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An integrated framework for parametric design using building energy models

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LBL
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the INSTITUTE for ENERGY EFFICIENCY

CENTER for ENERGY EFFICIENT DESIGN

Motivation:

- Comfort & energy models are refined but require a lot of partially certain user input

- The study of building dynamics is needed for efficient and effective controller design

- Buildings produce enormous amounts of data, too much to analyze

Motivation / Topics:

- Comfort & energy models are refined but require a lot of partially certain user input
  - Uncertainty / sensitivity analysis supporting optimization, model calibration, and FMEA.

- The study of building dynamics is needed for efficient and effective controller design
  - System level dynamic modeling for control analysis and Hardware in the Loop studies

- Buildings produce enormous amounts of data, too much to analyze
  - Spectral / modal decomposition of BMS data

Summary

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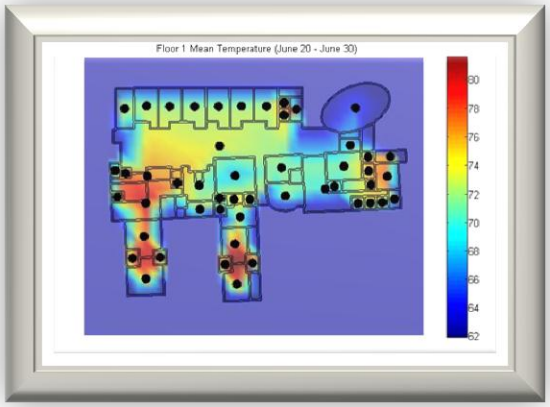
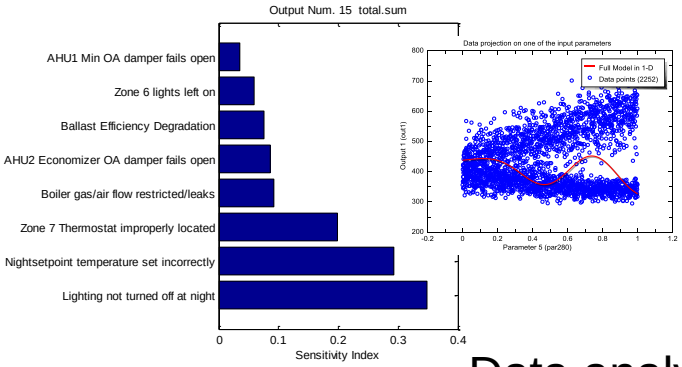
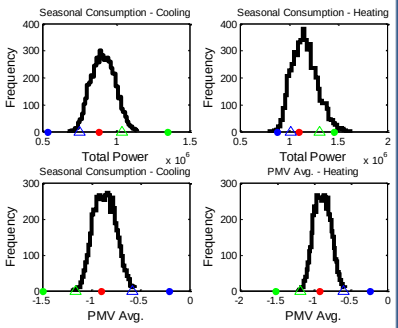
Energy Visualization



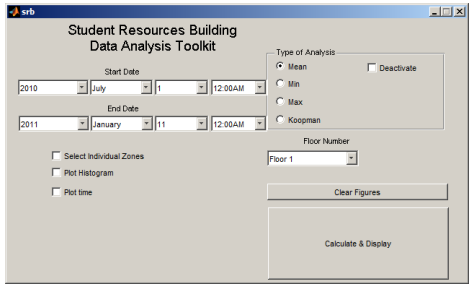
Failure Mode Effect Analysis



Energy/Comfort Optimization

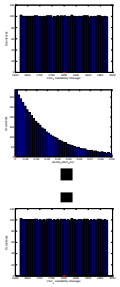


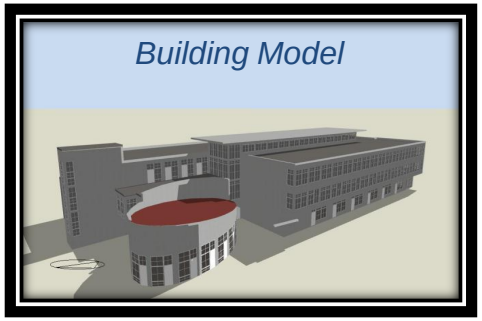
Data analysis toolkits



Uncertainty Analysis

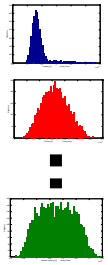
Uncertain Inputs



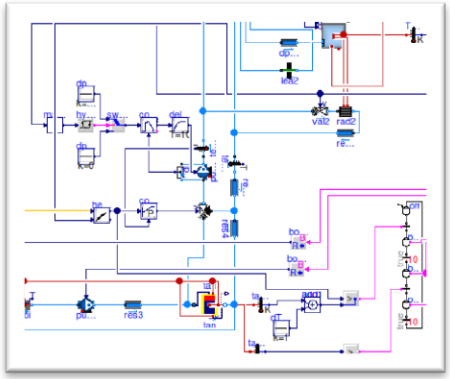


?

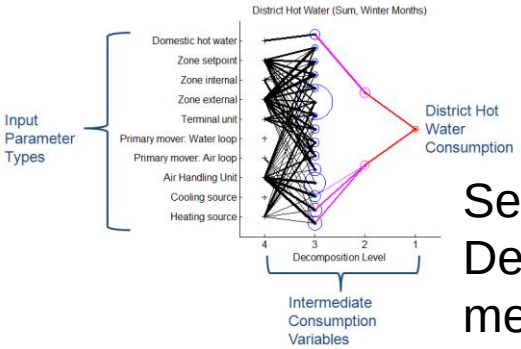
Uncertain Outputs



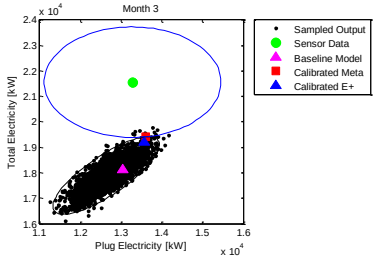
Advanced Energy Modeling



Sensitivity Decomposition methods



Model Calibration



Acknowledgements

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Collaborators:

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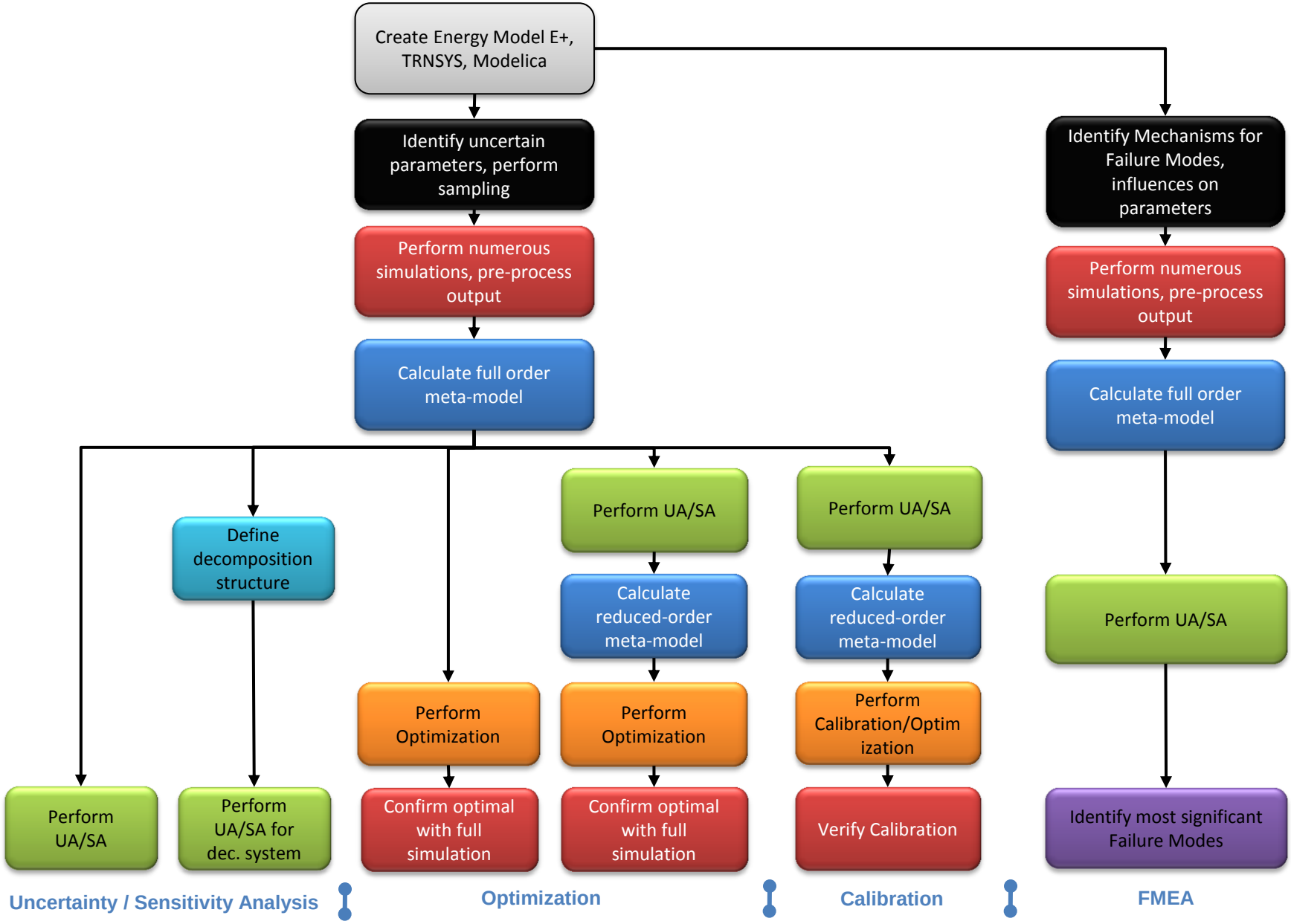
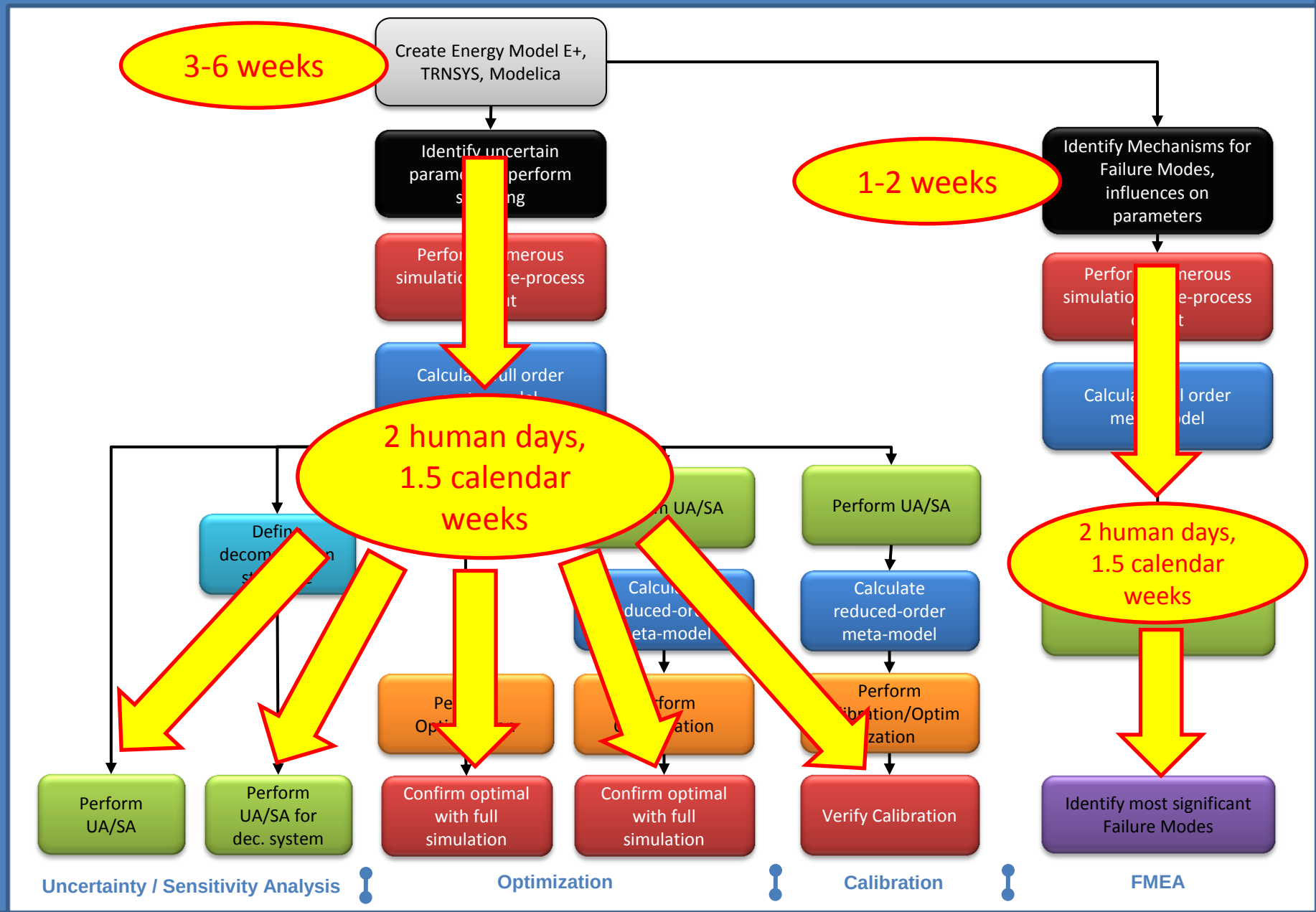
Kevin Otto RSS
Igor Mezic University of California, Santa Barbara
Michael Georgescu, Erika Eskenazi, Valerie Eacret UCSB

Analysis leveraging UA / SA

Flow


Create Energy Model E+, TRNSYS, Modelica
Identify uncertain parameters, perform sampling
Perform numerous simulations, pre-process output
Calculate full order meta-model
Identify Mechanisms for Failure Modes, influences on parameters
Perform numerous simulations, pre-process output
Calculate full order meta-model
Define decomposition structure
Perform UA/SA
Perform UA/SA for dec. system
Perform Optimization
Confirm optimal with full simulation
Perform UA/SA
Calculate reduced-order meta-model
Perform Optimization
Confirm optimal with full simulation
Perform UA/SA
Calculate reduced-order meta-model
Perform Calibration/Optimization
Verify Calibration
Perform UA/SA
Identify most significant Failure Modes
Uncertainty / Sensitivity Analysis
Optimization
Calibration
FMEA

Scalability



Case studies

Case Studies

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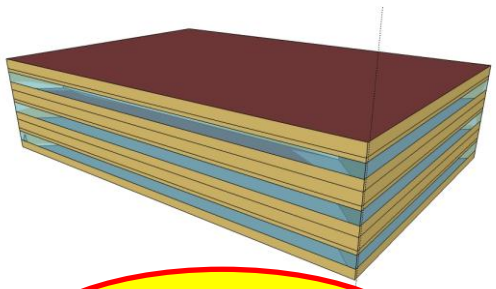
DOE benchmark models

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



5min/simyear on Linux cluster

Building 1225 in Ft. Carson with TRNSYS

30min/simyear on windows server

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

Case Studies

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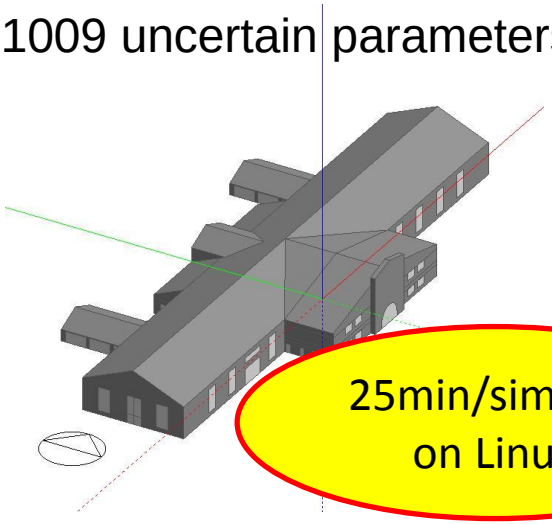
DOD: Atlantic Fleet Drill Hall

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



25min/simyear on Linux

Table 3. Parameter Types.

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

Table 2. Consumption outputs chosen for the analysis.

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

Case Studies

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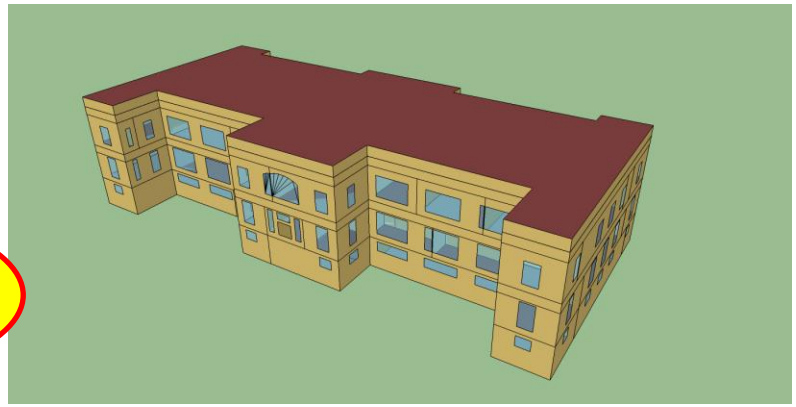
Building 26, Fleet and Family Support Center FFSC/Navy Marine Corps Relief Society NMCRS

- Naval Training Center, Great Lakes, IL
- Two-storey office building with basement.
- The gross area of this building is approximately 37,000 ft^2
- Two airside systems and two separated waterside systems
- The office and administrative area on the first and second floors is served by two variable-air volume VAV Air Handling Units, AHU with VAV terminal unit with hot water reheat heating and cooling capability.
- These AHUs have both heating and cooling capability
- The chilled water system consists of one 54.5-ton air-cooled rotary-screw type chillers with fixed-speed primary pumping.
- Heating is supplied from the existing base-wide steam system through a steam-to-water heat exchanger
- The hot water serves unit heaters, VAV box reheating coils, and air handling unit heating coils.
- The communication service room is served by one dedicated split system.
- Electric unit heater and baseboard are used to provide heating to stairwells and restrooms.

- Modeled in: EnergyPlus v6.0
- 1 year sim ~30 Min on 2.8GHz processor

30min/simyear
on Linux



Energy Modeling & Uncertainty

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- Discrepancy is often introduced because of uncertainty
  - Commissioning / Operation
  - Material selection
  - Usage
  - … Other unknowns

Energy Modeling & Uncertainty

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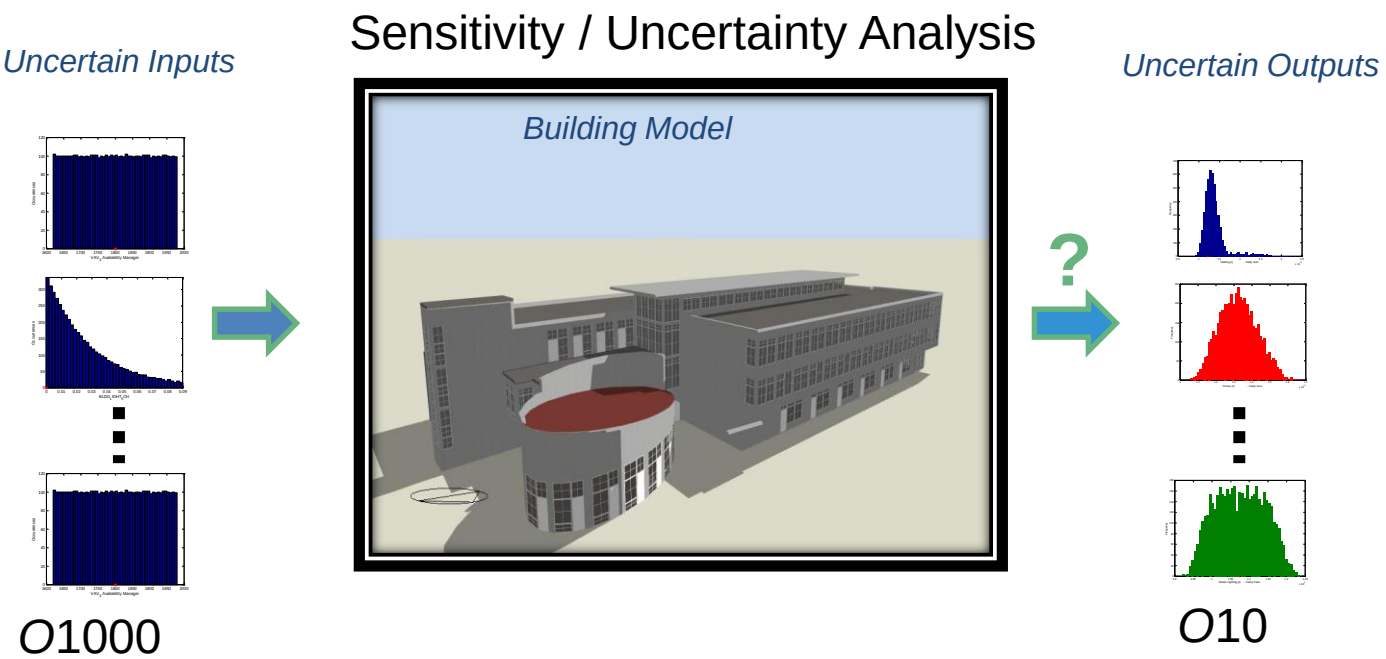
- Discrepancy is often introduced because of uncertainty
  - Commissioning / Operation
  - Material selection
  - Usage
  - … Other unknowns
- Sensitivity / Uncertainty Analysis helps manage these concerns



Energy Modeling & Uncertainty

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Sampling

- O.A.T.
- Monte Carlo
- Latin Hypercube
- Quasi-Monte Carlo deterministic
- All parameters at once

Uncertainty Analysis

- STD, VAR
- COV
- Amplification factors

Sensitivity Analysis

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

Disclaimer:
The methods here are what is historically done in building systems, and what we have applied in our work. Other methods exist that are not discussed here poly-chaos, waveform relaxation, etc.

Red: In this talk

UA / SA – Historically Building Sys.

