A US perspective on energy flexibility:

Energy Neighborhoods and DC reduction

A BEM fidelity perspective

Godfried Augenbroe

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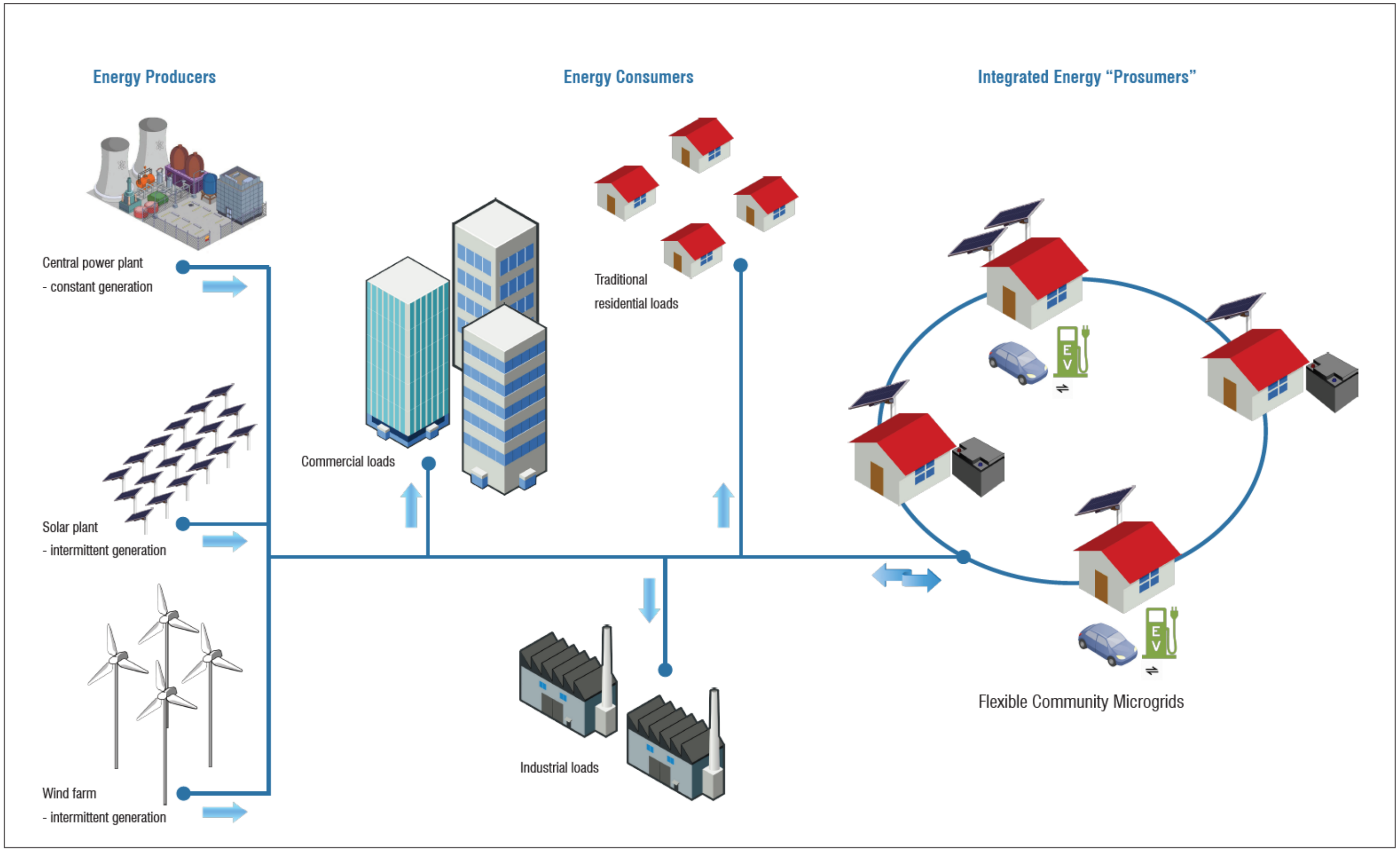
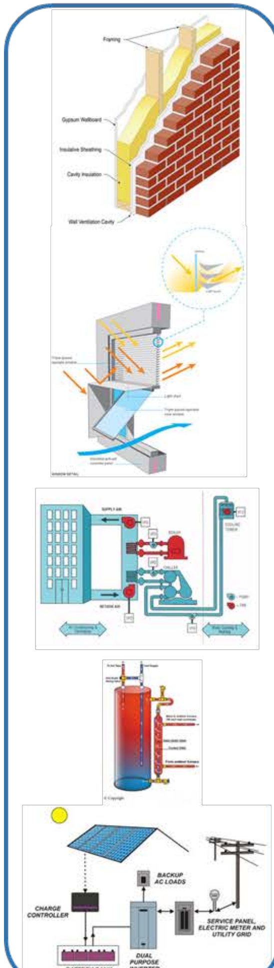
Energy n'hoods



