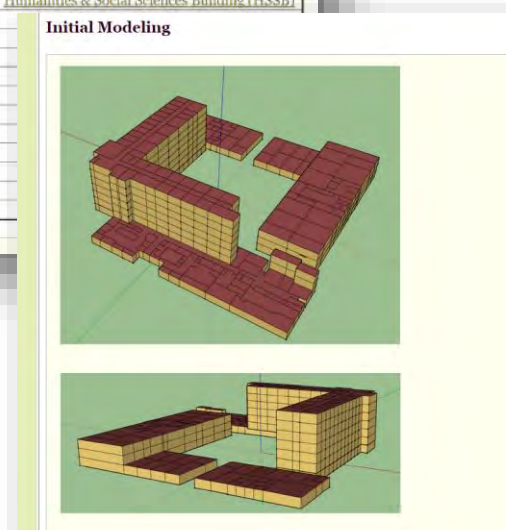
Class Project

A number of buildings will be studied for the class project. Approximately 2-3 people per building will be teamed to model and analyze the buildings performance. Here is a list of buildings that will be investigated.

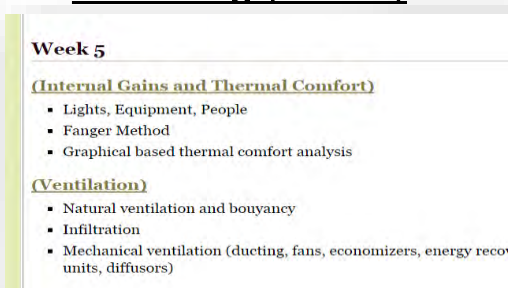
Team Number	Building Number	Building Name
1	588	Student Health
2	276	Social Sciences and Media Studies (SSMS)
3	560	Phelps Hall
4	515	Humanities & Social Sciences Building (HSSB)
5	615	
6	520	
7	521	
8	547	
9	572	
10	554	
11	235	
12	266	
13	221	
14	551	
15	503	

Building Consumption Data



More People (~40)

Archiving (Notes)


Week 5

(Internal Gains and Thermal Comfort)

- Lights, Equipment, People
- Fanger Method
- Graphical based thermal comfort analysis

(Ventilation)

- Natural ventilation and bouyancy
- Infiltration
- Mechanical ventilation (ducting, fans, economizers, energy recov units, diffusors)

Summary

- ❑ Systems engineering is supported by many initiatives / funding agencies

- ❑ Academic research can have a greater influence if integrated with policy decisions

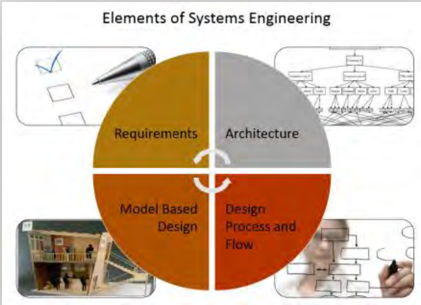
- ❑ Collaboration with field / industry takes patience and trust

Open Opportunities

- Highlight systems engineering needs -> more funding in this area
- Challenges in system engineering could be illustrated better to policy makers
- Closer collaboration within universities and local municipalities on projects and curricula

Summary Messages:

Model-based Design (MBD)
"Addressing design with computation"



- Time domain simulations rarely lead to design evolution
- More can be done with time domain simulations (wrappers)
- Dynamics matter!
- Continuity needed when modeling at different stages / fidelity
- Models need be appropriate for the intended use and user base
- Uncertainty analysis up front and throughout
- Critical parameter management at all levels
- The decomposability of a system cannot be ignored
- New curricula needed that addresses all of this
- …

Funding & Collaborators

Funding: NSF, DOE, AFOSR, ARO, UTC, UTRC, UCSB

Collaborators *(chronological order…)*

Andrzej Banaszuk	UTRC
Clas Jacobson	UTC Systems and Control Engineering
Satish Narayanan	UTC Systems and Control Engineering
Scott Bortoff	Mistsubishi Electric Research Labs
Thordur Runolfsson	Univ. of Oklahoma
Christoph Haugstetter	Hamilton Sundstrand
Karl Astrom	Lund University
Hubertus Tummescheit	Modelon
Tobias Seinel	Carrier Commercial Refrigeration
Yu Chen	Schaeffler Greater China
Lily Zheng	Carrier Asia
Julio Concha	Pragma Securities
Prashant Mehta	UIUC
Prabir Barooah	Florida State
Umesh Vaidya	Iowa State
Pengju Kang	GE Global Research
Michael Wetter	LBNL
Igor Mezic	UCSB
Vladimir Fonoberov	Bruker Nanoscience
Zheng O'neill	University of Alabama
T. Maile, M. Fischer	Stanford
Kevin Otto	MIT & Singapore Uni. of Tech. and Design
P. Gomez, T. Wilson, M. Georgescu	UCSB
Gregor Henze	U. Colorado
Bassam Bamieh	UCSB
Chakrit Bhamornsiri	ETH Zurich
Raktim Bhattacharya	Texas A&M University