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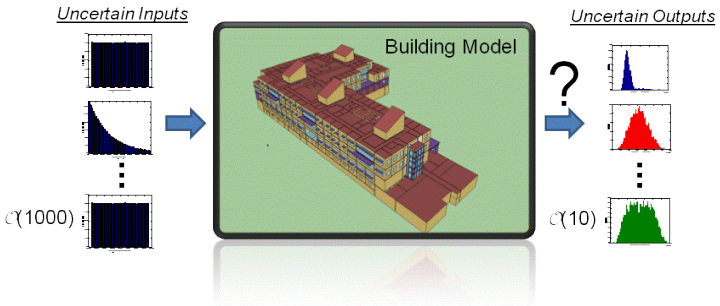
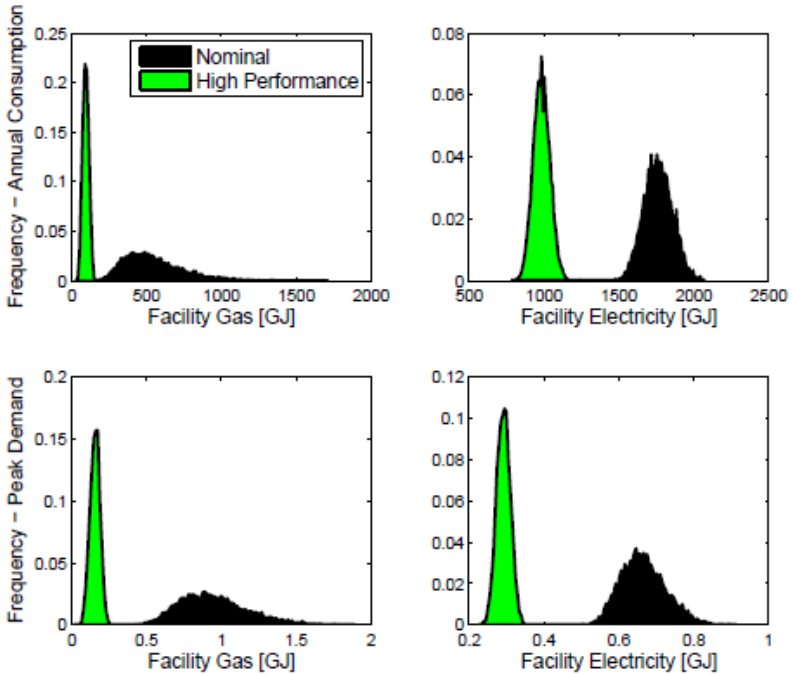
Authors	# Param.	Technique	Notes
Rahni [1997]	390->23	Pre-screening	
Brohus [2009]	57->10	Pre-screening / ANOVA	
Spitler [1989]	5	OAT / local	Residential housing
Struck [2009]	10		
Lomas [1992]	72	Local methods	
Lam [2008]	10	OAT	10 different building types
Firth [2010]	27	Local	Household models
de Wit [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 , to 2000	Deterministic sampling, global derivative sensitivity	'All' available parameters in building

UA / SA Results

Uncertainty analysis investigates the forward influences of parameter variance

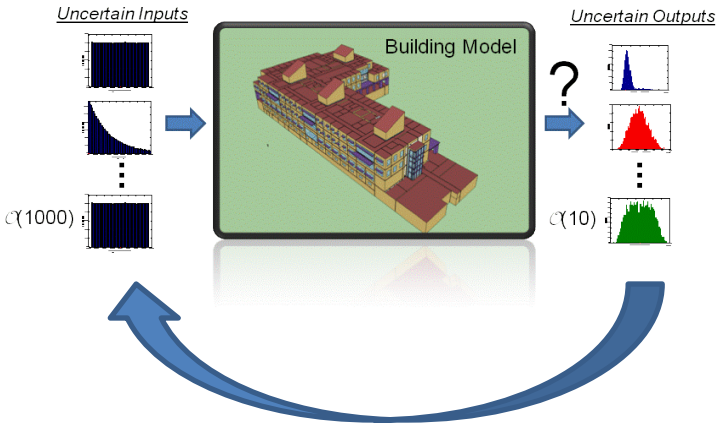


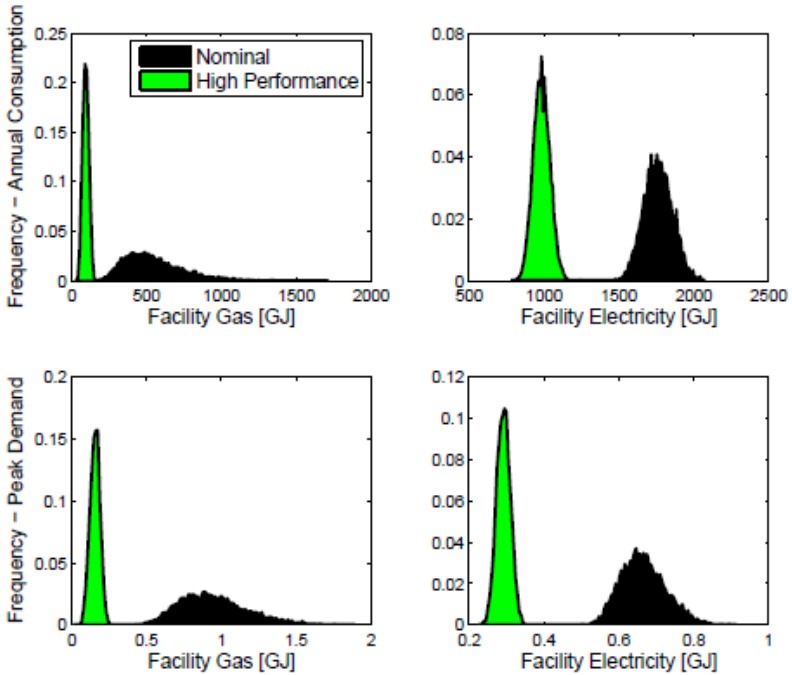


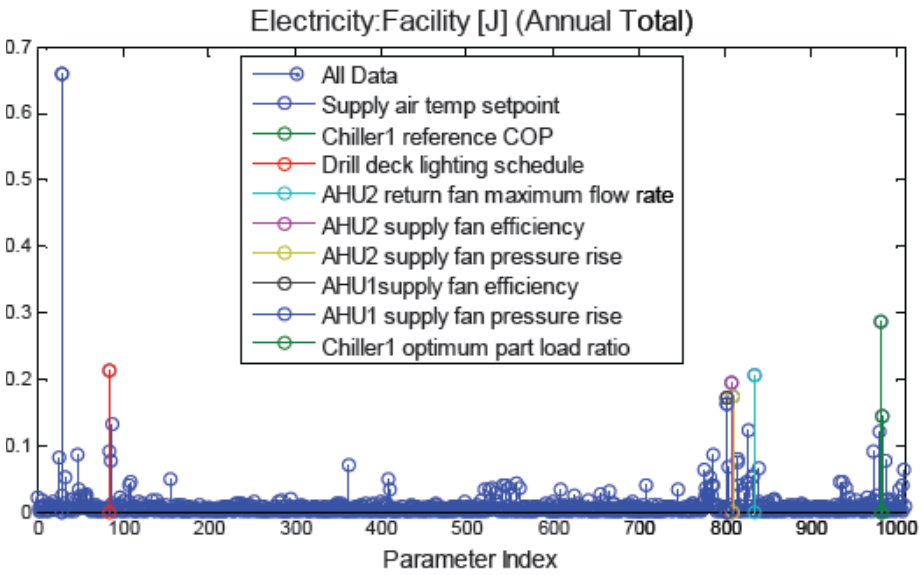
UA / SA Results

Uncertainty analysis investigates the forward influences of parameter variance

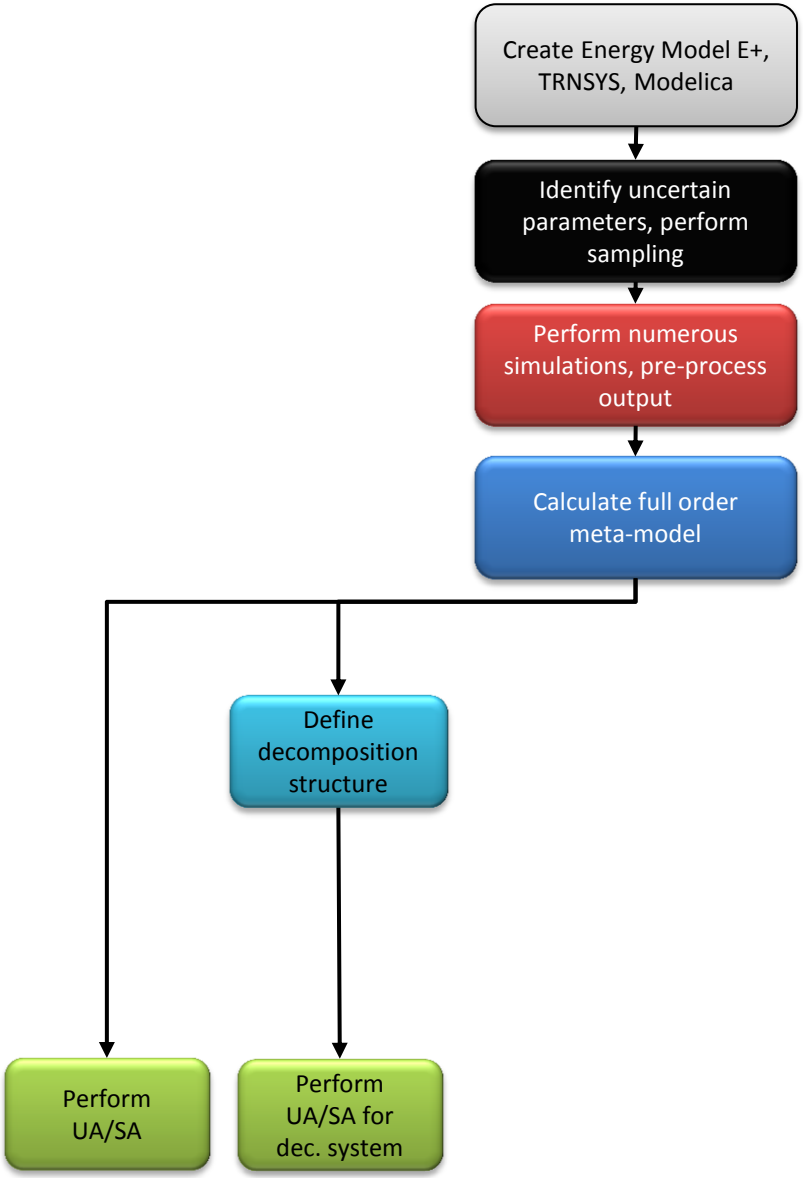
Sensitivity analysis identifies which of the parameters are most influential







Flow



Uncertainty / Sensitivity Analysis

Parameter Variation

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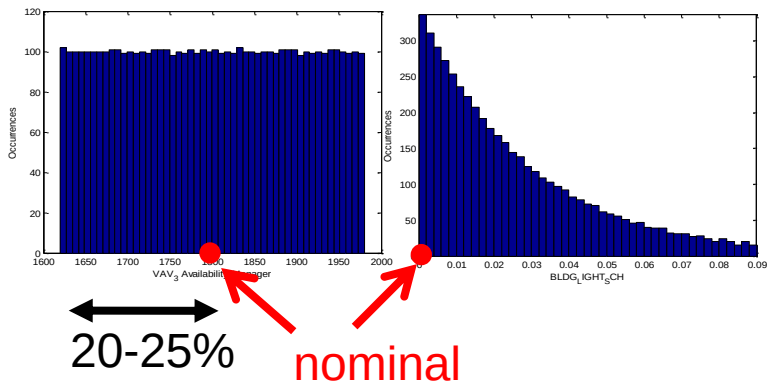
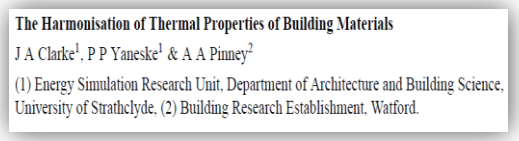
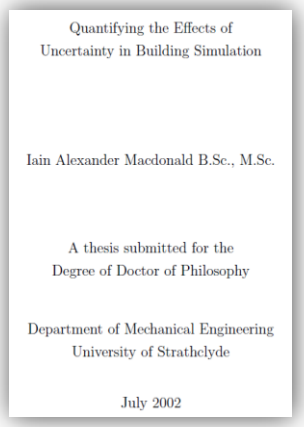
All numerical design & operation scenario (DOS) parameters in the model are varied concurrently (not architectural design)




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

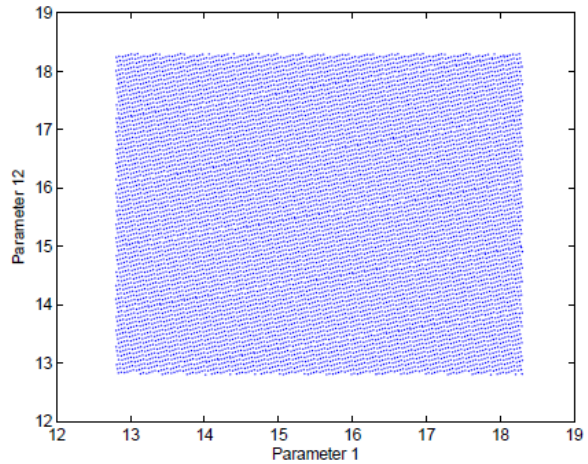
Distribution types are available in literature but not applied because of the large number of parameters

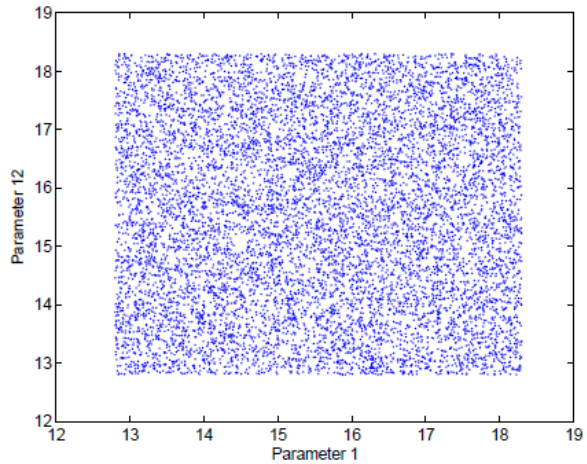
- Parameters varied 20-25% of their mean
- Some parameters are of the form a+b < 1

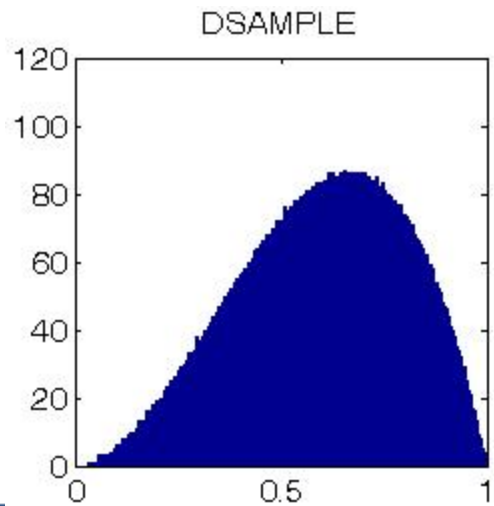
Parameter Type	Examples
Heating source	Furnace, boiler, HWGSHP etc
Cooling source	chiller, CHWGSHP etc
AHU	AHU SAT setpoint, coil parameters etc
Air Loop	Fans
Water Loop	Pumps
Terminal unit	VAV box, chilled beam, radiant heating floor
Zone external	Envelope, outdoor conditions
Zone internal	Usage, internal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

Parameter Variation

- ❑ Large number of parameters and lengthy simulation time require efficient parameter selection for parameter *sweeps*
- ❑ Deterministic sampling provides uniformly ergodic samples

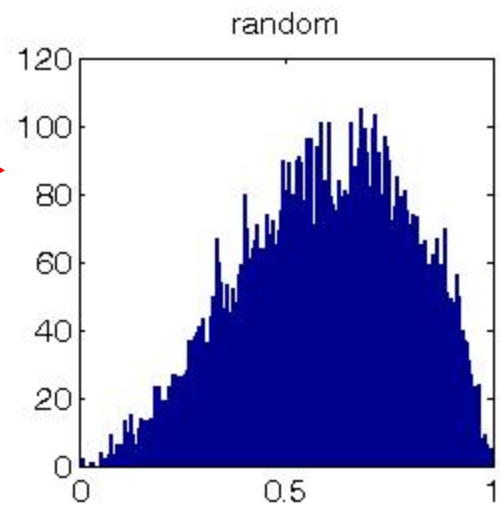






Random →

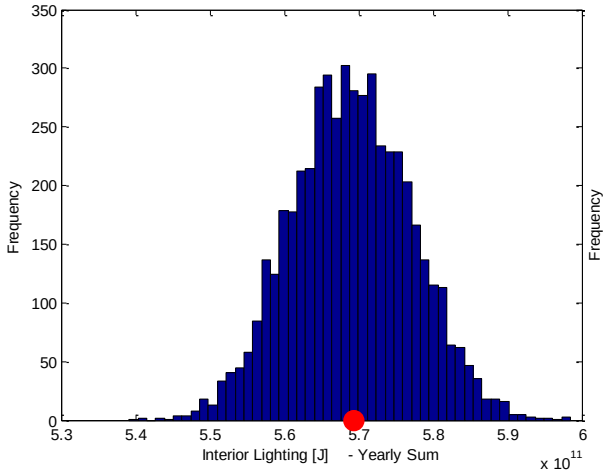
← Deterministic

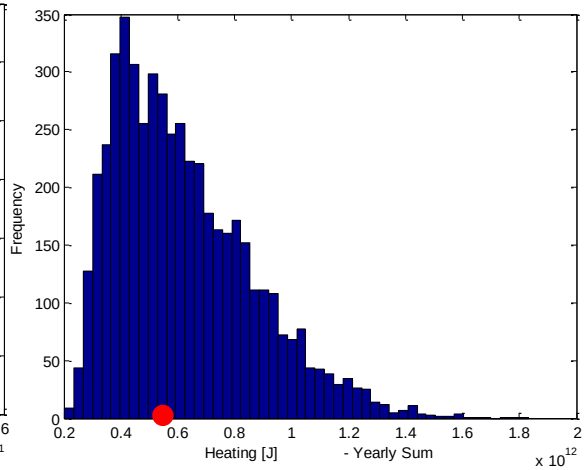


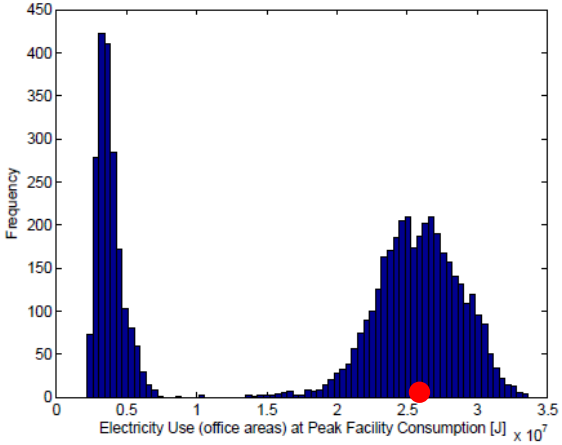
Typical Output Distributions

Facility and Submetered Outputs
+ Gas Facility
+ Electricity Facility
Heating
Cooling
Pump
Fan
Interior Lighting
Interior Equipment

- 5000-6000 realizations performed to obtain convergence
- The 'control' mechanisms in the model drive distributions towards Gaussian although others exist as well







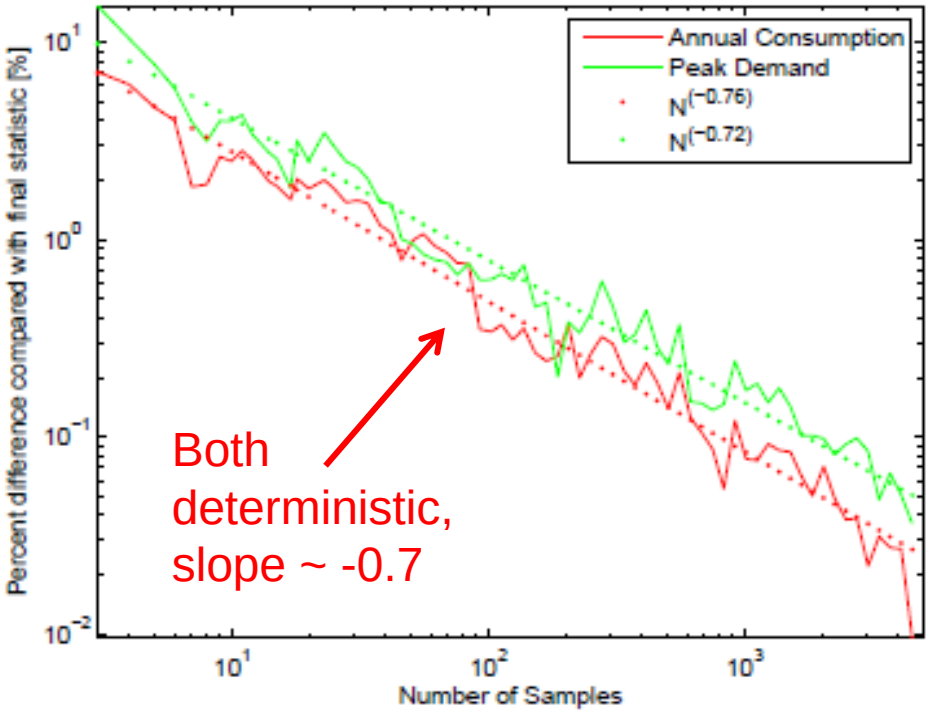
* TRNSYS results

Convergence Properties

- ❑ Monte Carlo bound ~ 1/sqrtN
- ❑ Deterministic bound ~ 1/N

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

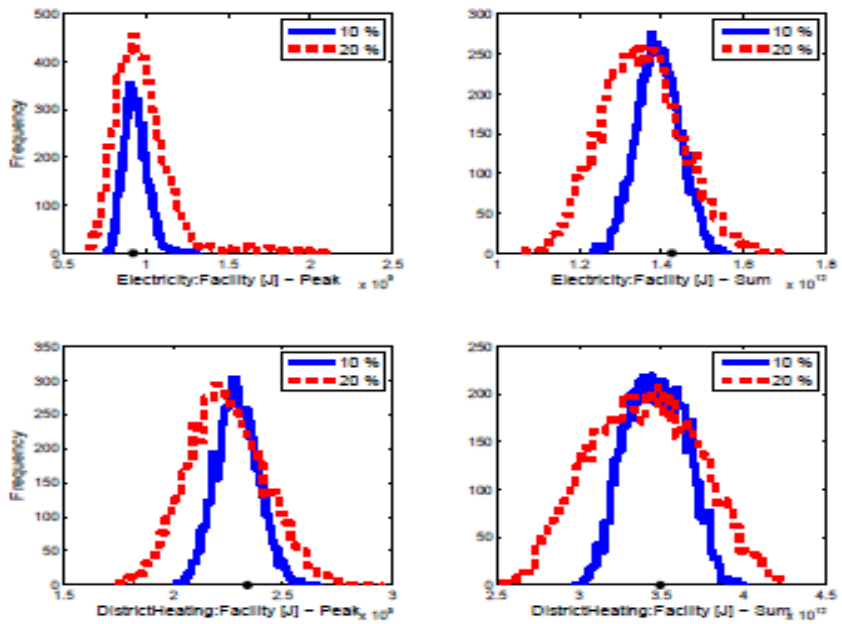
Example Convergence from Building Simulation



Model Results - UA

Characteristics of the output based on *different inputs*

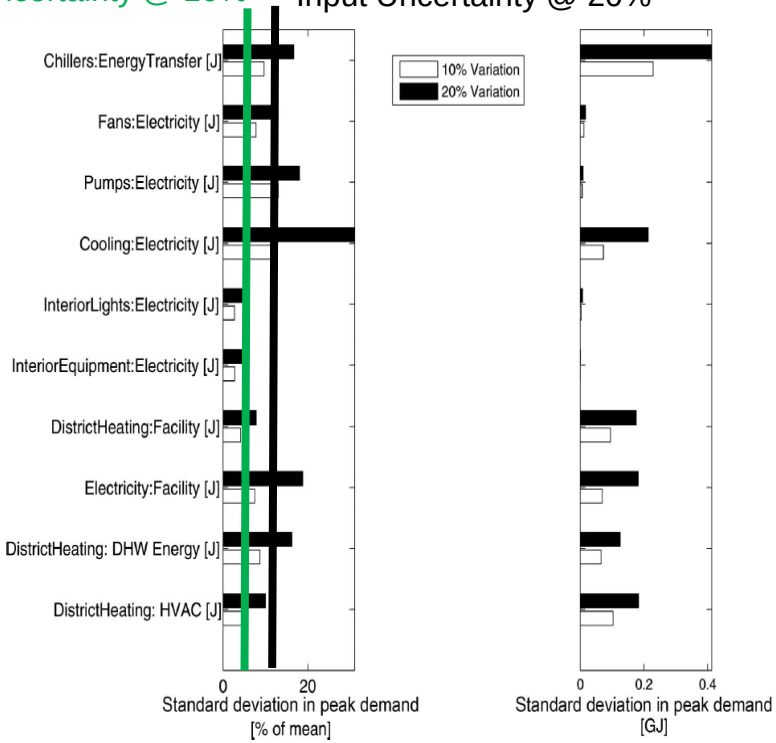
Influence of Different Parameter Variation size



[E+ Drill Hall]