BEM: Scale and scope

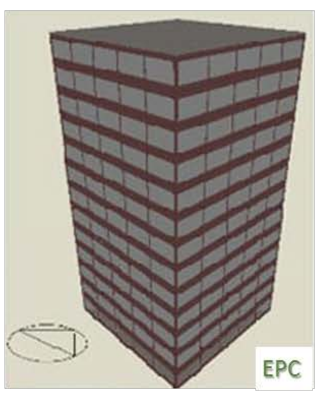
Building systems and components



Whole-building

Detailed building model

Reduced-order building model



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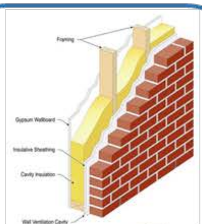
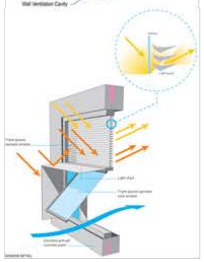
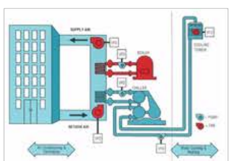
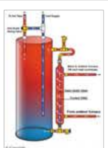
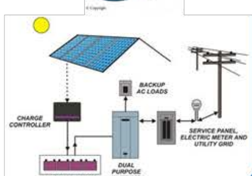






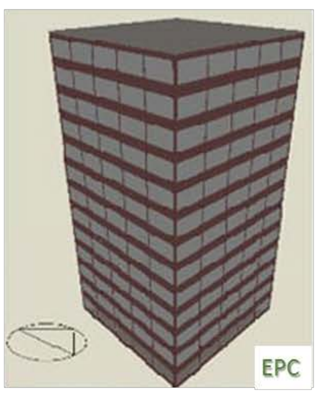




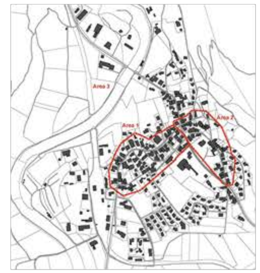
Whole-building

Detailed building model

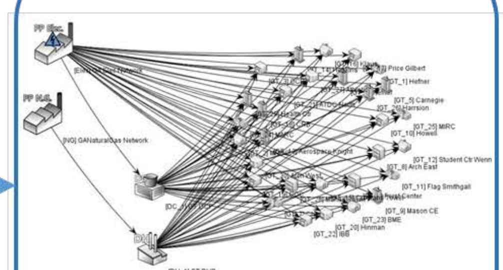
Reduced-order building model



Neighborhood scale

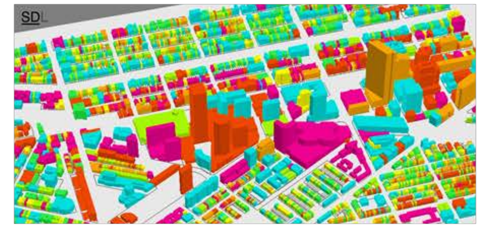


(Orehounig et al., 2014)

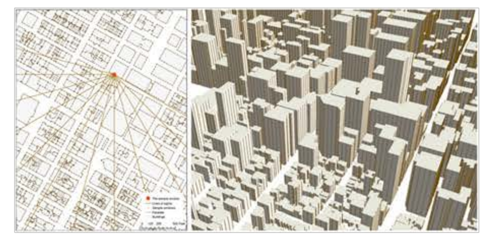


(Lee, 2012)