Input Uncertainty @ 10%

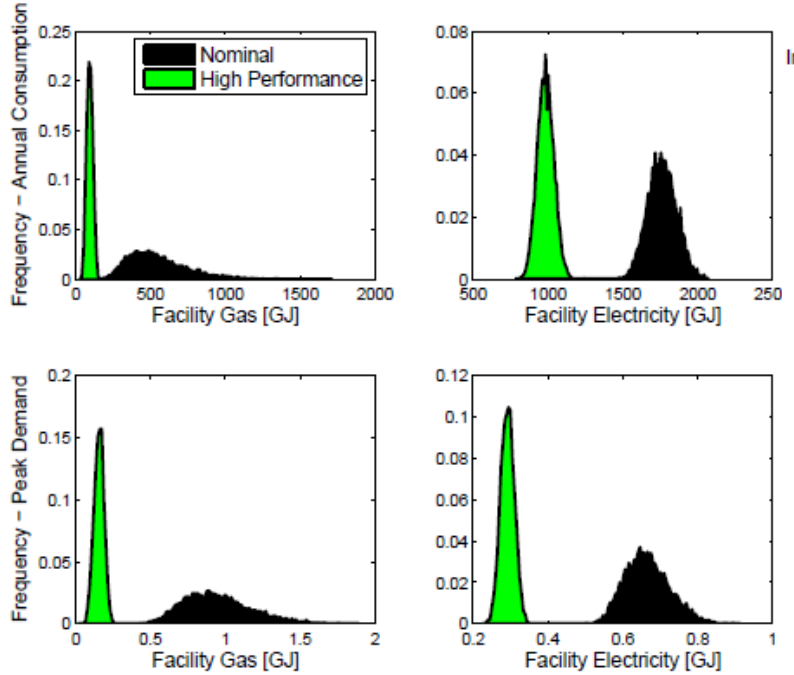
Input Uncertainty @ 20%



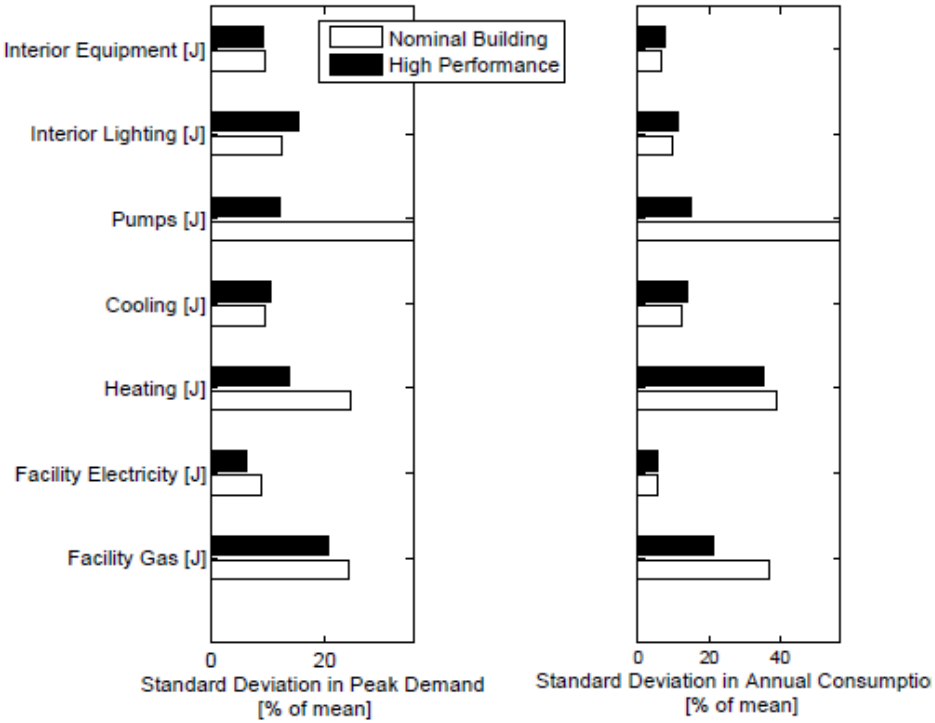
Model Results - UA

Characteristics of the output are considered based *different models*

Nominal vs. High Efficiency Design

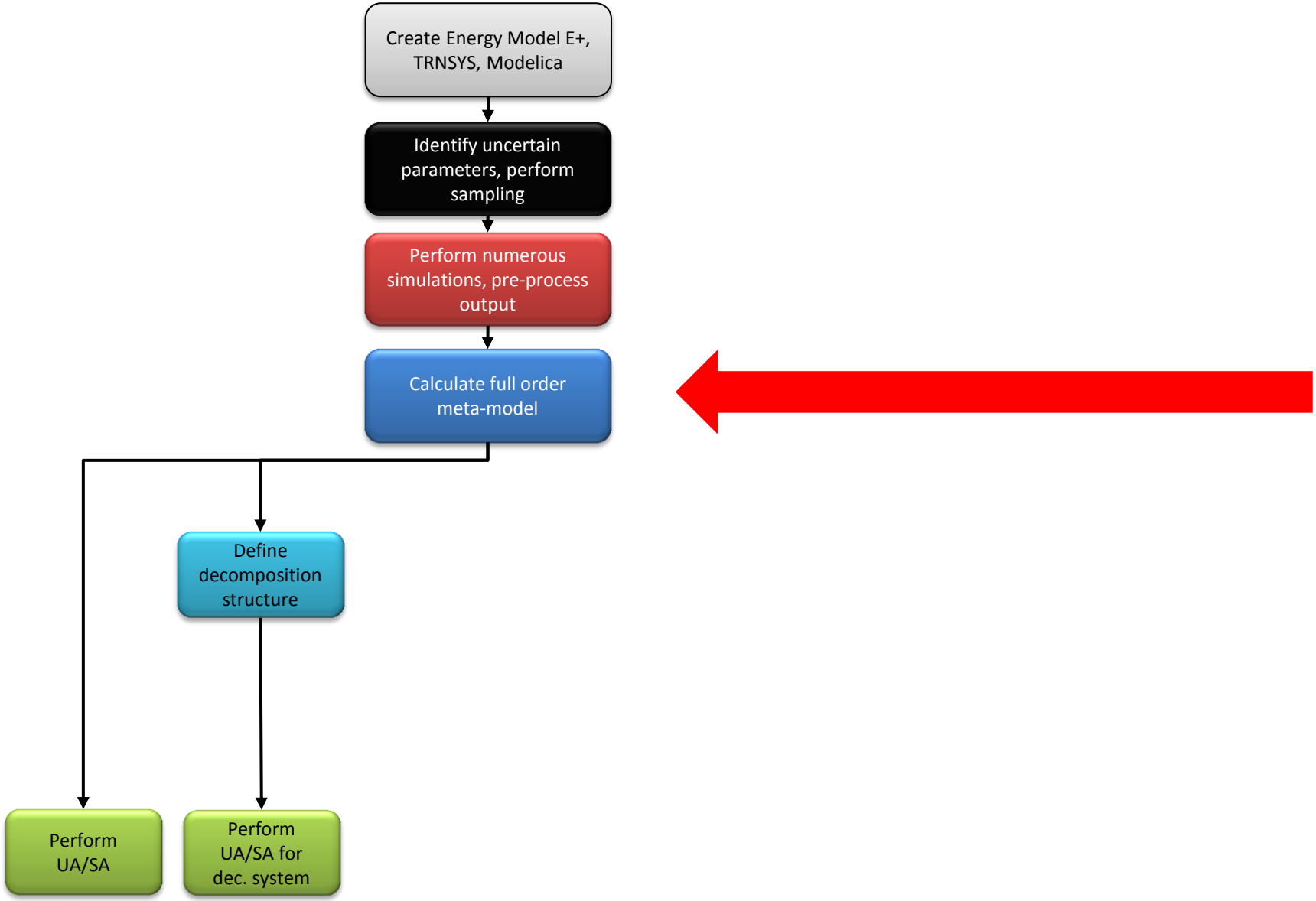


[E+ DOE Models]



B. Eisenhower, et al. A COMPARATIVE STUDY ON UNCERTAINTY PROPAGATION IN HIGH PERFORMANCE BUILDING DESIGN *Accepted: International Building Performance Simulation Association, BuildSim 2011*

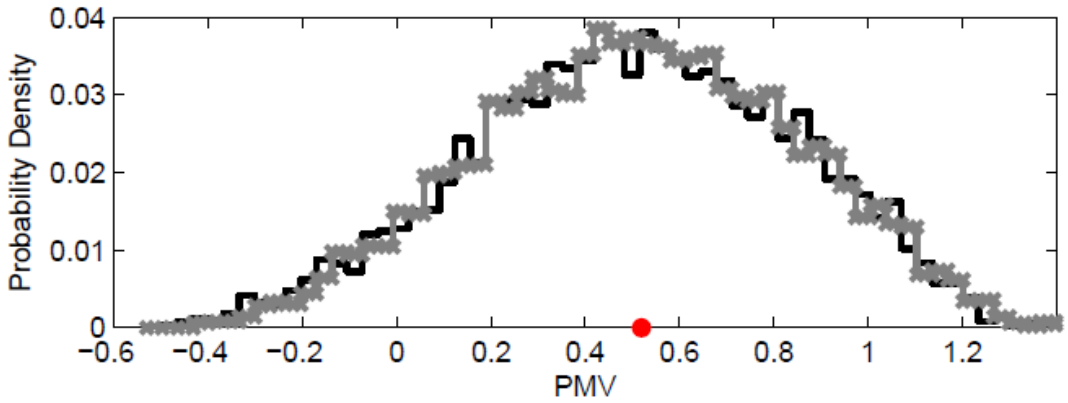
Flow

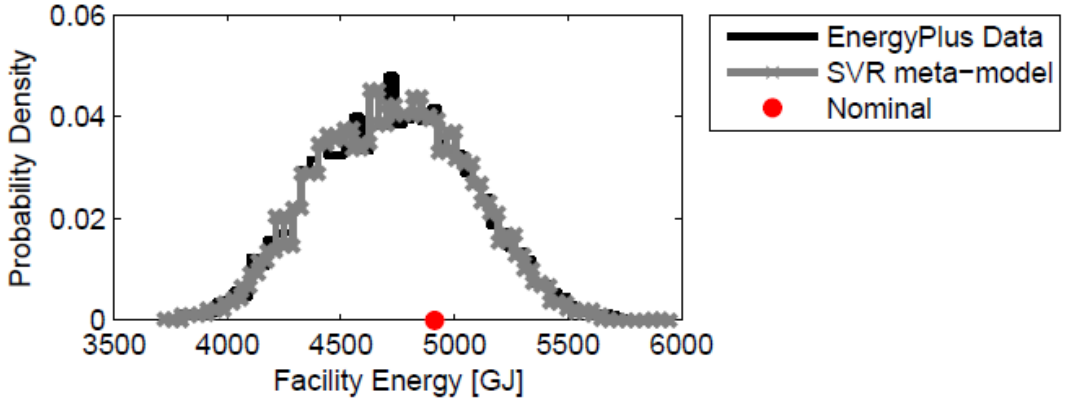


Uncertainty / Sensitivity Analysis

Meta-modeling - Results

- A *model of a model* (meta-model) is created to provide means for analytic assessment of building energy predictions
- Structure of the model is similar to the full order energy model, not a line fit to the data.



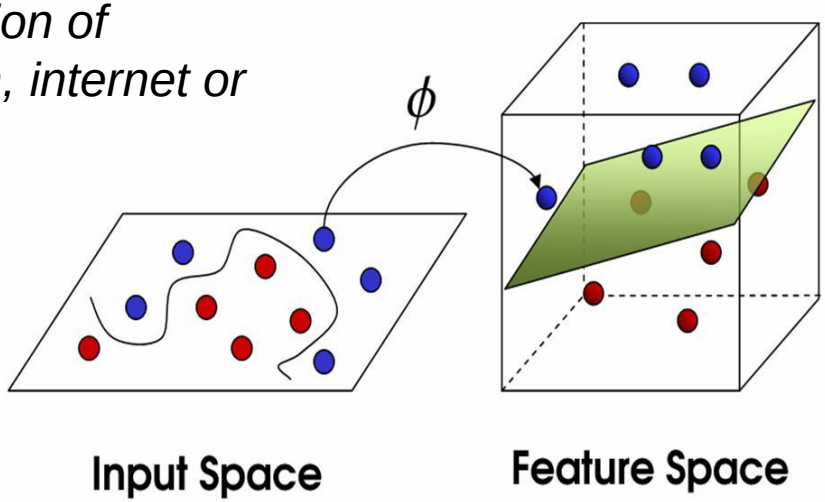


2063 inputs,
2 outputs

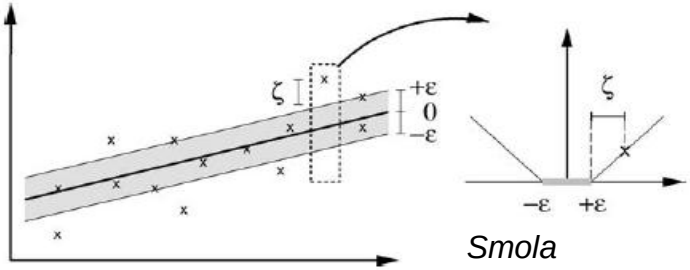
Machine Learning / Regression

- Identify characteristics within data without prior knowledge of the regressors
- Applications: *object detection, classification of biological data, speech or image recognition, internet or database searching…..*
- Soft margin set up to identify outliers….

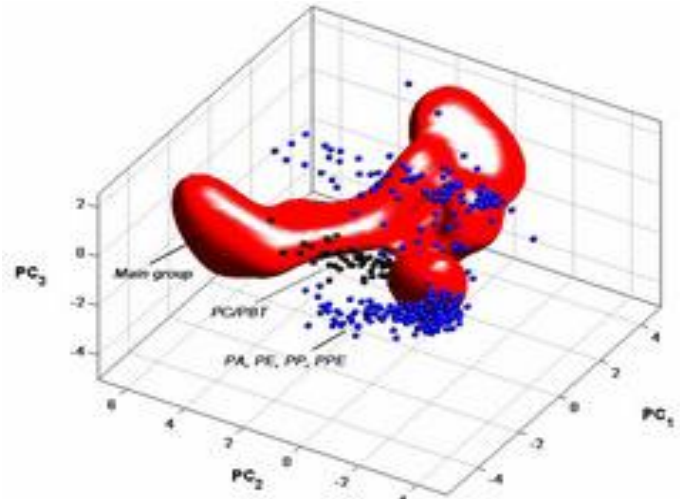
Principle of Support Vector Machines (SVM)



http://www.imtech.res.in/raghava/rbpred/svm.jpg



Smola [2004]



http://www.da-sol.com/en/resources/starter-pages/svm-starter/

Machine learner

Credit: Ben Hider/Getty Images

Machine Learning / Regression

UC SANTA BARBARA engineering

Support vector solution is obtained by solving a convex optimization problem

$$\text{maximize} \quad \begin{cases} -\frac{1}{2}\sum_{i,j=1}^{\ell}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)\langle x_i, x_j\rangle \\ -\varepsilon\sum_{i=1}^{\ell}(\alpha_i + \alpha_i^*) + \sum_{i=1}^{\ell} y_i(\alpha_i - \alpha_i^*) \end{cases}$$

$$\text{subject to} \quad \sum_{i=1}^{\ell}(\alpha_i - \alpha_i^*) = 0 \quad \text{and} \quad \alpha_i, \alpha_i^* \in [0, C]$$

Kernel, e.g.:

$$k(x, x') = e^{-\frac{\|x-x'\|^2}{2\sigma^2}}$$

$$f(x) = \sum_{i=1}^{\ell}(\alpha_i - \alpha_i^*)\langle x_i, x\rangle + b$$

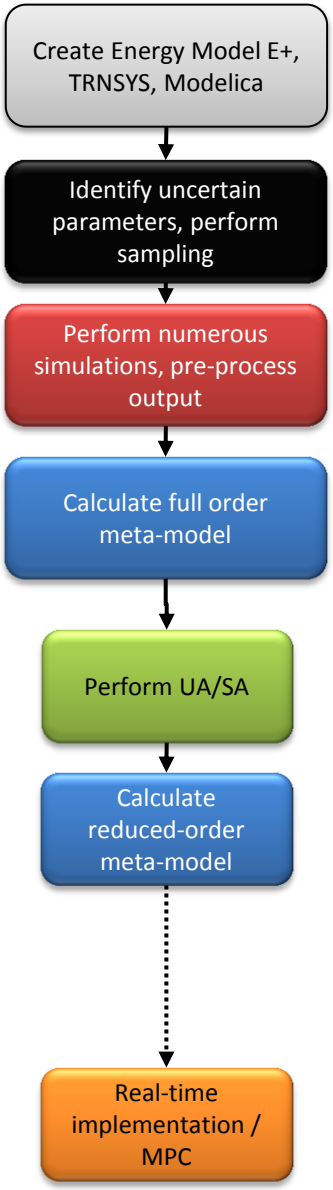
Lagrange multipliers

Solved by KKT conditions

Derivation from *[Smola 2004]*

* See also: www.**support-vector-machines**.org

Future possibilities….



Use of SVR-based models for prediction e.g. MPC is not new. Integration with UA would be useful.

Support Vector Machine Predictive Control for Superheated Steam Temperature Based on Particle Swarm Optimization

Dandan Zhao, Ping Liang
School of Electric Power

INTERNATIONAL JOURNAL OF ROBUST AND NONLINEAR CONTROL
Int. J. Robust Nonlinear Control 2006; **16**:843–862
Published online 22 August 2006 in Wiley InterScience (www.interscience.wiley.com). DOI: 10.1002/rnc.1094

Support vector machines-based generalized predictive control

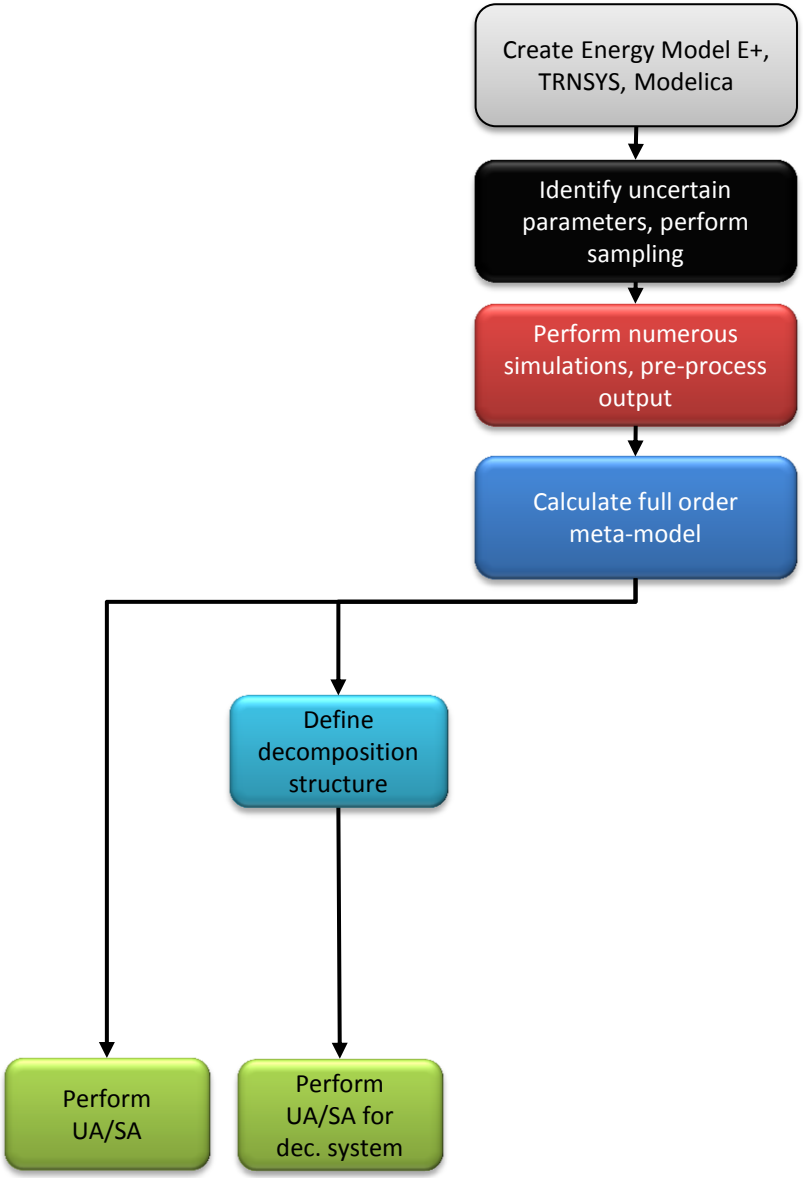
S. Iplikci*,†

Journal of Building Performance Simulation
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/tbps20

Kernel regression for real-time building energy analysis

Matthew Brown [a] , Chris Barrington-Leigh [b] & Zosia Brown [c] †Work completed whilst Zosia was at the University of British Columbia

Flow



Uncertainty / Sensitivity Analysis

Sensitivity Calculation

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ANOVA-based approach:

Functional decomposition

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

$2^k - 1$ 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

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

Sensitivity Calculation

UC SANTA BARBARA engineering

ANOVA-based approach:

Functional decomposition

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

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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 $\rho(x_i)$

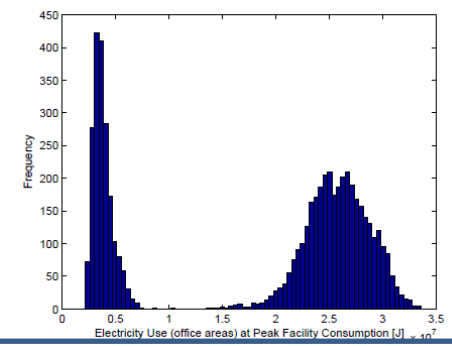
- L1-norm derivative sensitivity indices can be calculated as

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

- Average derivatives can be calculated as

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

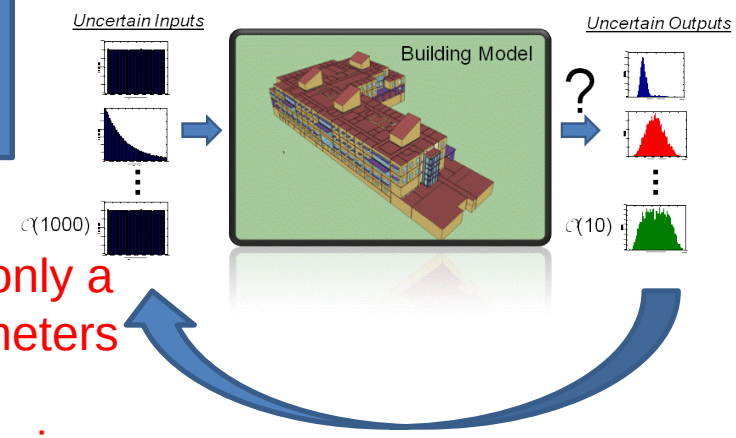
Variance is not always best to describe distribution

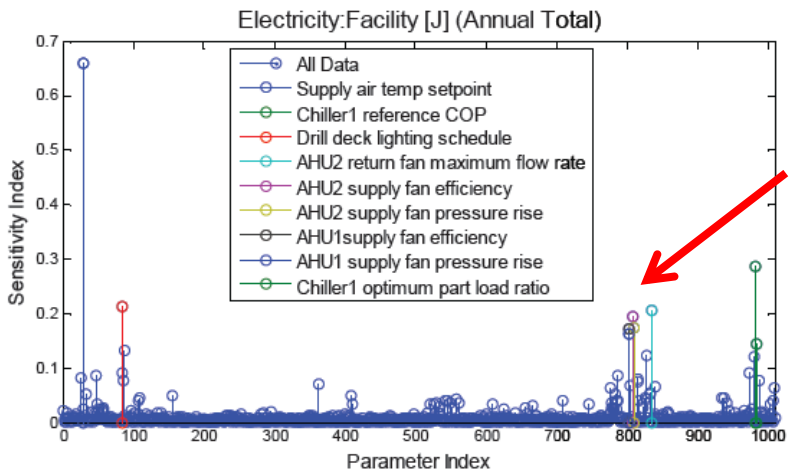


Sensitivity Analysis

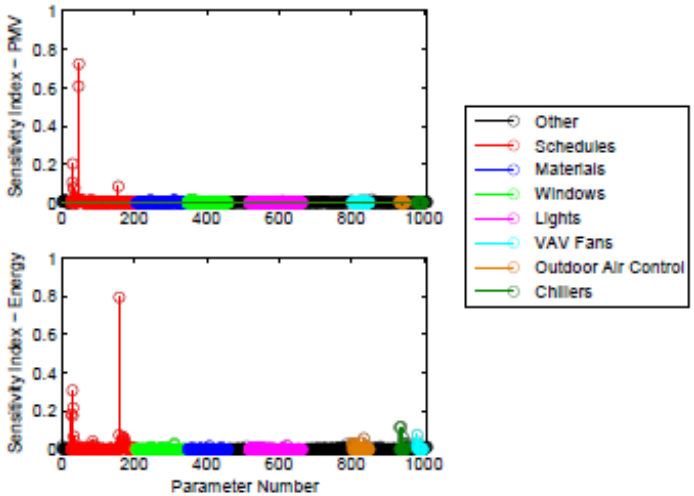
UC SANTA BARBARA engineering

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

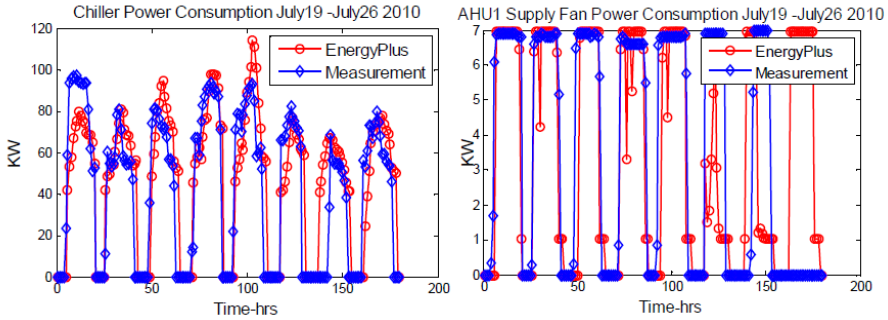




Typically only a few parameters drive uncertainty in output



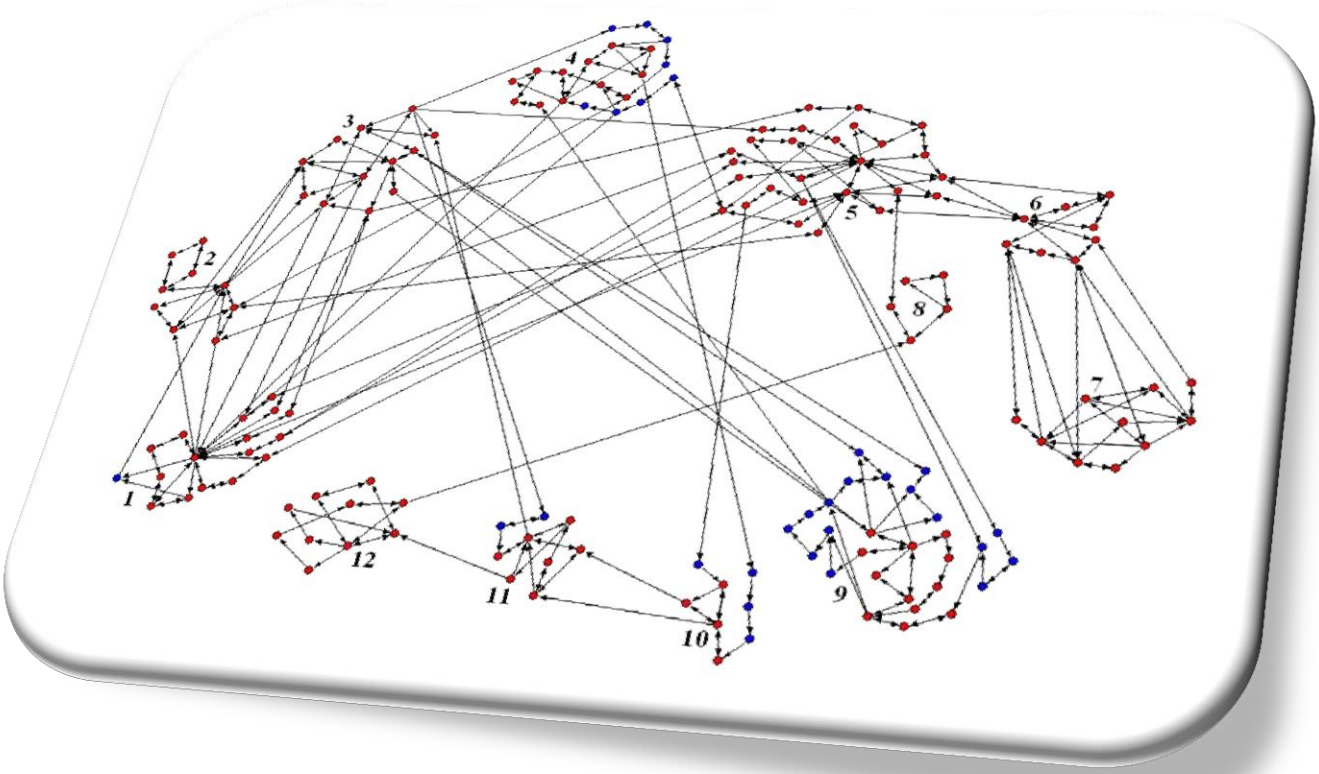
Hand calibration from SA



[E+ Drill Hall]

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

System Decomposition



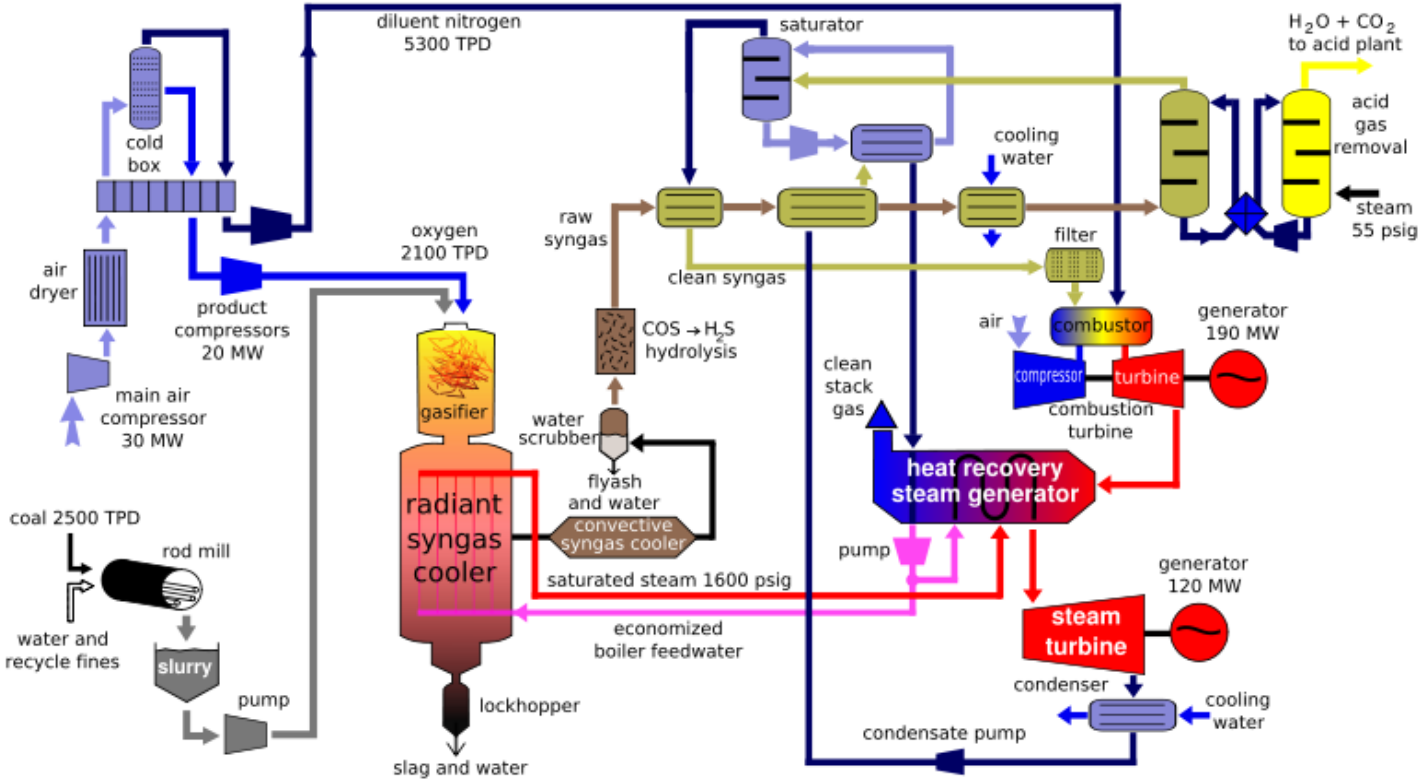
http://www.biomedcentral.com/14712105/7/386/figure/F2?highres=y

Decomposition Methods

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

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

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



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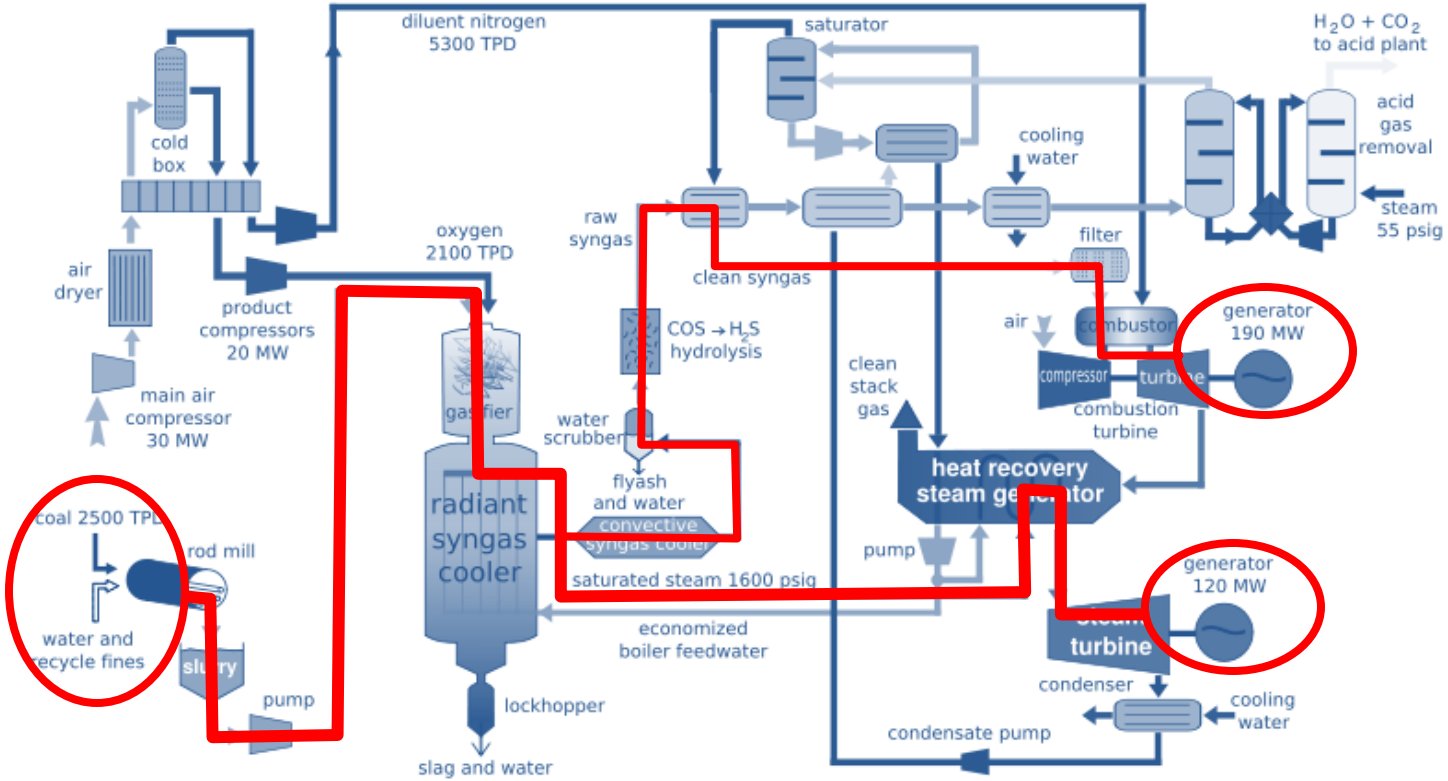
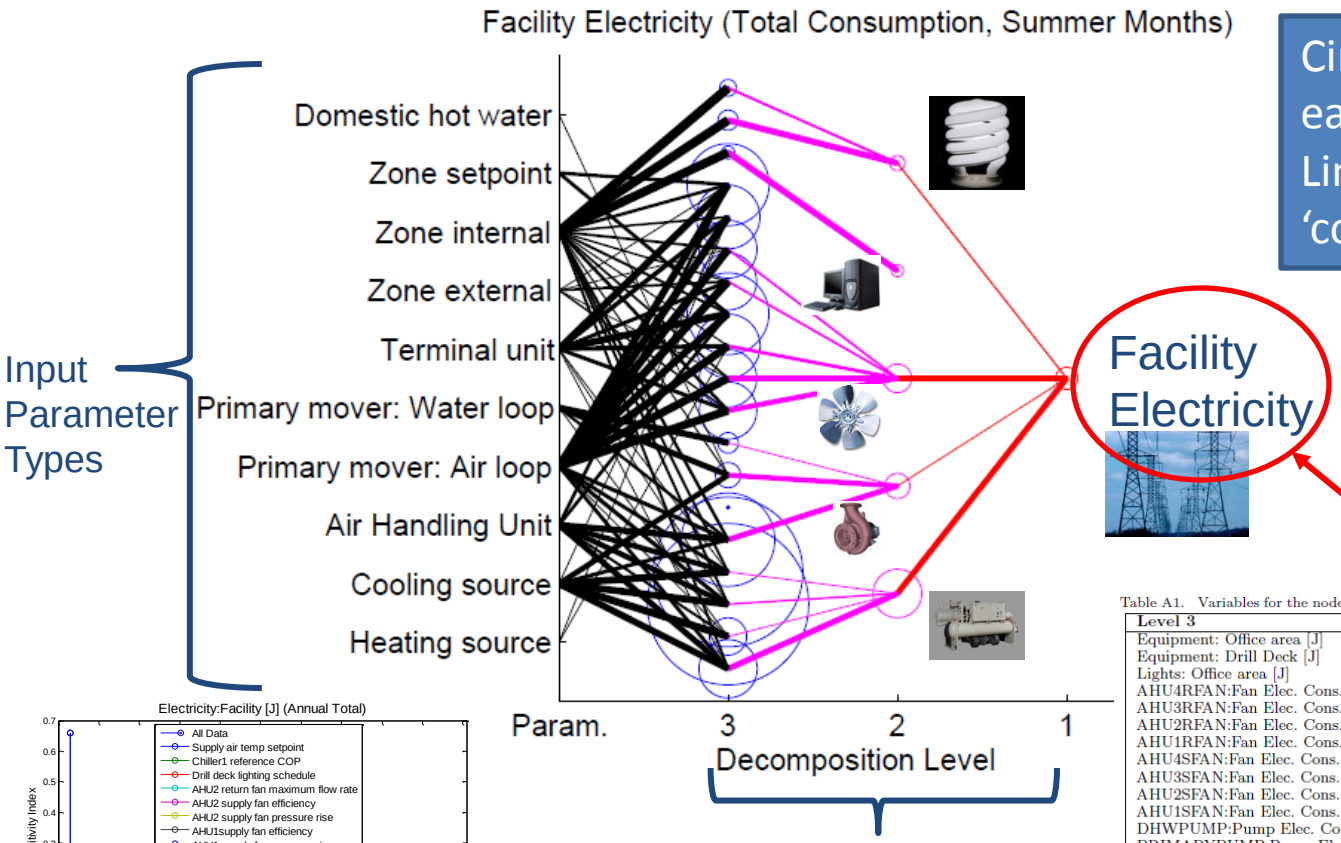


Decomposition Methods – Building Energy

UC SANTA BARBARA engineering

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



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

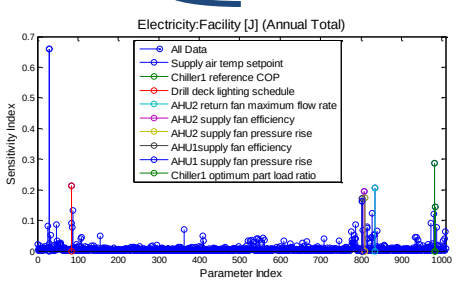
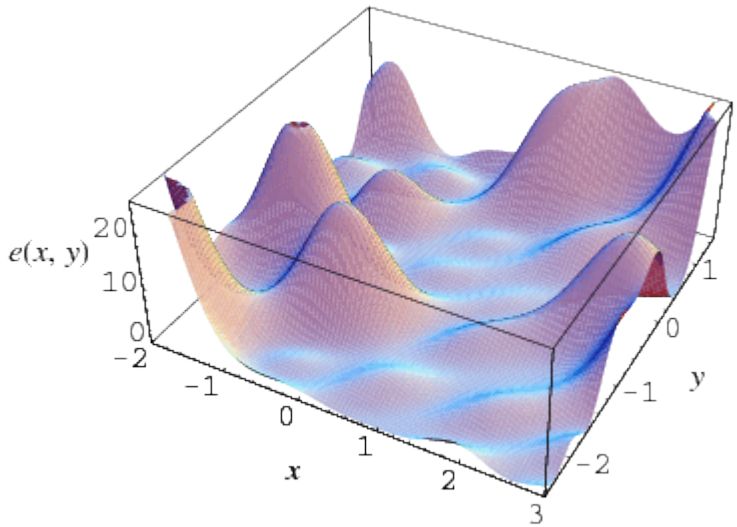


Table A1. Variables for the nodes of the sensitivity decomposition of Facility Electricity (Figure 7).

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

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



Optimization

$$\underset{x}{Min} \quad F(x, Y, Y')$$

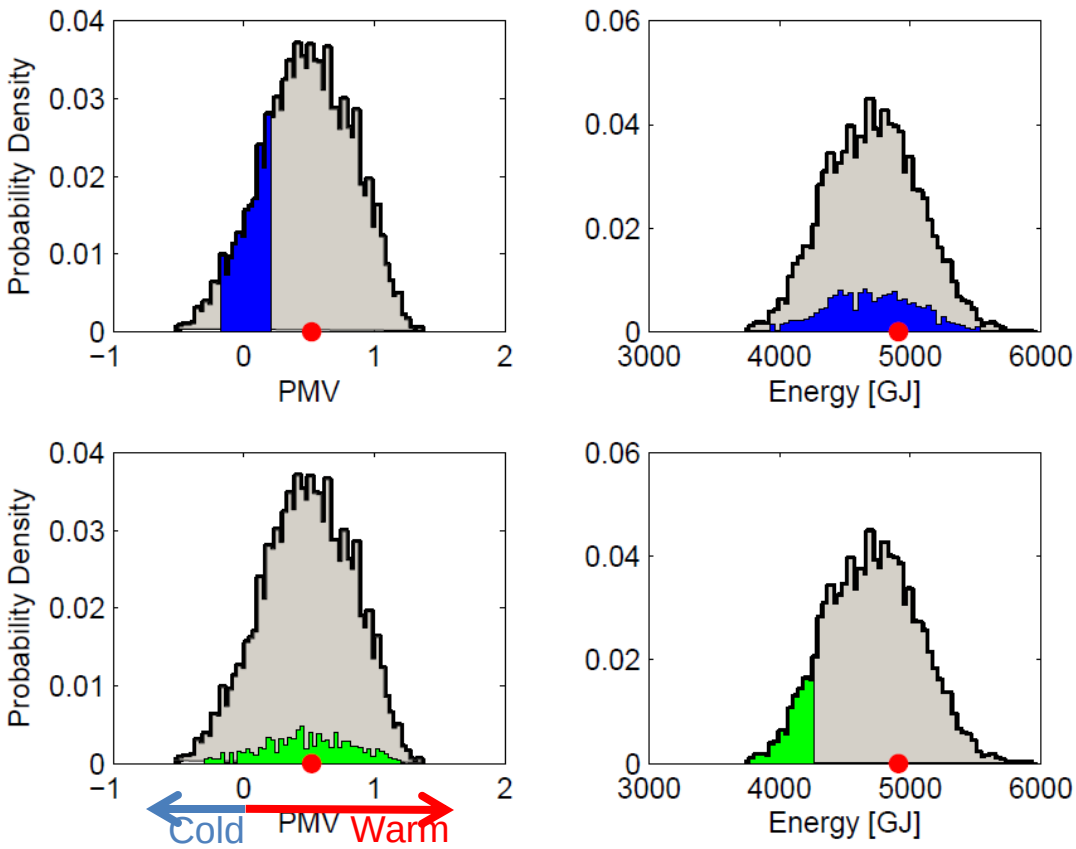
$$Subject\ to:$$

$$g_i(x) = 0 \quad i = 1,..,m$$

$$h_j(x) \le 0 \quad j = 1,..,n$$

Multi-objective Optimization

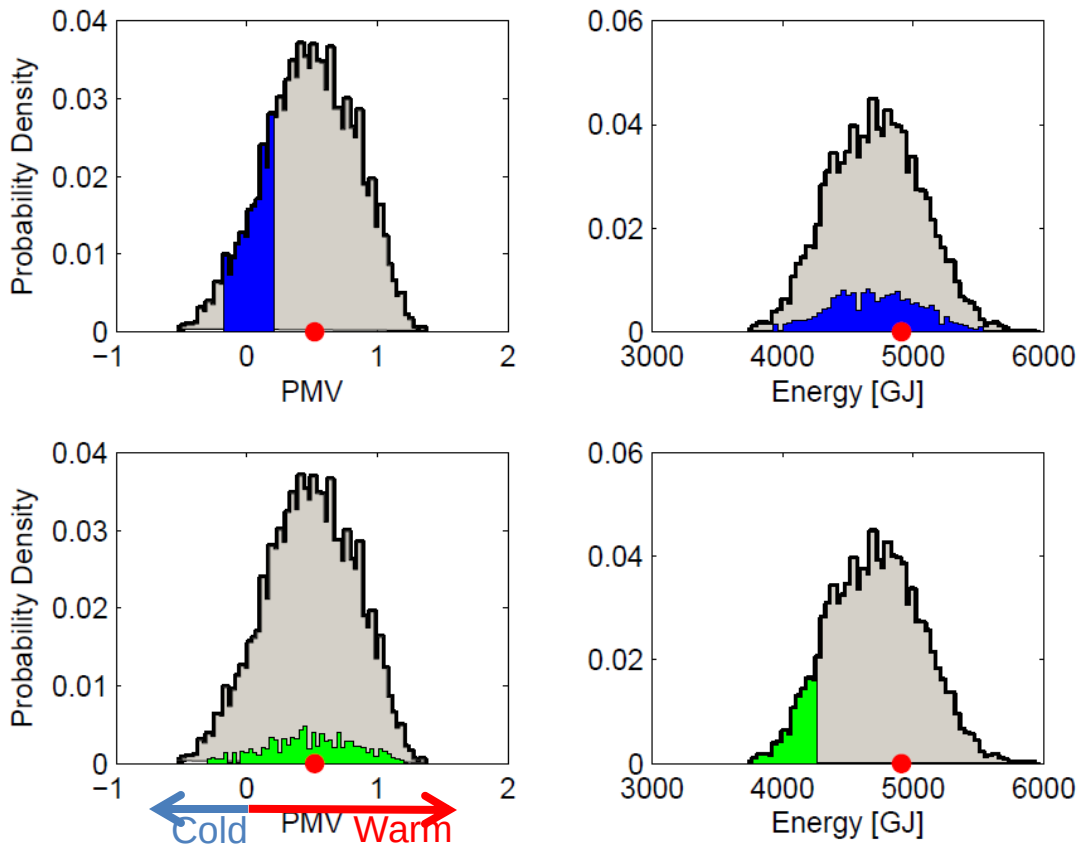
- Objectives in buildings are naturally competitive

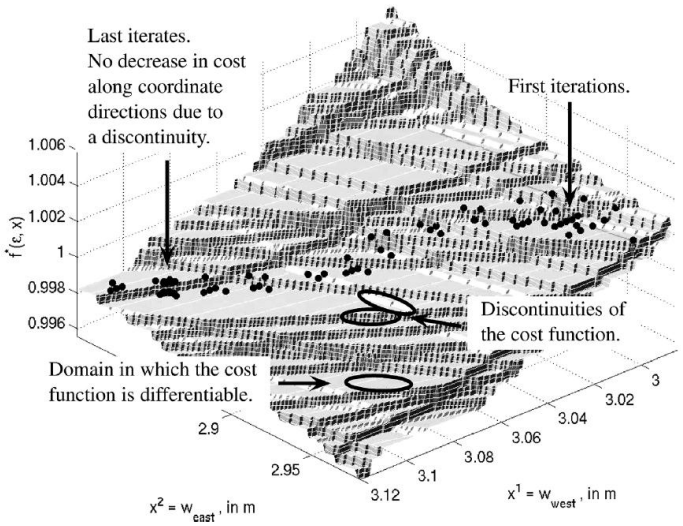


B. Eisenhower, et al Metamodel-based Optimization of Building Energy Systems *Submitted*

Multi-objective Optimization

- ❑ Objectives in buildings are naturally competitive
- ❑ Many whole-building energy simulators do not lend themselves wel to optimization





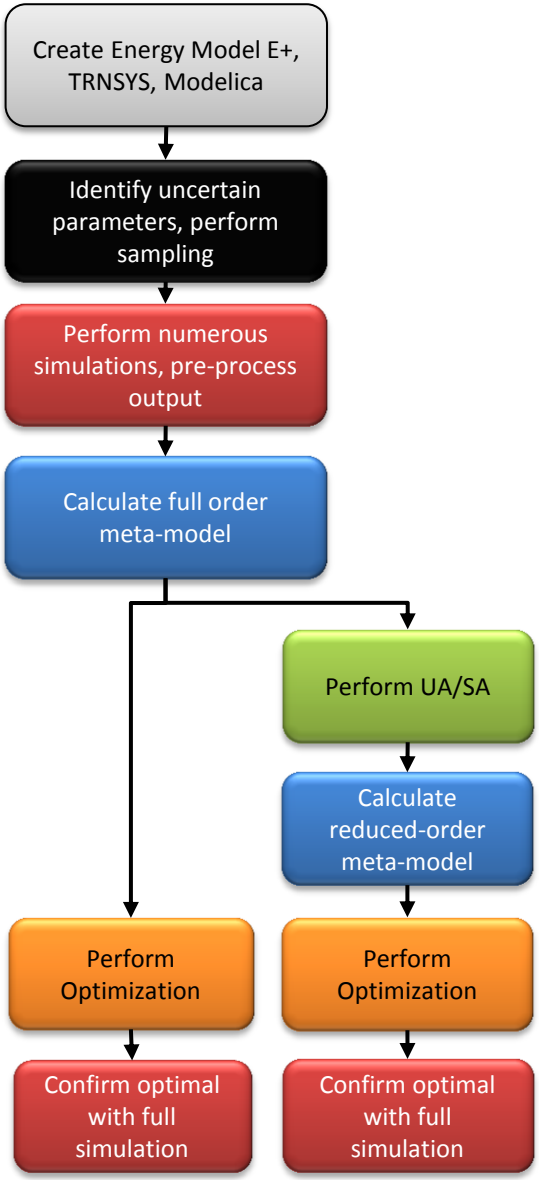
Wetter & Polak 2004

Optimization – Historically Building Sys.

UC SANTA BARBARA engineering

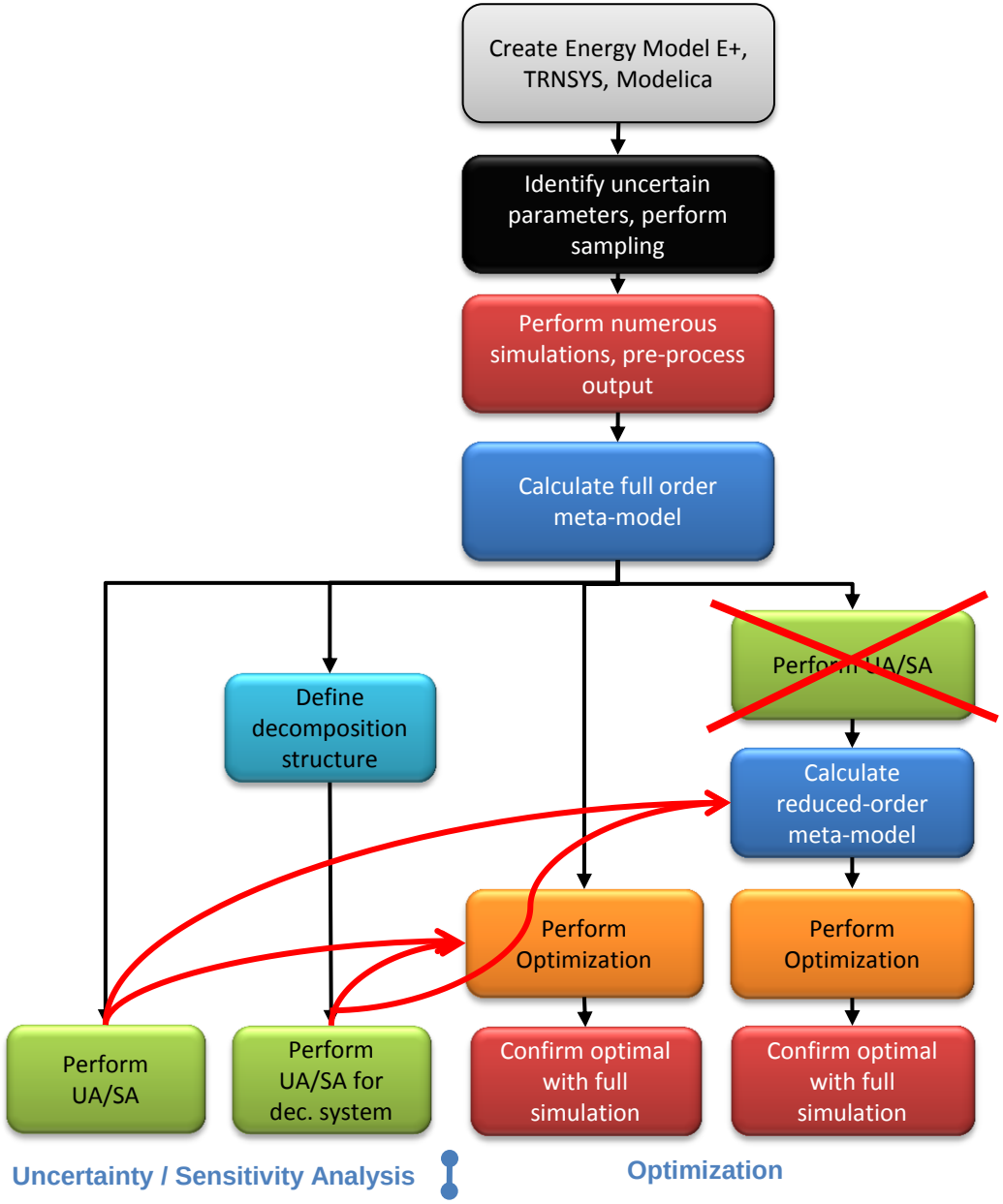
Authors	# Param.	Technique	Type of model / cost function
Kampf [2011]	13	Genetic, Particle swarm	Full E+ model, energy only
Djuric [2007]	3	GENOPT	Full E+ model, energy consumption, investment costs, comfort
Wang [2005]	27	Genetic algorithm	ASHRAE sim. Program, LCC/LCEI optimized
Caldas [2003]	16	Genetic algorithm	RC network model, energy and first cost
Peippo [1999]	30	Hooke Jeeves coordinated	Algebraic, energy and capital
Wright [2002]	9	Genetic algorithm	RC network model, energy and comfort
Gustafsson [2000]	183	MILP	Algebraic, life cycle costs
Marks [1997]	20	NLP	Algebraic, construction/ operation costs
Djuric [2007]	10	GENOPT	Energy Plus, energy, comfort, construction
Lozano [2009]	10	LINGO	Algebraic, annual energy & fixed cost
Wetter [2004]	13	GENOPT	Energy Plus, annual energy
Diakaki [2008]	9	MILP, LINGO	Algebraic, energy & construction
Eisenhower, submitted [2011]	1009 up to 2063	Meta-model based optimization, IPOPT & der free	E+/meta-model 'All' available parameters in building

Flow



Optimization

Flow



Previous results can certainly be used!