City scale



Boston, MA (Davila et al., 2015)



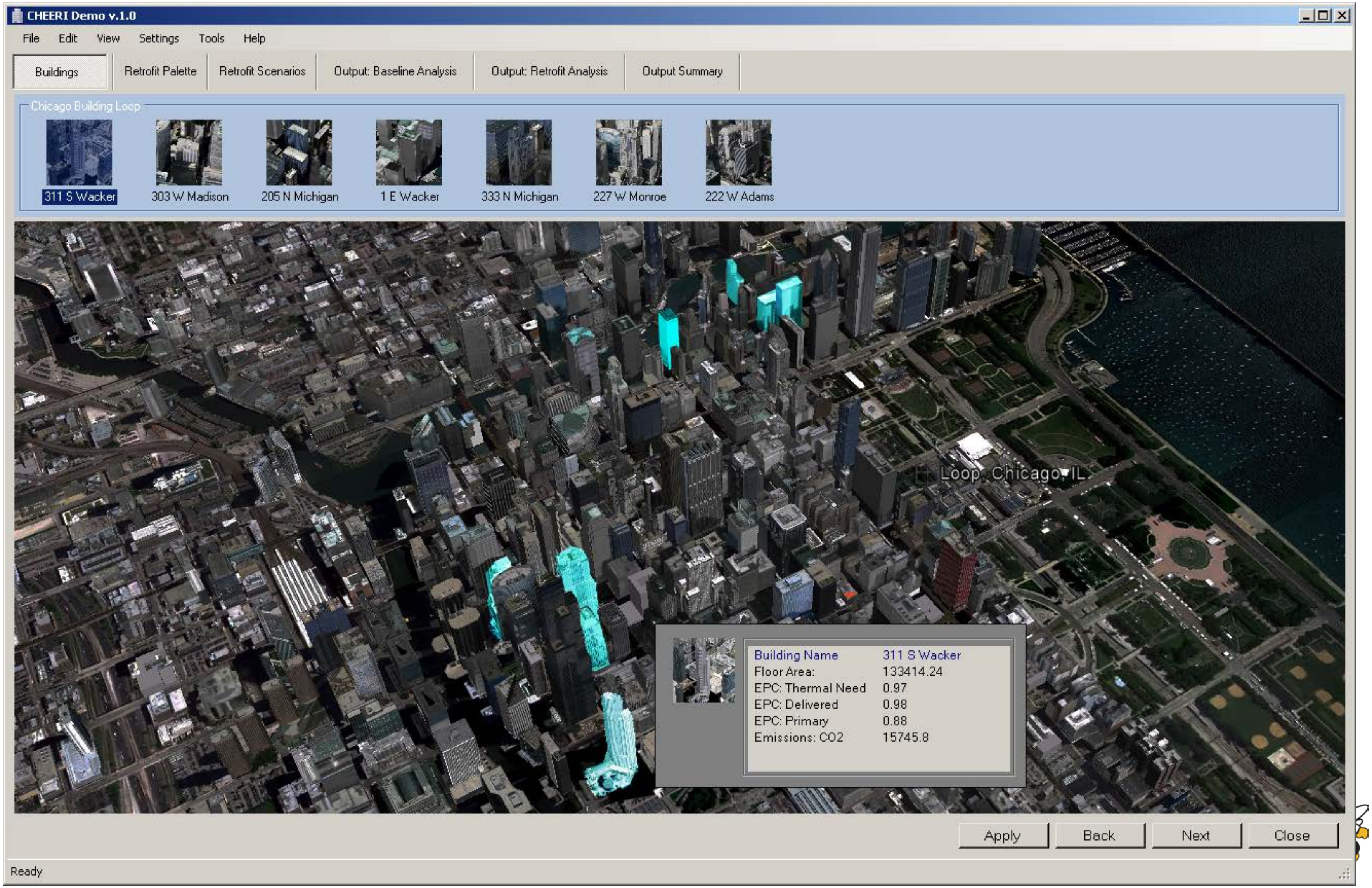
Manhattan, NY (Quan et al., 2015)