Optimization Strategy

UC SANTA BARBARA engineering

Cost is typically some combination possibly weighted of comfort and energy

$$
\begin{aligned}
C_1 &= \mathrm{PMV}^2 \\
C_2 &= \frac{\mathrm{Energy} - min(\mathrm{Energy})}{max(\mathrm{Energy} - min(\mathrm{Energy}))} \\
C_3 &= C_1 + C_2
\end{aligned}
$$

Two methods used:

1. IPOPT - Primal-Dual Interior Point algorithm with a filter line-search method for nonlinear programming *Wachter - Carnegie Melon / IBM*

   ← Works well with analytic / continuous cost

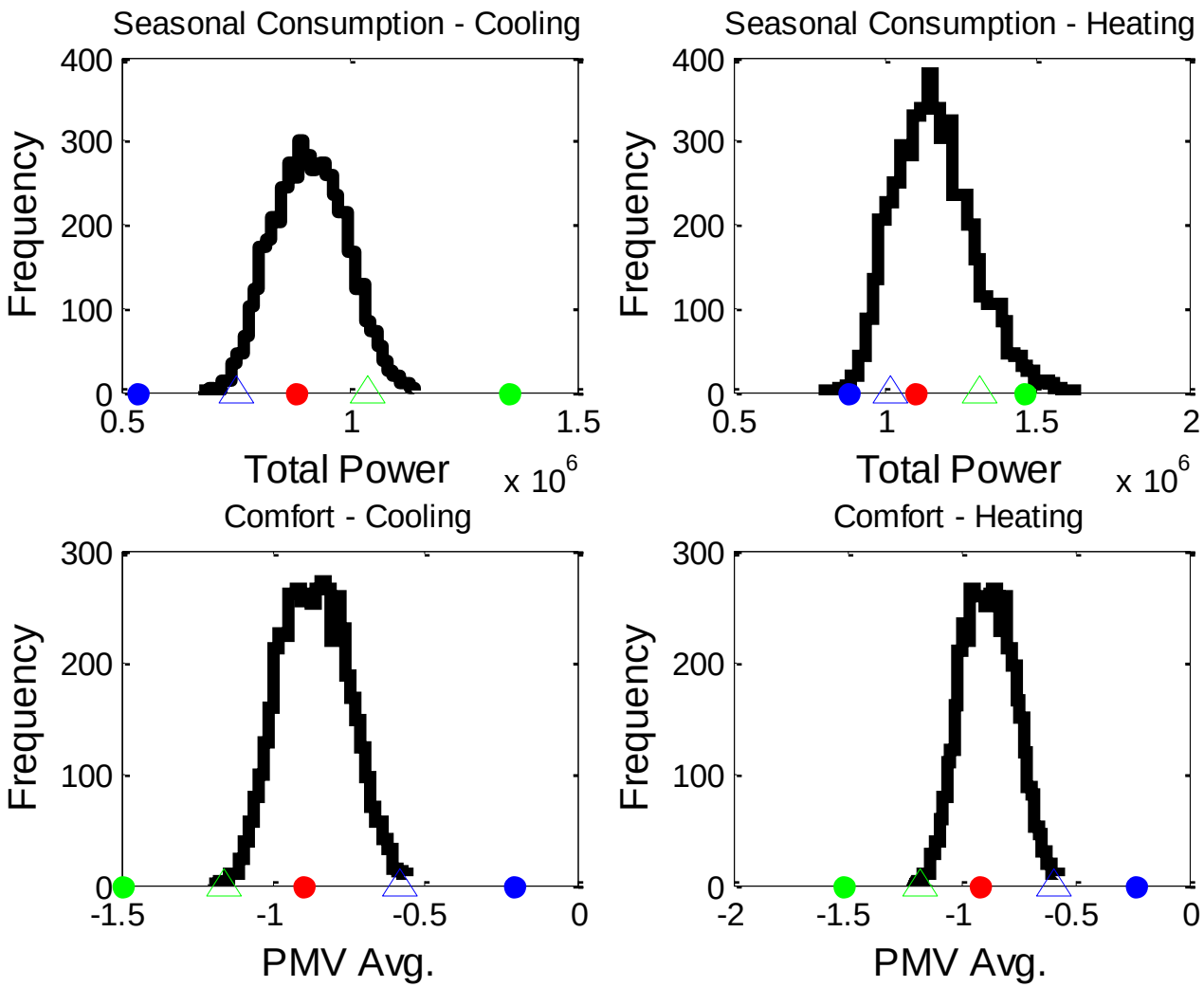
2. NOMAD - Derivative free Mesh Adaptive Direct algorithm *Digabel - Ecole Polytechnique de Montreal*

   ← Compare with previous work

Optimization Results

- Optimization results compared to uncertainty distributions cooling & heating seasons

Fort Carson
TRNSYS



Red dot = nominal simulation

Green = Maximized solution

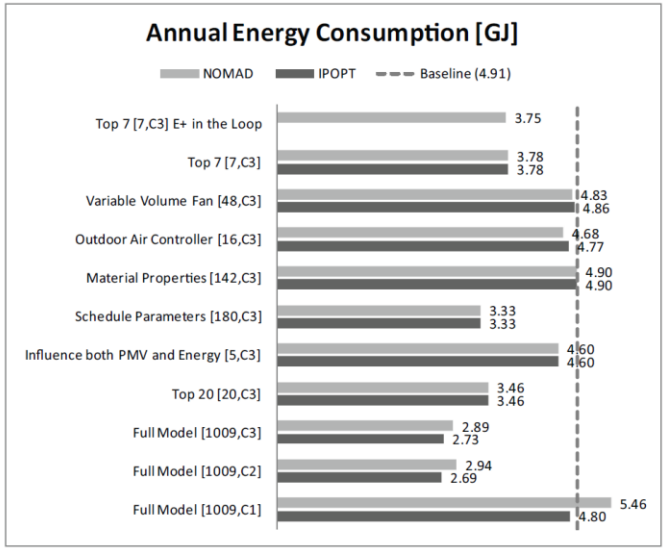
Blue = Minimized solution

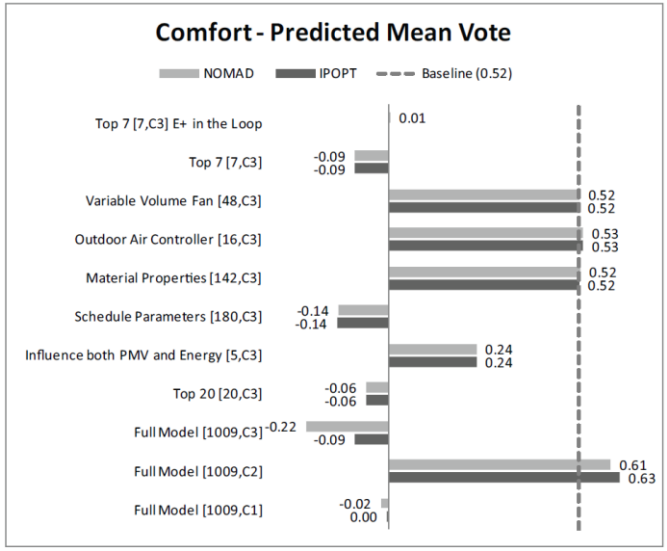
Dot = 317 para
Triangle = 16 para

Optimization Results

Building26
E+

45% annual energy reduction while increasing comfort by a factor of two





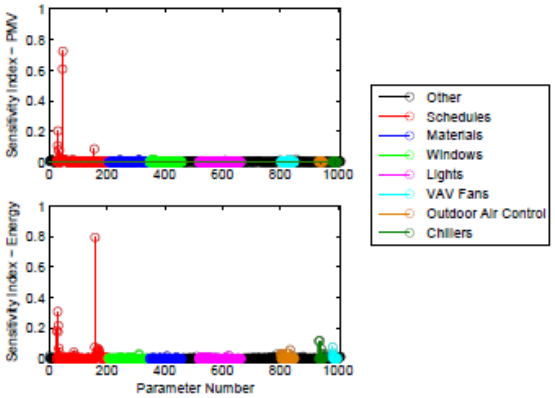
Traditional approach

Reduced meta-models

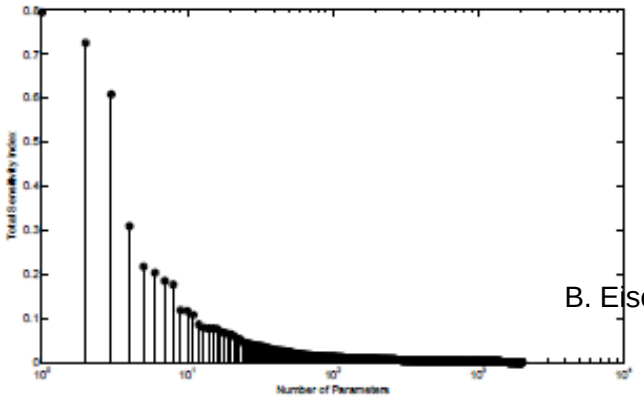
Full meta-model

Model reduction based on parameter type or parameter influence

Parameters collected by type



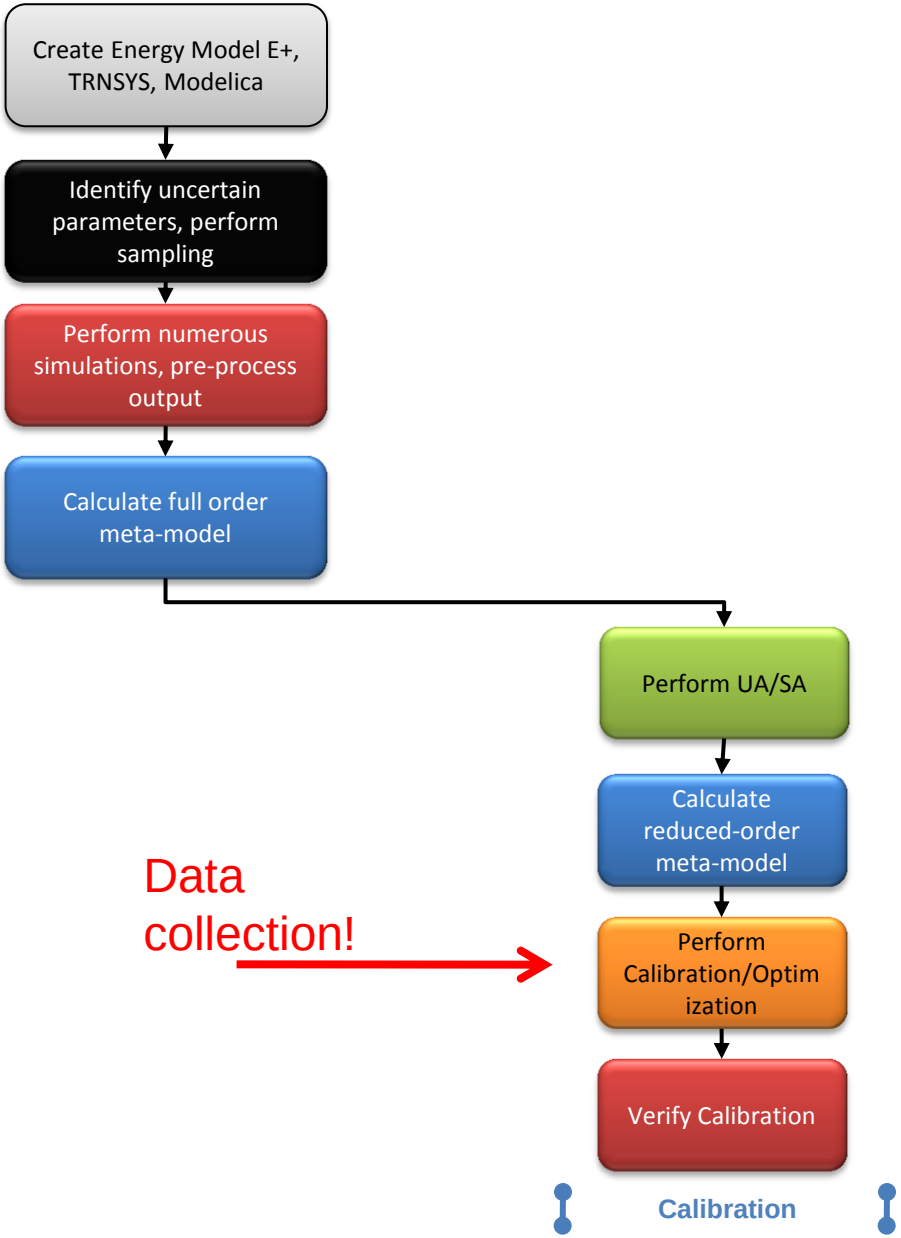
Rank ordering of parameter sensitivity



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

Model Calibration

Flow


Create Energy Model E+, TRNSYS, Modelica
Identify uncertain parameters, perform sampling
Perform numerous simulations, pre-process output
Calculate full order meta-model
Perform UA/SA
Calculate reduced-order meta-model
Perform Calibration/Optimization
Verify Calibration
Data collection!
Calibration

Calibration Results

Calibration approach tested on DOD Building 26
Data available 2009, 2010, some 2011:

Plug electricity
Total electricity
Steam consumption

Used for calibration

Optimization performed to minimize $\sqrt{\sum(\text{model} - \text{data})^2}$

Per month, year, etc.

Calibration Results

Calibration approach tested on DOD Building 26
Data available 2009, 2010, some 2011:

Plug electricity
Total electricity
Steam consumption

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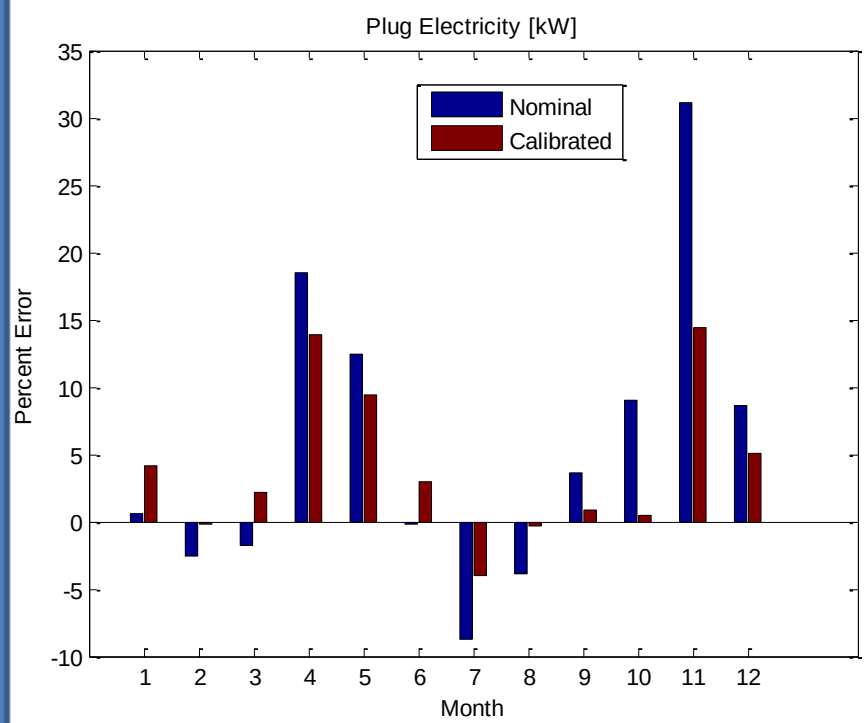
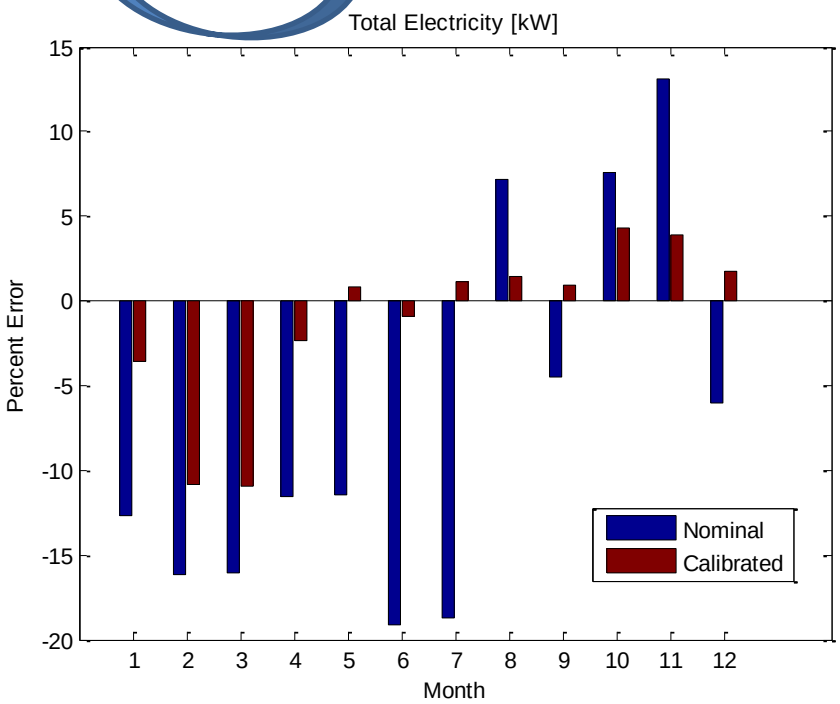
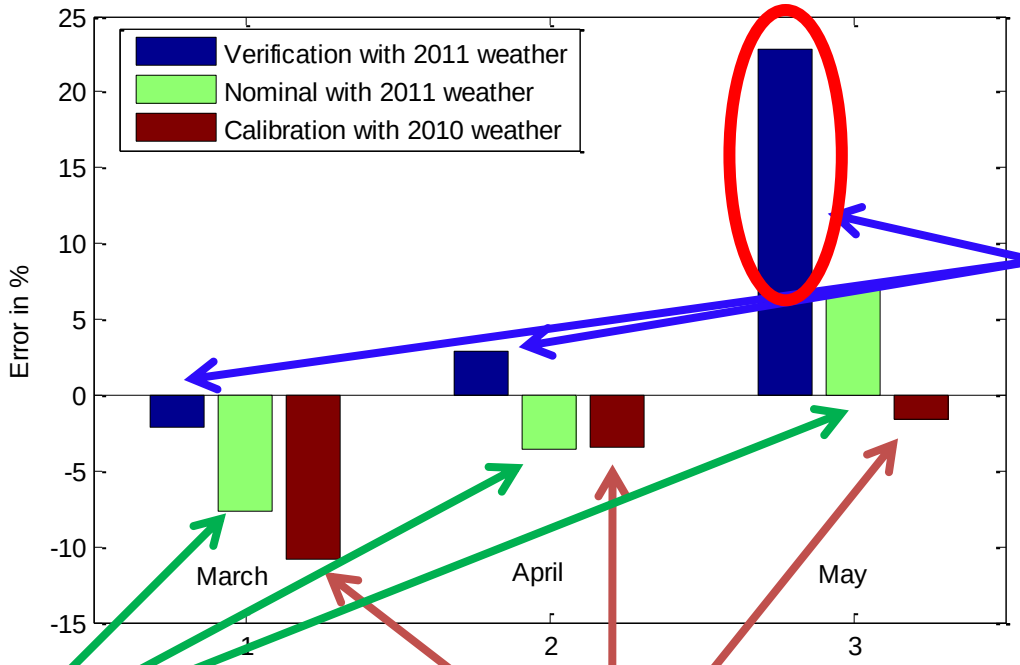




Verification Results

Calibration performed on 2010 data
Verification performed with 2011 data

Chiller not broken in 2010
Chiller broken in 2011



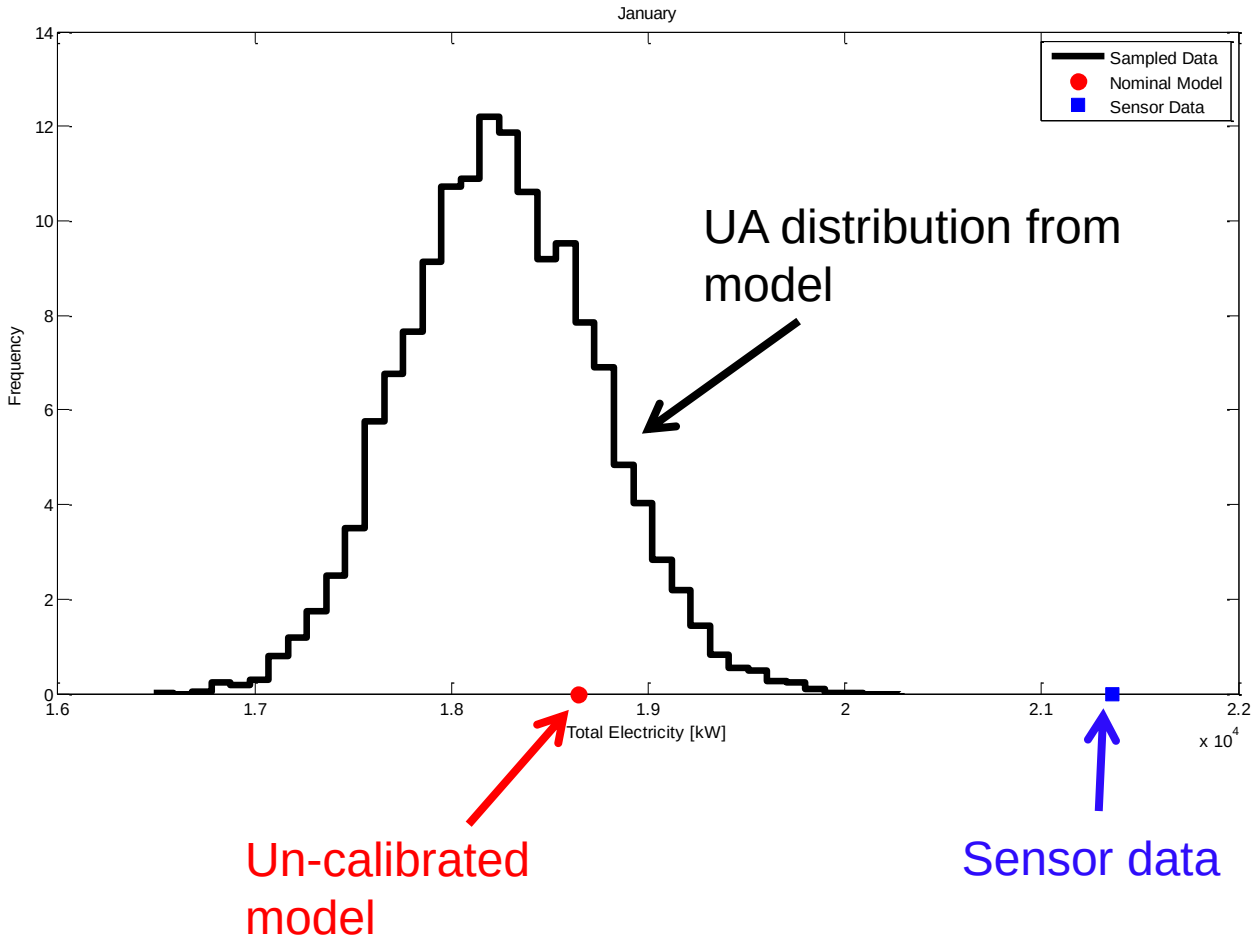
Calibrated model with new 2011 data

Uncalibrated model with new 2011 data

Results from previous slide

Calibration approach

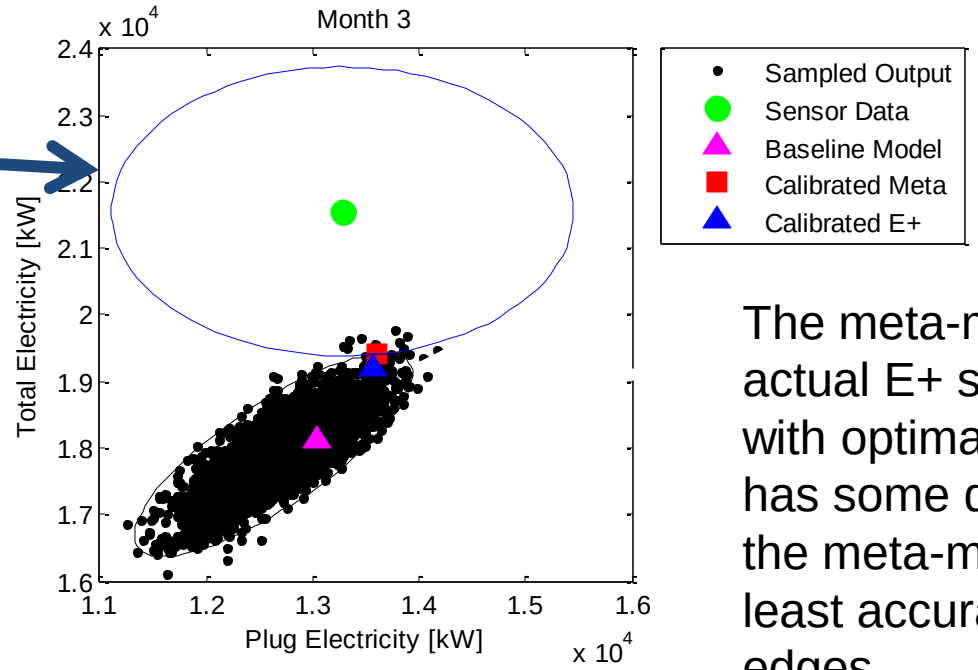
As is often the case, sensor data fall outside of the conservative output distribution



Constrained optimization

The optimization is performed while having an elliptical constraint on its output

This is really a circle, its intersection with the ellipse is as close as we will let the optimization go

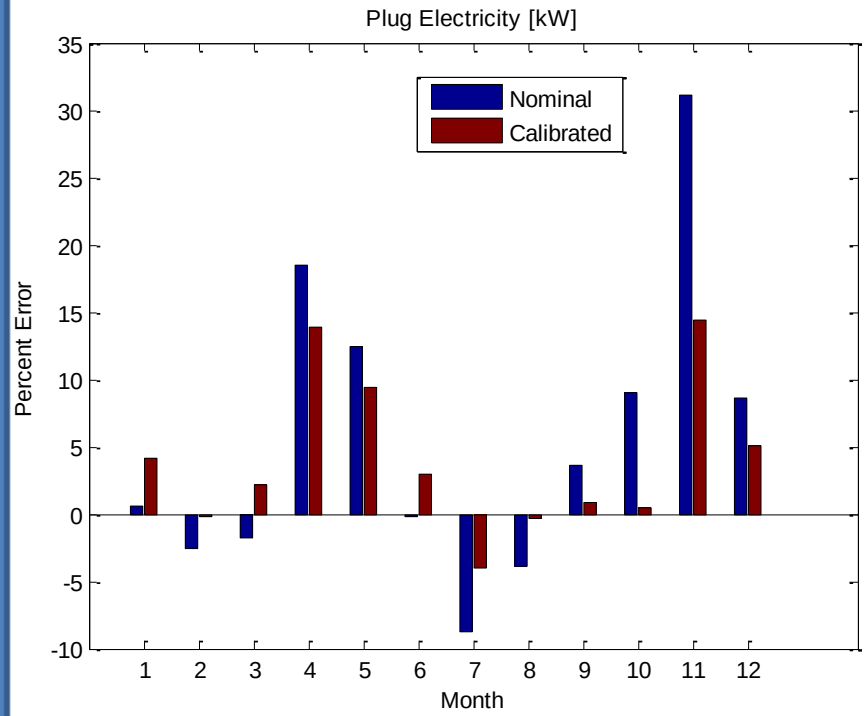


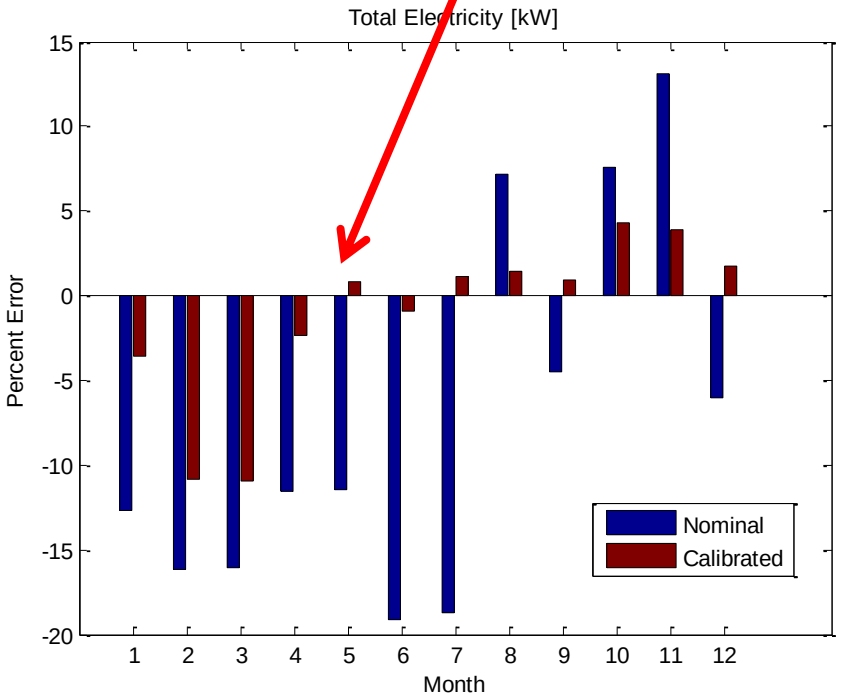
The meta-model and actual E+ simulation with optimal values has some difference, the meta-model is least accurate at its edges

Calibration Results

To circumvent these issues, outputs are constrained, only top 20 or so parameters varied for optimization

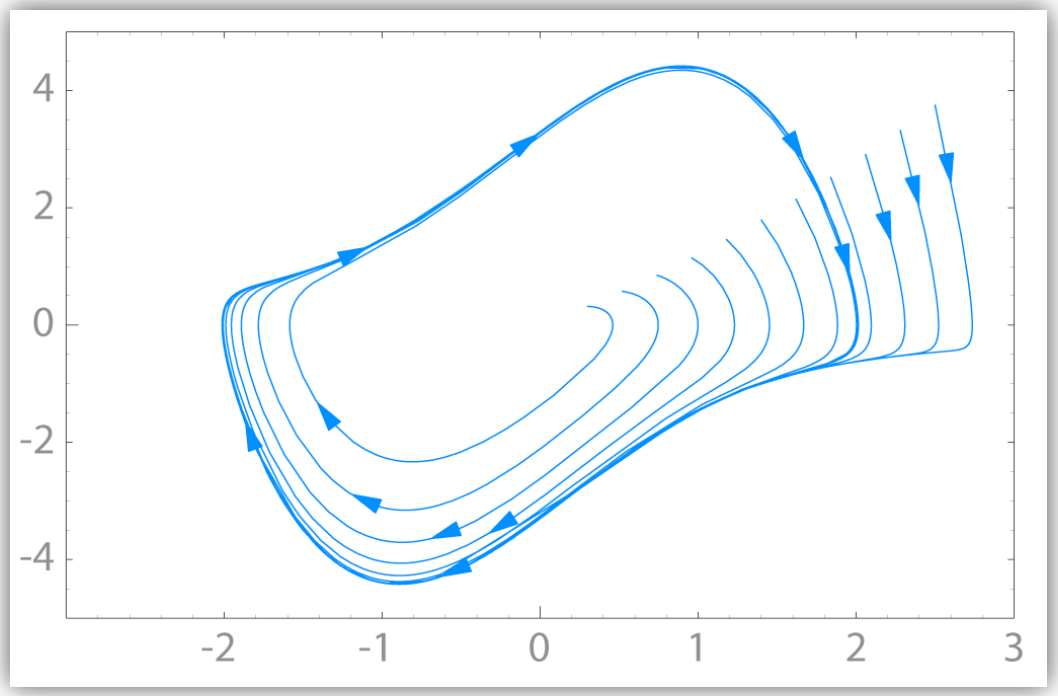
Constrained to not be any better than this





Future approach

Do quick UA/SA to identify key parameters and where distribution is → Use SA to hand tune the model closer to sensor data → Perform detailed UA/SA and calibration



Part II

Analysis of dynamics

Use of Modelica for:

1. Controller certification (testing) in a Hardware in the Loop environment
2. Control education

UTC PureComfort™ CHP System

UC SANTA BARBARA engineering

…Two different control systems, one common function

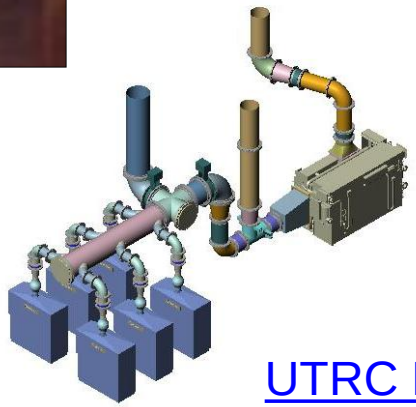
Carrier Chiller
Gas fired burner -> Cold / hot water
Carrier control system

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

UC SANTA BARBARA engineering

Adjust to operation of chiller to different heat source:

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

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

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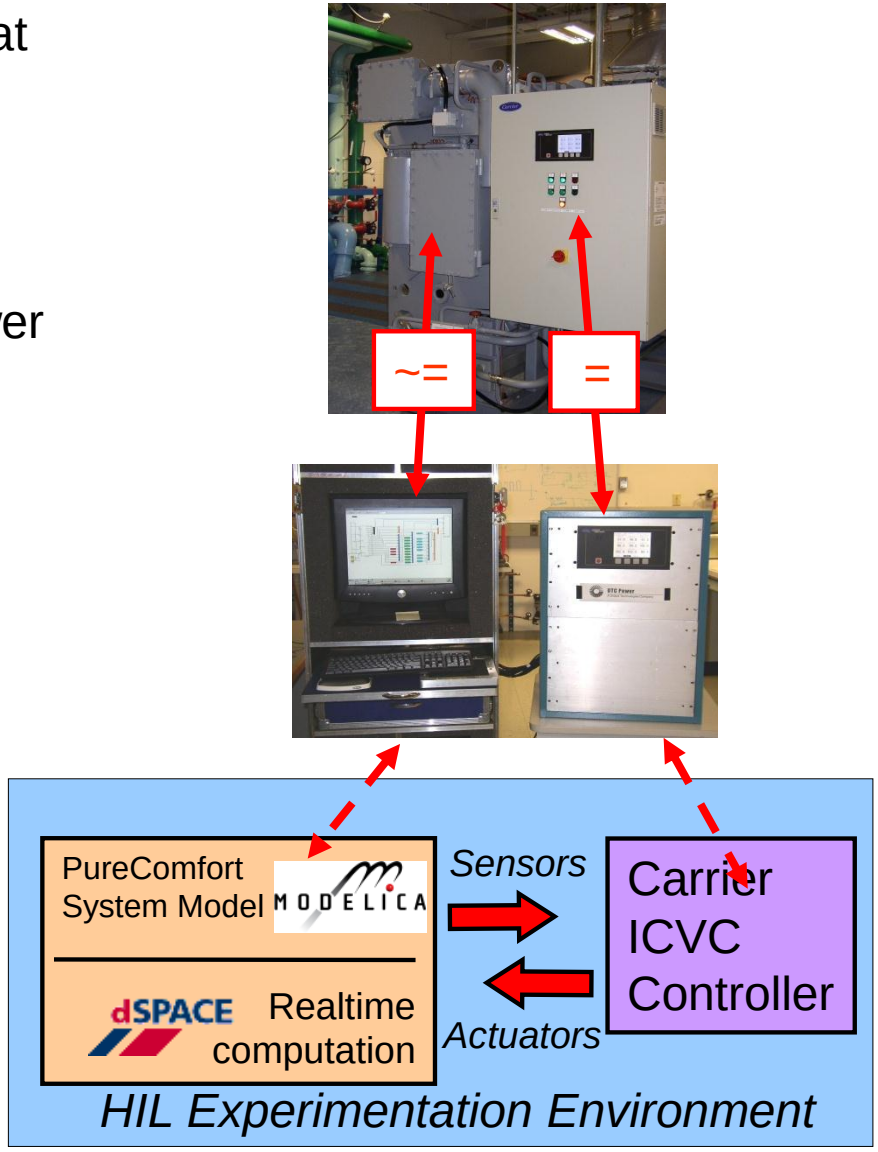


Modelica Modelling for HIL

UC SANTA BARBARA engineering

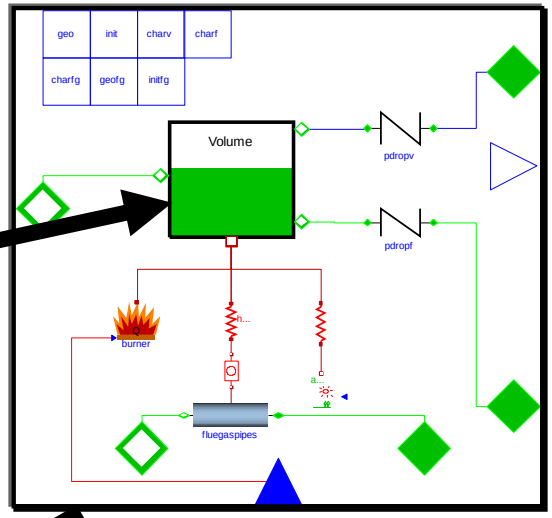
上海交通大學 SHANGHAI JIAO TONG UNIVERSITY

LiBr Modelica component libraries built in collaboration with SJTU

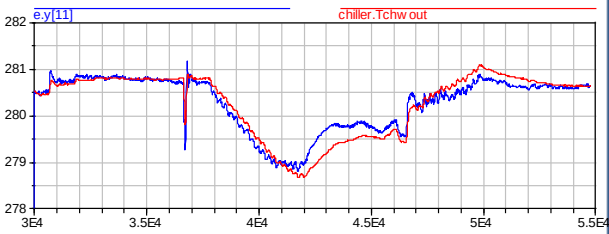
Conservation Equations

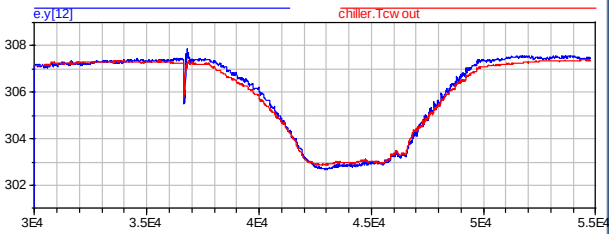
```
//Dynamic Mass Balance
M_x = transposex*M;
for i in 1:nspecies loop
  derM_x[nspecies] = summdot_x[:, nspecies]
end if;
//Dynamic Energy Balance
U = M*h - p*Vt;
derU = sumqdot + sumheat.Q_s + sumheat.W_loss;
// Volume conservation
M[1] = d[1]*V[1];
```

Subcomponent Level Models

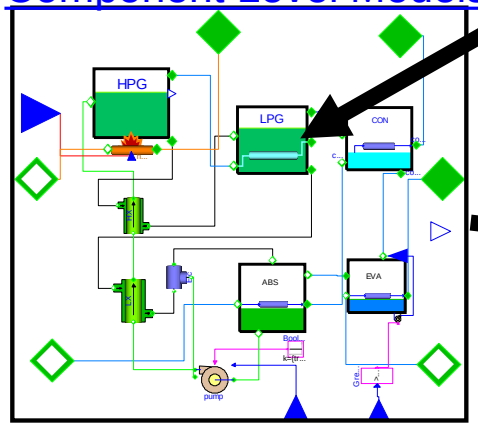


Sensor to model validation

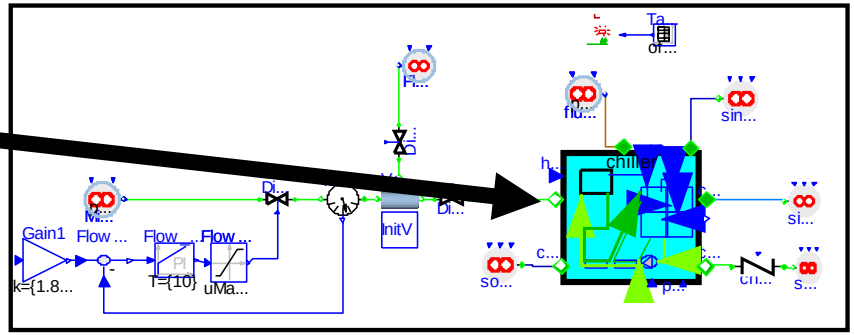




Component Level Models



System Level Model



Use of Modelica for:

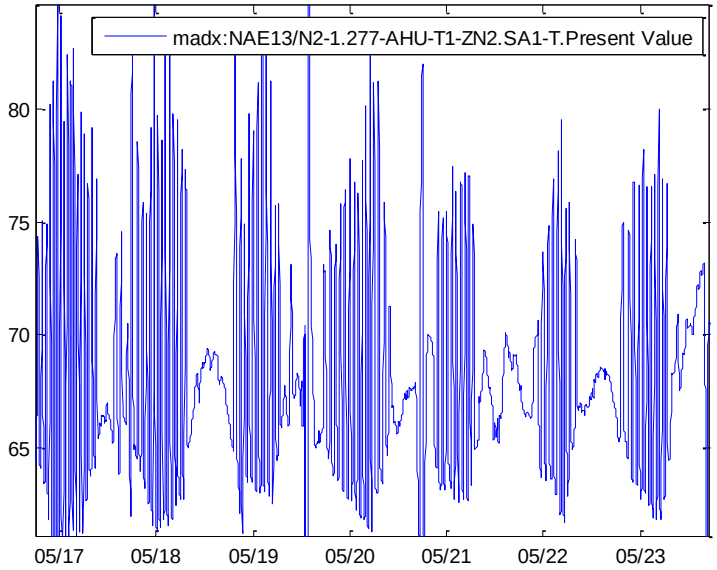
1. Controller certification (testing) in a Hardware in the Loop environment
2. Control education

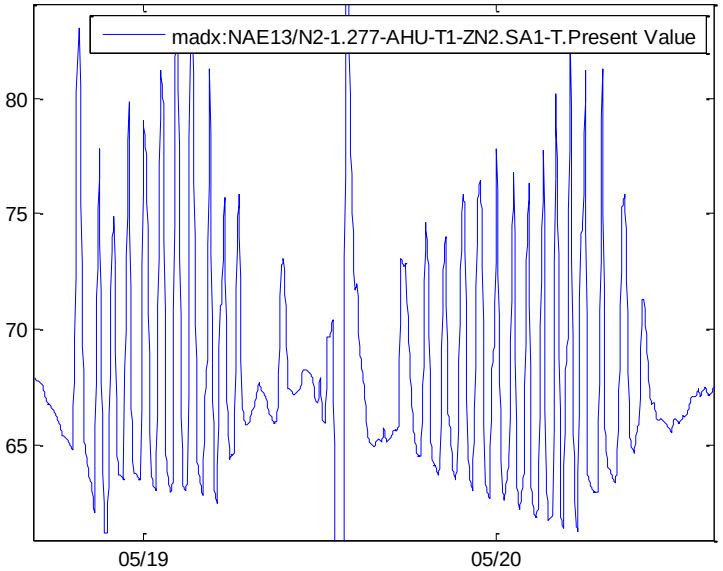
Modelica Modelling for Control Education

Pollock Theater est. 2010
298 stadium-seat auditorium
Sony 4K forever imaging
Meyer Sound offers Dolby 5.1 sound with 14 surround speakers.
2 Dual Kinoton16MM/35MM Film Projectors

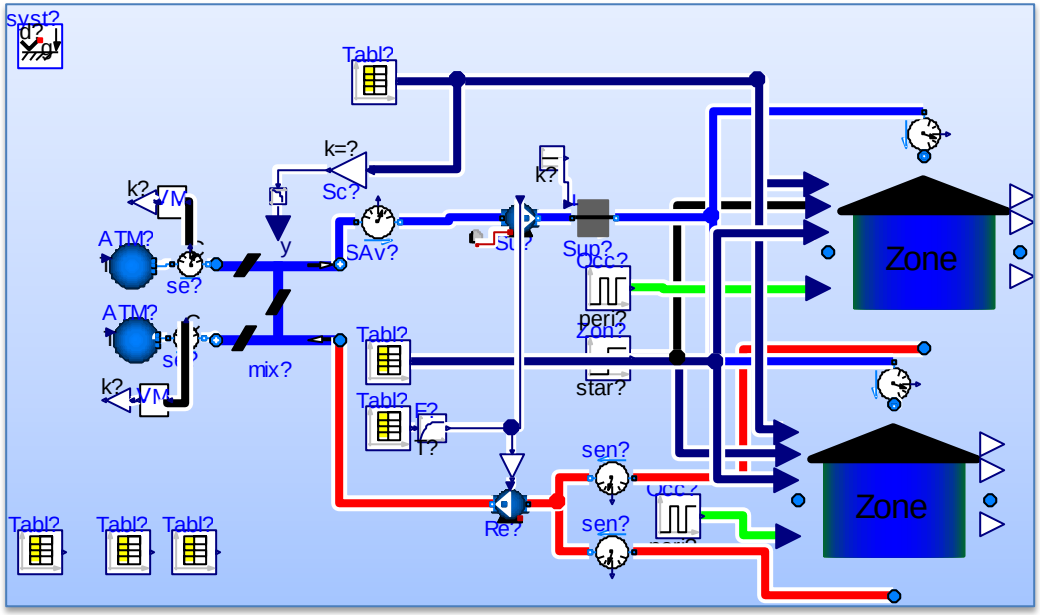
Modelica Modelling for Control Education

UC SANTA BARBARA engineering



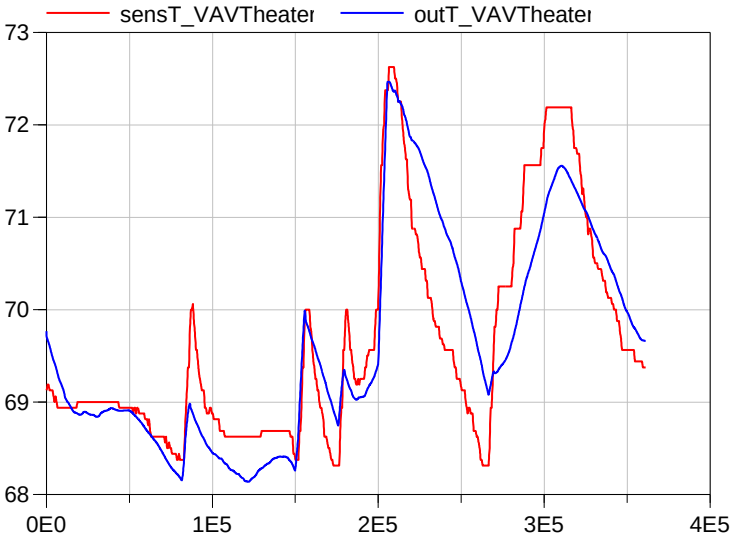


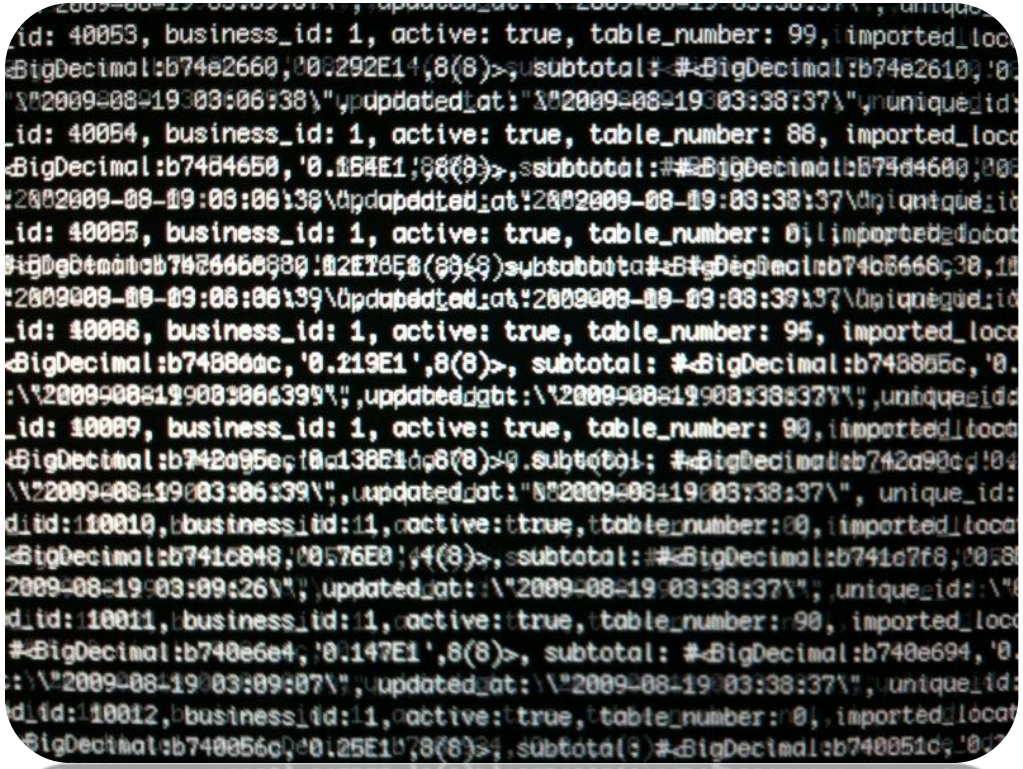
Modelica Modelling for Control Education



Objective
-Create a virtual theater to illustrate benefits of alternative control approaches

Approach
- Create a simple validated Modelica model using the LBL buildings library

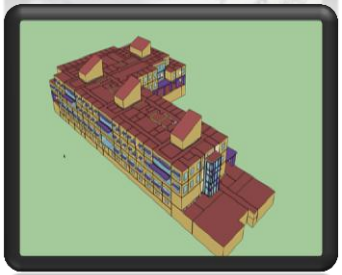




Part III

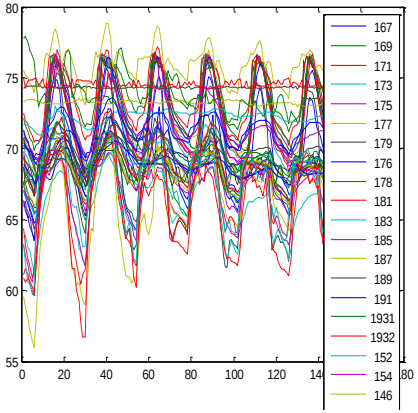
Data-based analysis

Spatial-Frequency Analysis



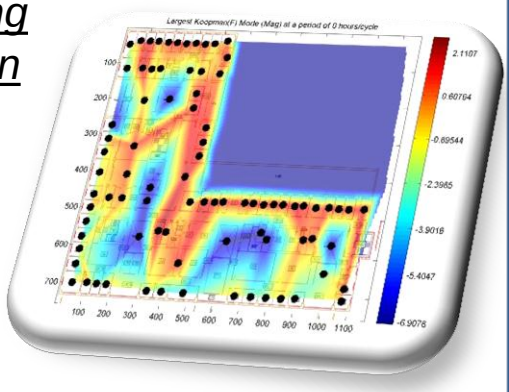
Sensor Information

$\mathcal{O}1000$



Engineering Information

$\mathcal{O}10$



With I. Mezic UCSB

Spatial-Frequency Analysis

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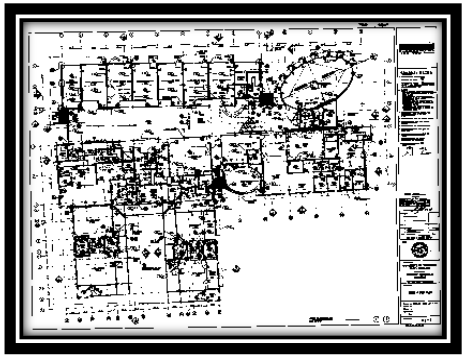
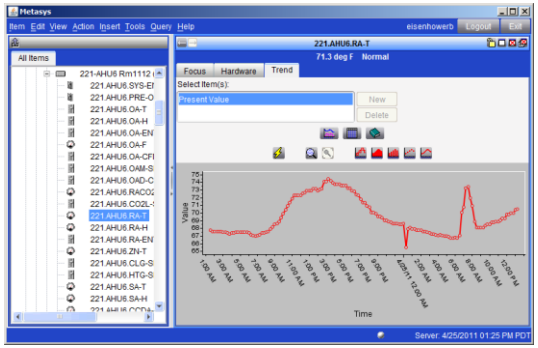
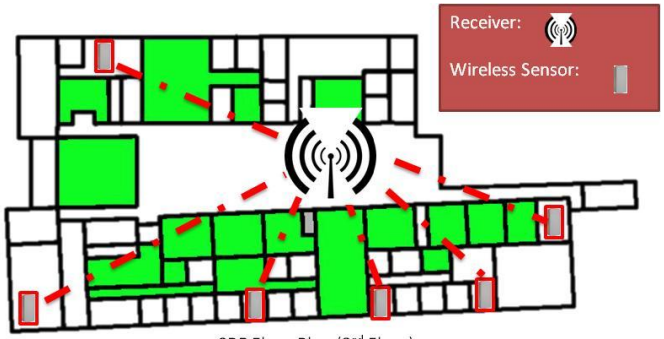
Building Information + Installed Sensor Information + Wireless Mesh Information





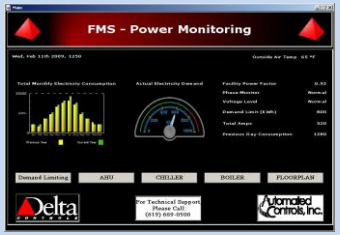


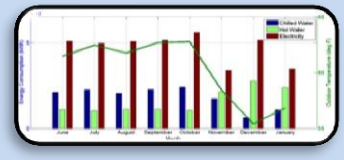
SRB Floor Plan (3rd Floor)

Information

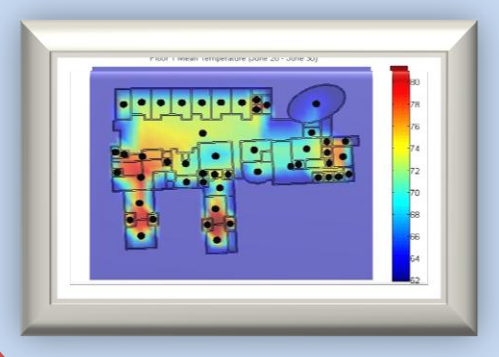
$$Ug(x) = g(f(x))$$

Mathematics

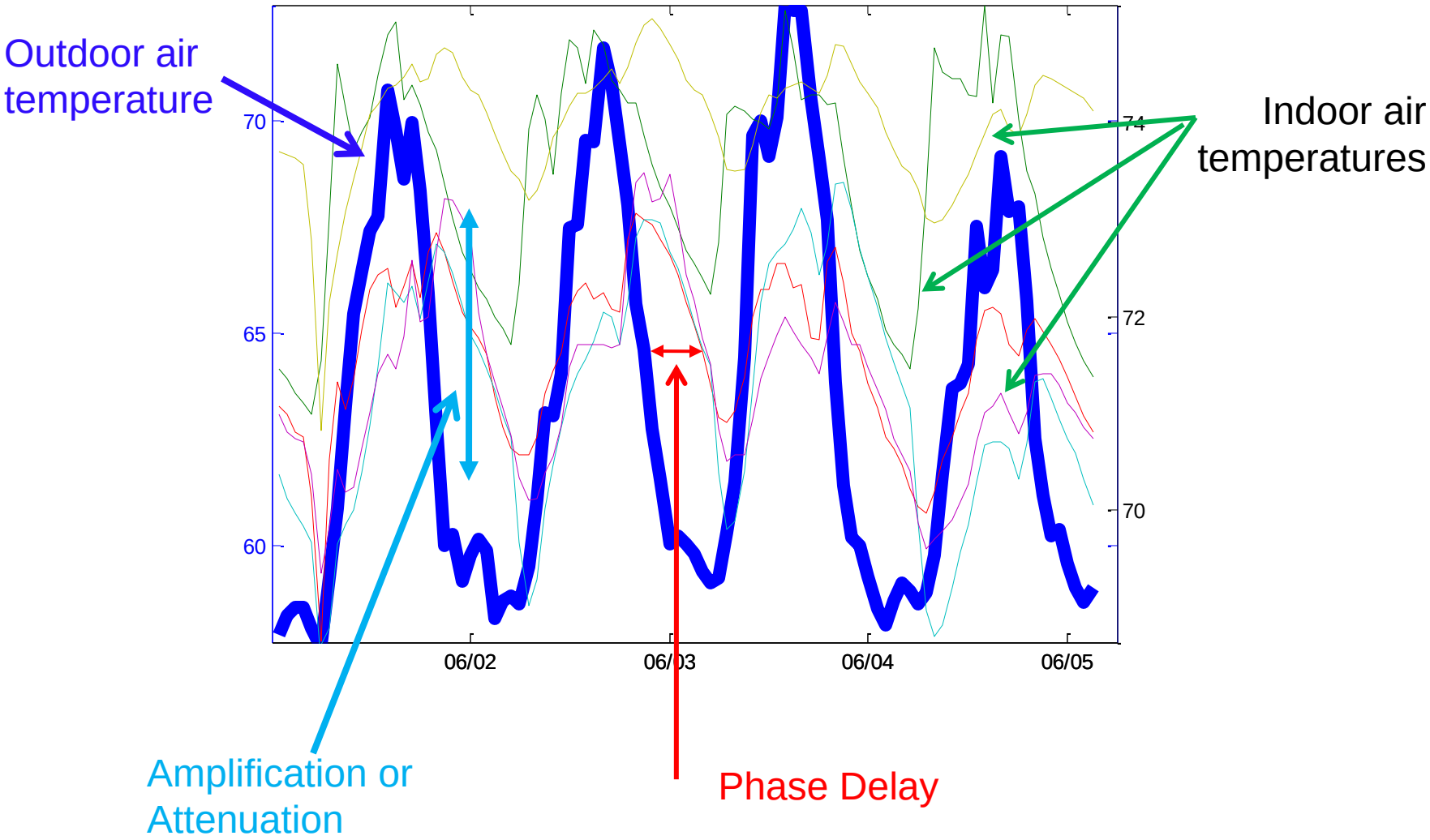




Spatial Energy Visualization



Typical Sensor Trends



Challenge and Solution

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The challenge:

numerous data outputs

+ numerous frequencies

too much data to process

- Control
- Meetings / classes
- Diurnal
- Weekly
- Seasonal

The solution:

inter-dependent global output

+ spectral decompostion

minimal & definitive output

Useful for analysis and model validation

Decomposition methods

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Previous work

Principle Component Analysis PCA, Proper Orthogonal Decomposition POD, etc

[Lam 2010]: PCA over long periods of time 29 years to study climate vs. energy usage in a building

[Ruch 1993]: PCA to study before and after performance of building retrofits

[Du 2007]: Fault detection

[Reginato 2009]: Prediction of energy usage

……

Gaps / Drawbacks:

Gaps:
- Not used for model calibration

Drawback of POD methods:
- An energy based method, energy may not be best way to sort modes
-Time dependencies are lost e.g. spectral content
- Phase information is lost

Mathematical Preliminaries

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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

$$U g(x) = g(f(x))$$

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

[*Mezic 2005, Nonlinear Dynamics*]

Mathematical Preliminaries

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To analyze building system data generated from model or sensors, consider a snapshot matrix:

$$Y_1^K = \{y_1, y_2, \ldots, y_K\}$$

y_i has N data points in it

Note that

$$Ug(x_i) = g(f(x_i)) = g(x_{i+1}) = y_{i+1}$$

$$\boxed{Y_1^K = \{y_1, Ug(y_1), Ug(Ug(y_1)) \ldots, Ug(Ug(\cdots(y_1))\}}$$

Mathematical Preliminaries

UC SANTA BARBARA engineering

*sidenote

If the original process is linear

$$y_{i+1} = g(Ax)$$

$$Y_1^K = \{y_1, Ay_1, A^2y_1 \ldots, A^{K-1}y_1\}$$

Analysis of Ug:

Note that $Y_1^K \equiv \mathcal{K}_K(Ug, y)$ is a Krylov sequence

There exists iterative methods e.g. the Arnoldi method for spectral analysis of a Krylov sequence

Also, $Ug^*_\omega(x) = \lim_{n\to\infty} \frac{1}{n} \sum_{j=0}^{n-1} e^{i2\pi j\omega} g(f(x))$

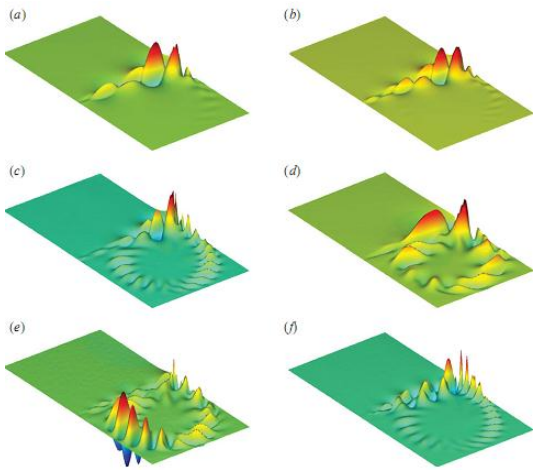
where $\omega \in [-0.5, 0.5)$ and $e^{i2\pi j\omega}$ are eigenvalues, and g^* is a harmonic average

[Schmid 2009 *J. Fluid Mech.*]

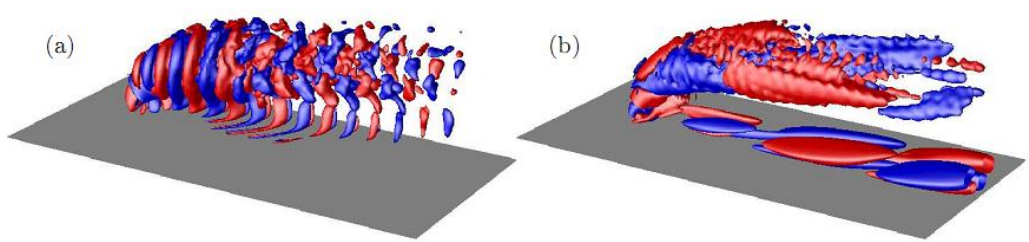
Koopman Approach in other works

The Koopman operator defined in the 1930s, recently been used for analysis of other dynamical systems

Fluid Flow

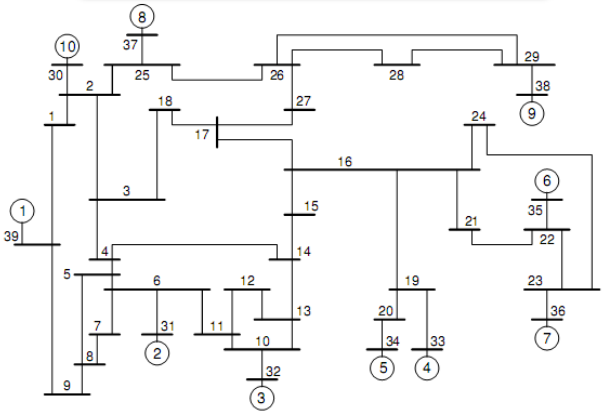


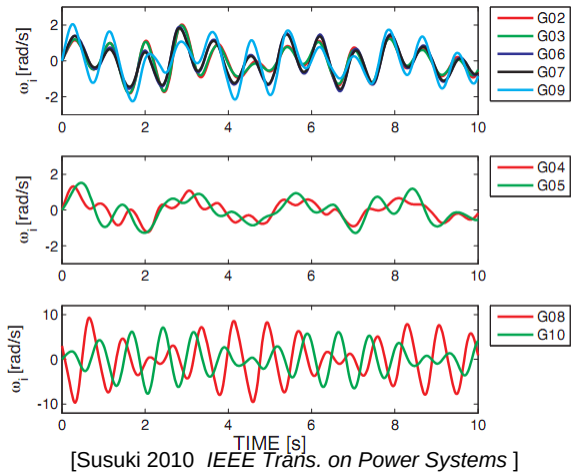
[Schmid 2009 *J. Fluid Mech.*]



[Rowley 2009 *J. Fluid Mech.*]

Power Grid Swing Instability

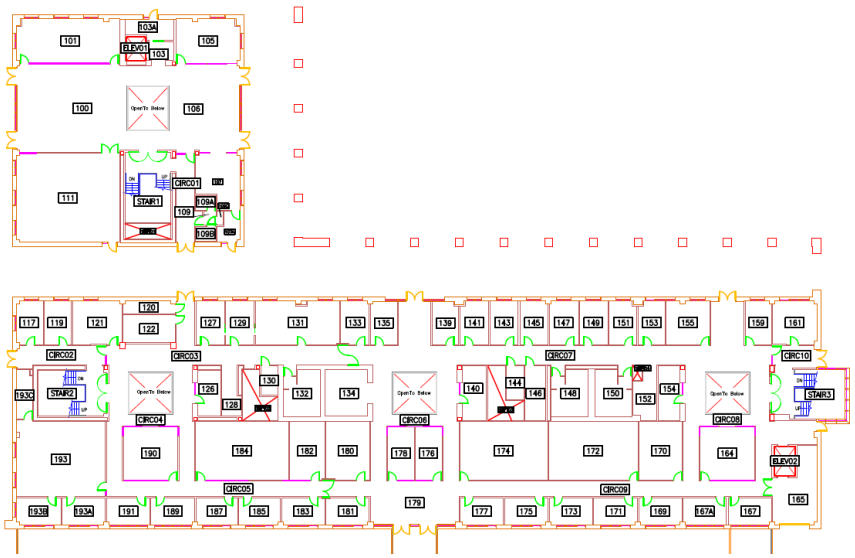




[Susuki 2010 *IEEE Trans. on Power Systems*]

….building system examples

Example – Y2E2 Stanford*



- Yang and Yamazaki Environment and Energy Building
- 166,000 ft^2 15k m^2
- Designed 50% below ASHRAE 90.1.2004
  - Passive daylighting, heating, cooling and ventilation; automatically controlled operable windows, sunshades and fins; radiant floor heating; active chilled beam cooling; heat recovery ventilators; photovoltaics; recycled water

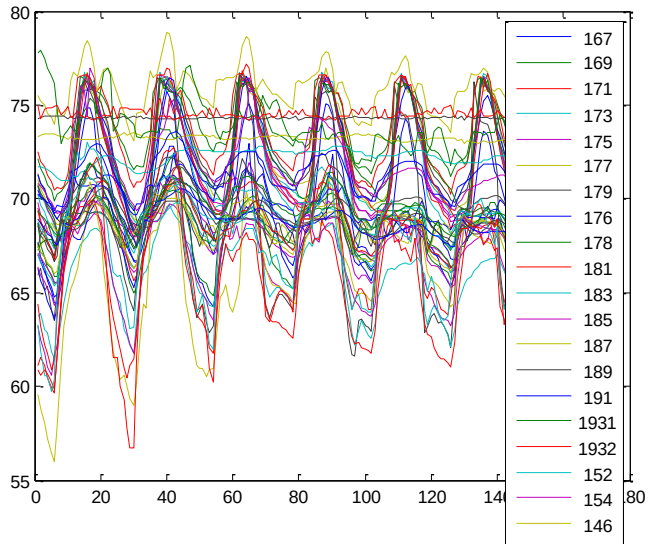
Sensors:

- ~2400 data points, down to the minute

* With Tobias Maile, Martin Fischer Stanford

Koopman Approach

.....Step 1



Original and complicated time domain data

Koopman Approach

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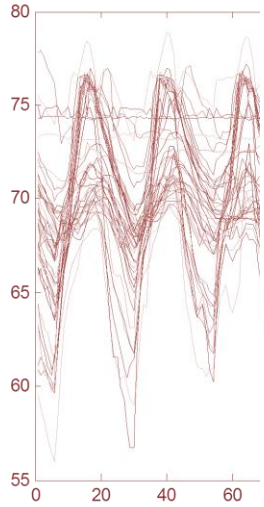
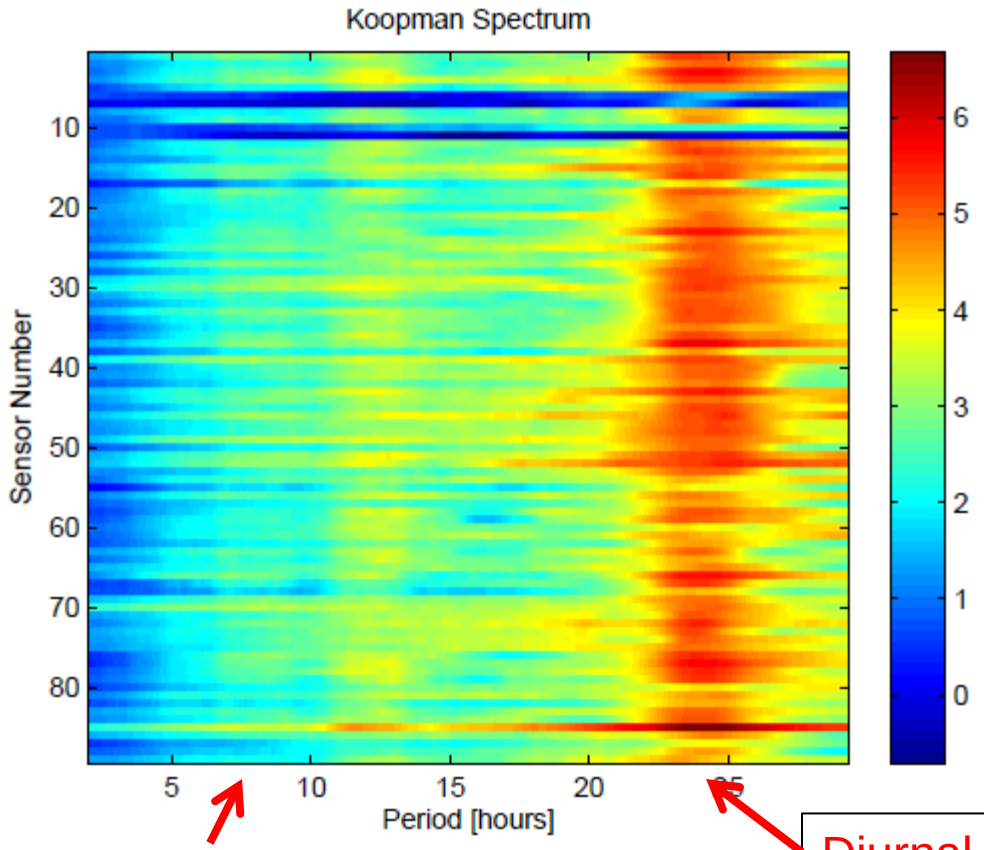
.....Step 2





Work-day 7-8 hrs

Diurnal

Investigate and choose freq. in Koopman spectrum

Koopman Approach

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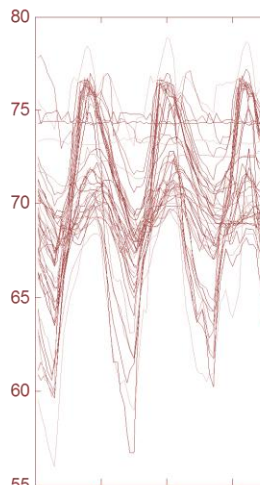
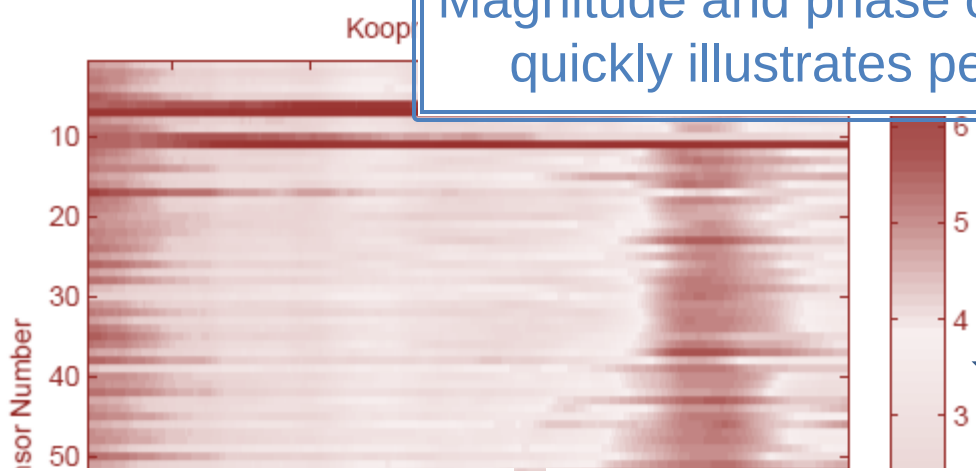
…..Step 3

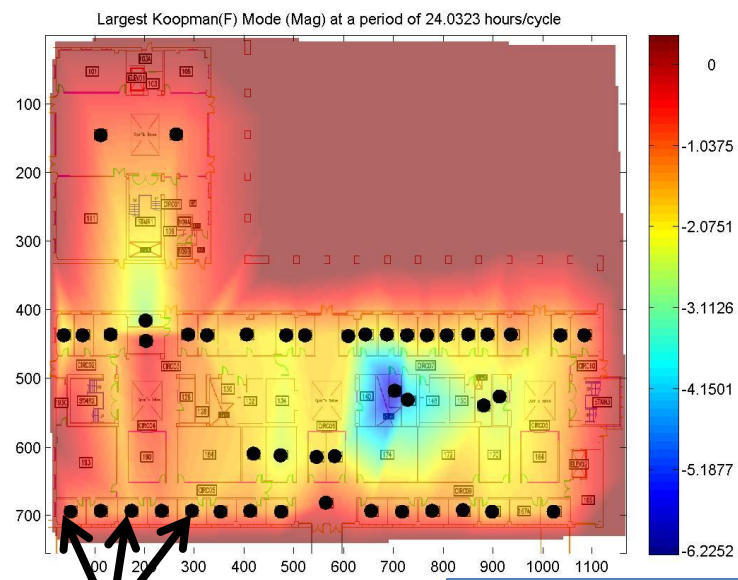
Magnitude and phase of Koopman mode quickly illustrates performance

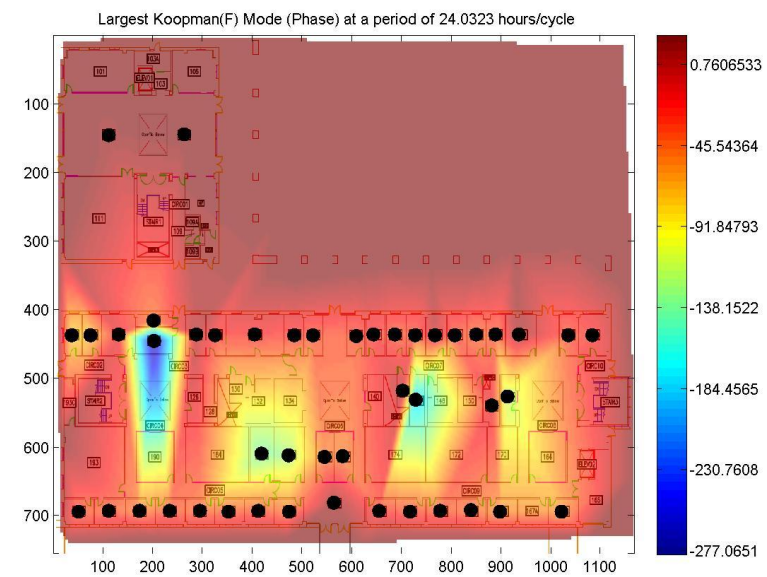




$$|KM(i)| = 20\log_{10}\left|\frac{\psi_i}{\psi_{OAT}}\right|$$

$$\angle KM(i) = \angle\psi_i - \angle\psi_{OAT}.$$





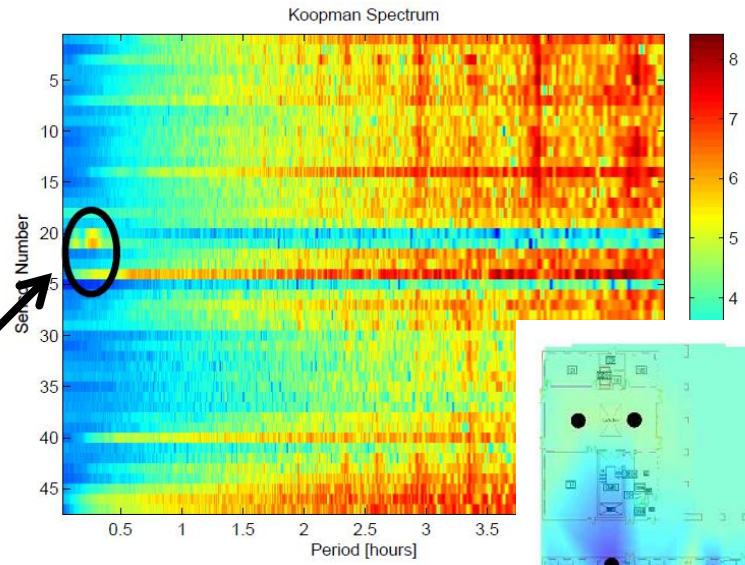
sensors

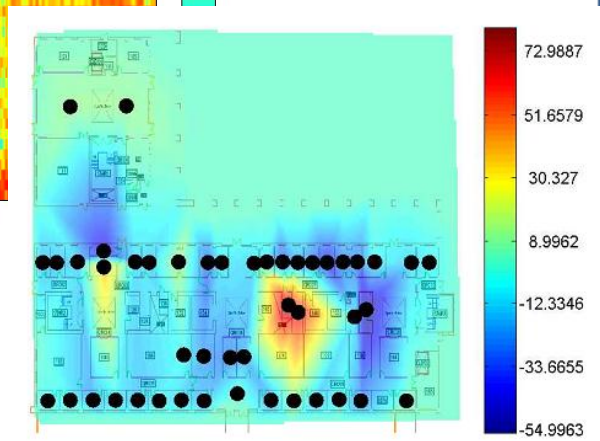
Architectural floor plan, first floor

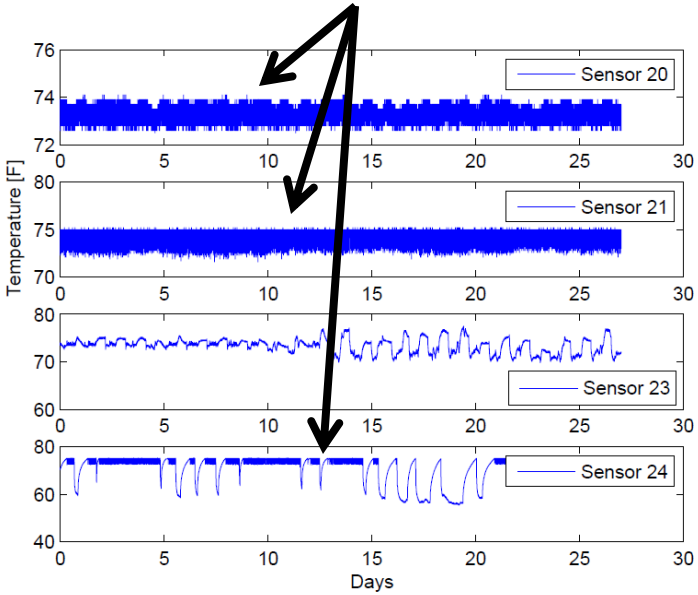
Example: Inefficient Control

- Method quickly isolates sensor / control issues

Energy at unexpected frequencies







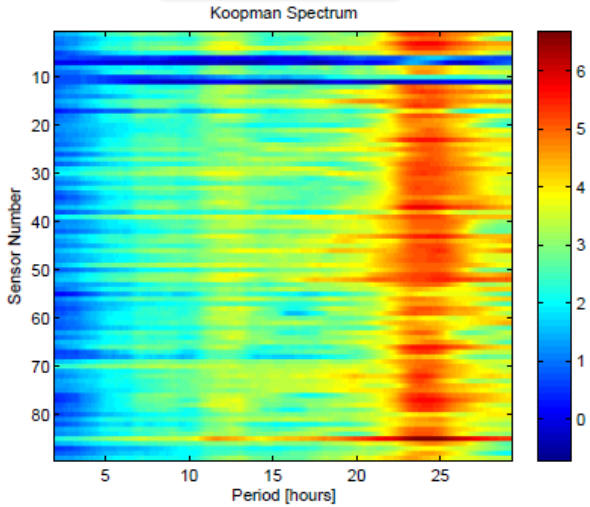
- Cycling found in control system
- System retuned to reduce cycling

Example – Model Tuning

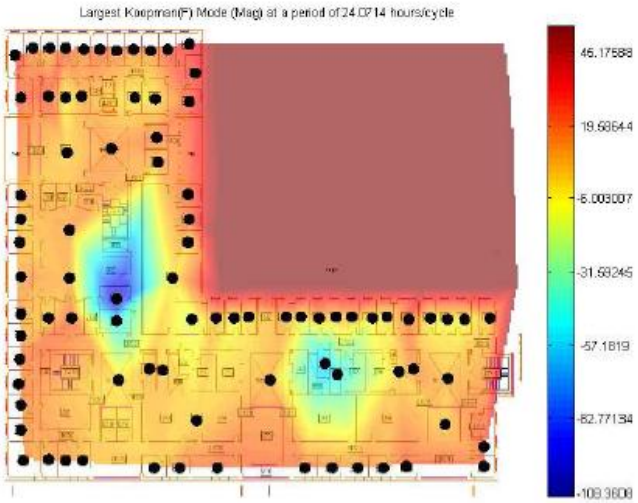
- Comparison between extensive EnergyPlus model and data

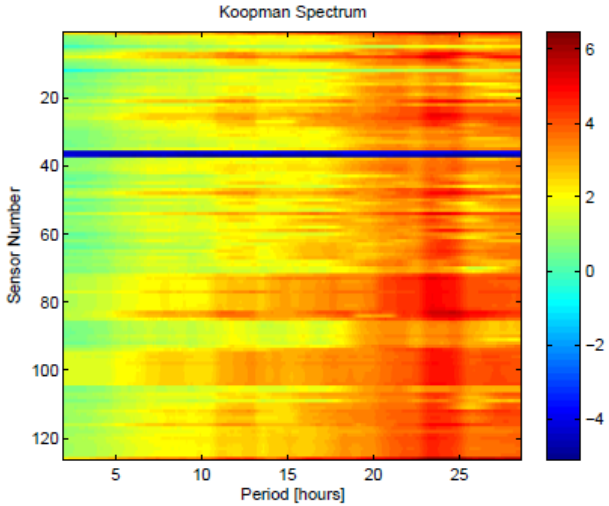
Spectrum

Magnitude

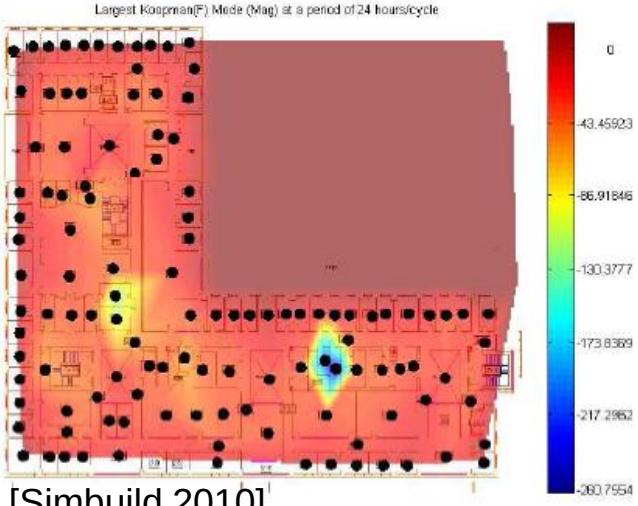


Data





Model



Eisenhower [Simbuild 2010]

Example – Model Tuning

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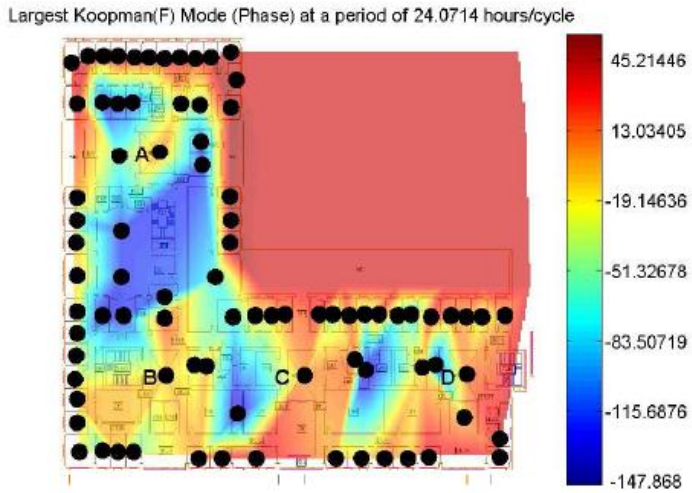
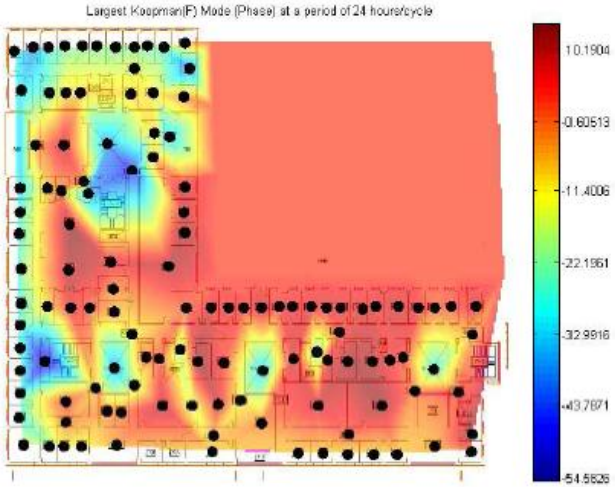
Phase



Data



Model

- Comparison of magnitude and spectra between model / data looks good.
- Phase information between outside conditions and building temperatures has some discrepency
- Phase delay occurs due to occupancy / HVAC scheduling, thermal mass, etc.

Example – Model Tuning

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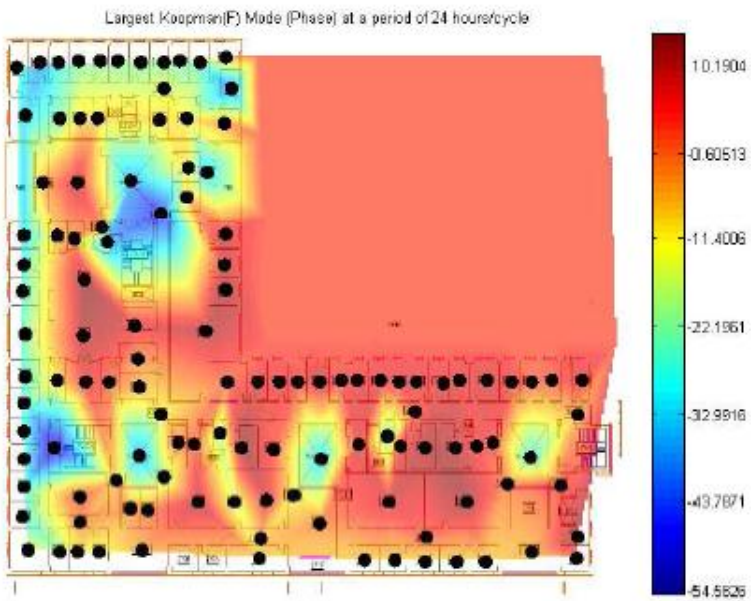
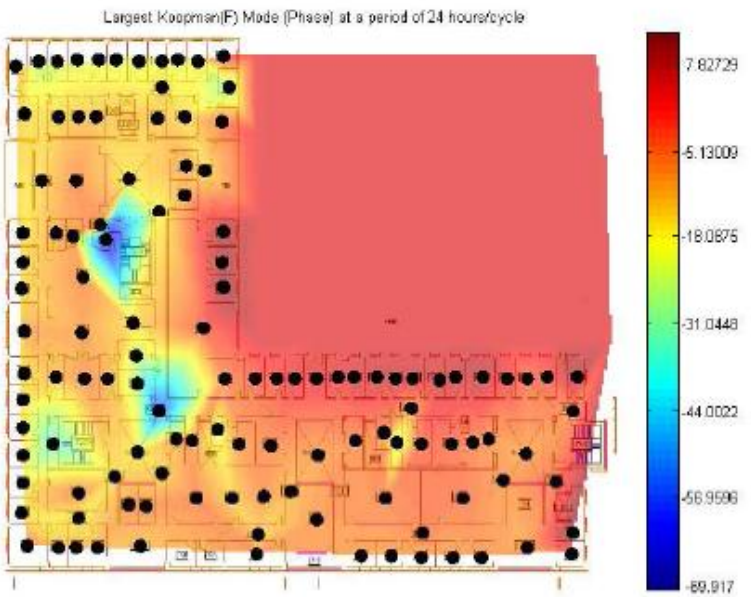
- To better capture phase, model was altered
  1. Active beam induction ratio was changed from 50% to 75% recirculated air
  2. Infiltration values were increased
  3. Natural ventilation was introduced between corridors and offices

Phase – Before Tuning



Model

Phase – After Tuning



Hong Kong: Efficiency analysis*

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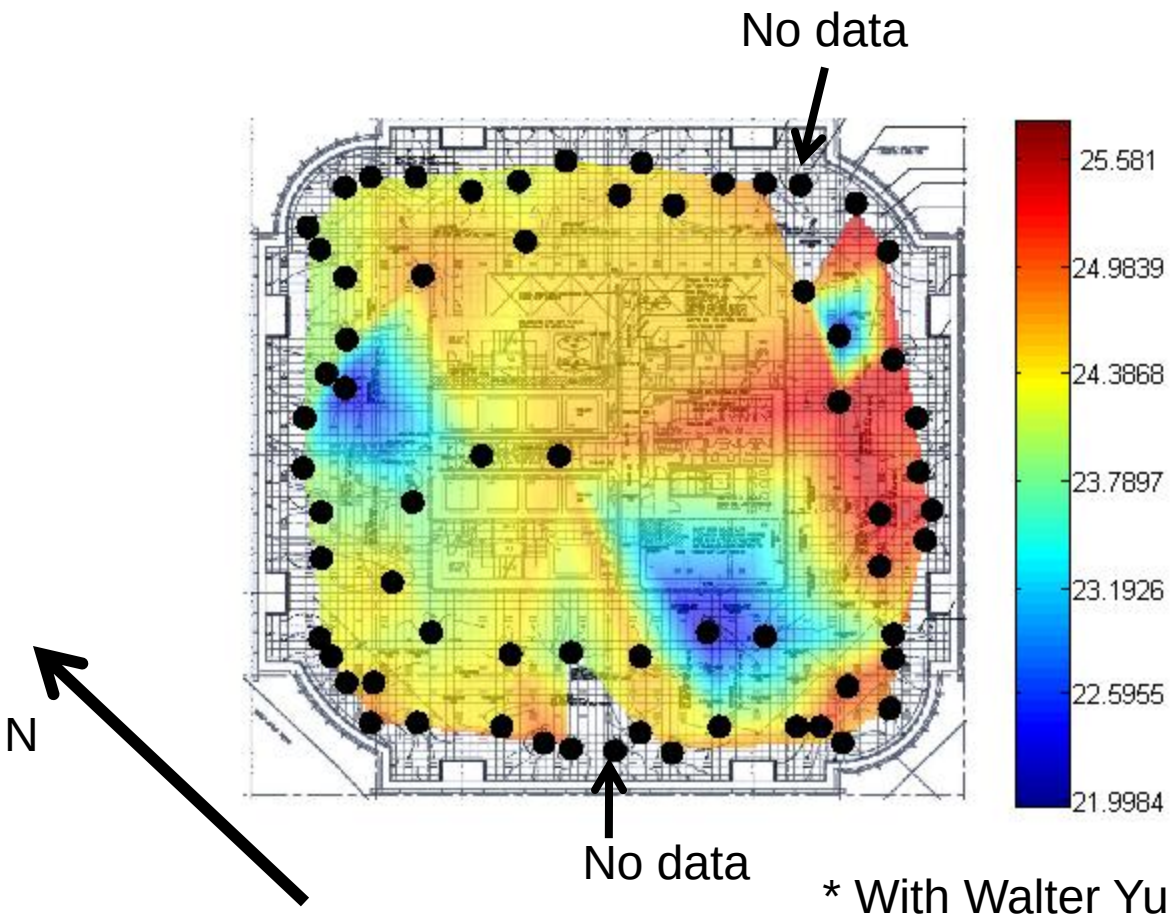
- One Island East – Westlands Rd. Hong Kong
  - 70 story sky-scraper
  - Data: 11/1/2009 – 11/15/2009

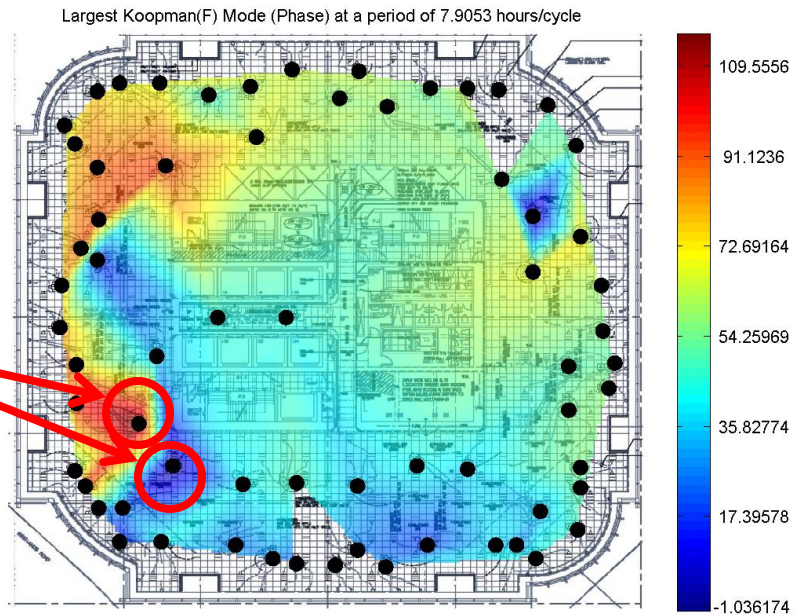


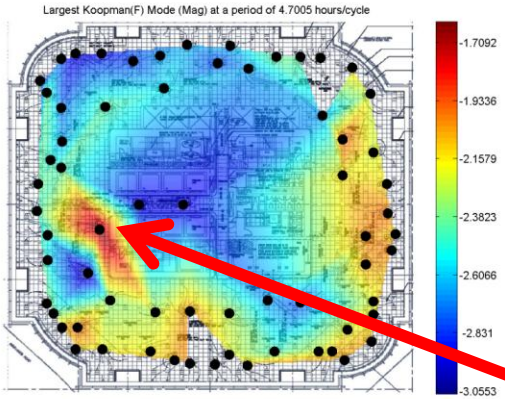
* With Walter Yuen, Hong Kong Poly. Univ.

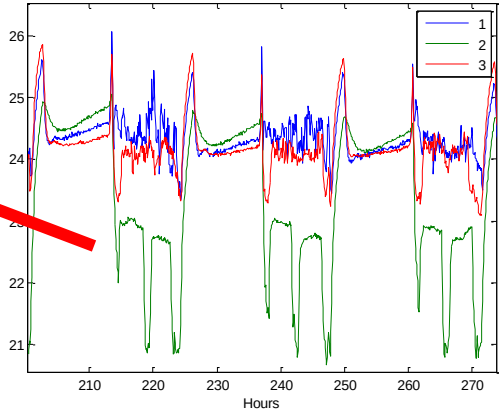
Hong Kong: Efficiency analysis

UC SANTA BARBARA engineering

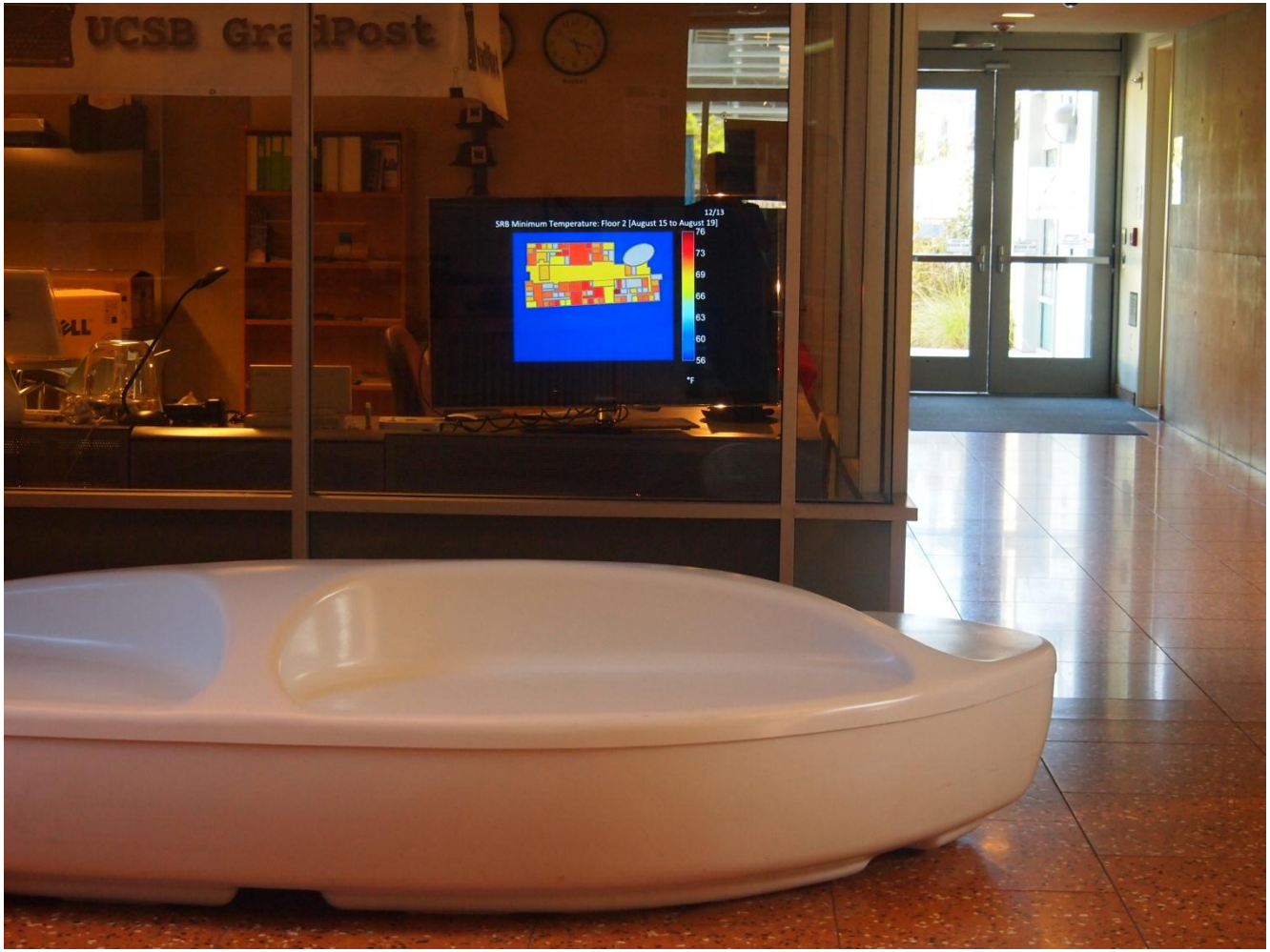
- Out-of-phase controller response one heating, one cooling is usually indicative of inefficient operation







- Irregular lunch-time scheduling in some loops are leading to awkward control response


UCSB GradPost
SRB Minimum Temperature: Floor 2 [August 15 to August 19]
12/13
76
73
69
66
63
60
56
°F

Questions?