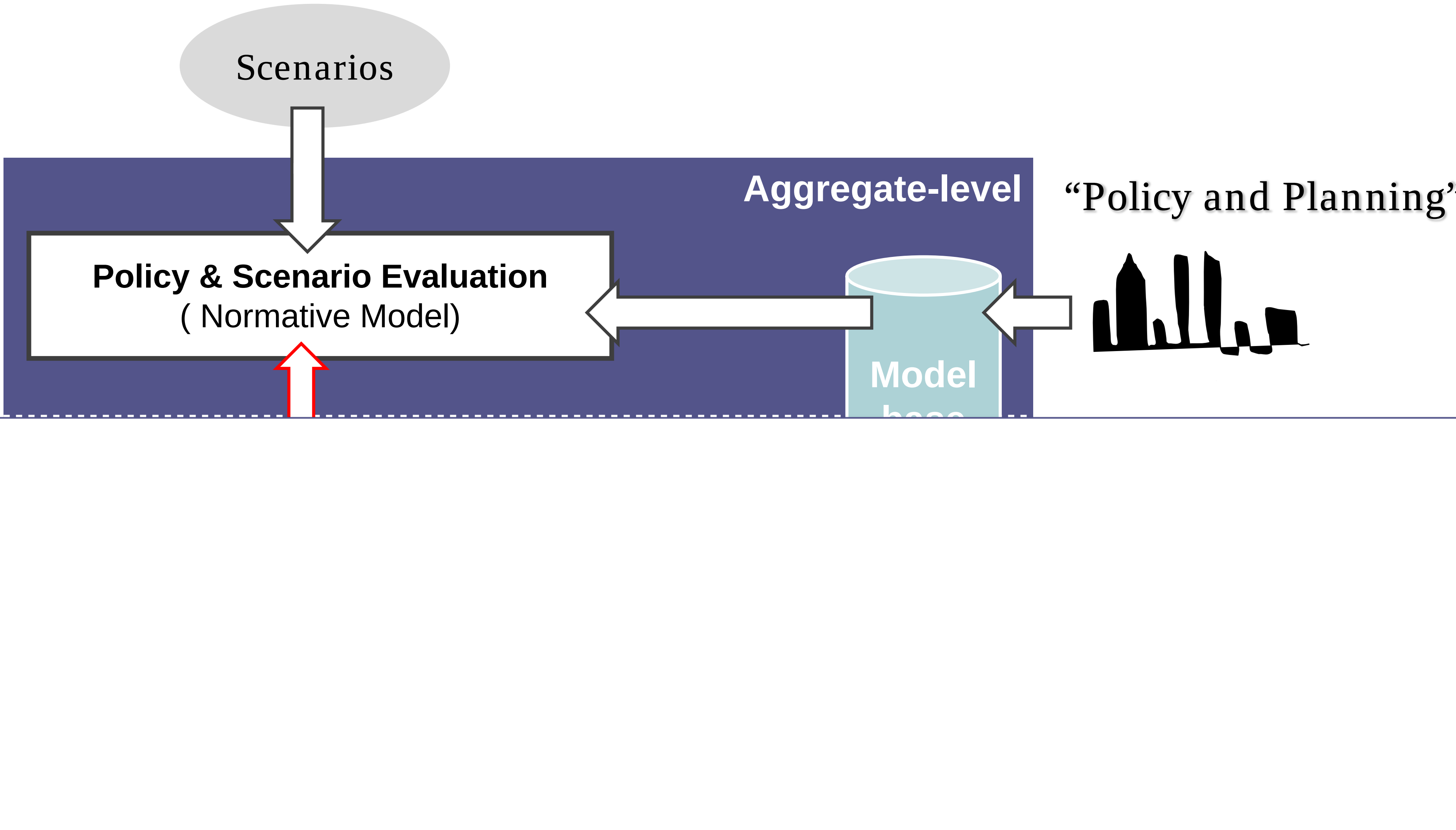
(Zhao, 2012)

Overview of some efforts in our lab

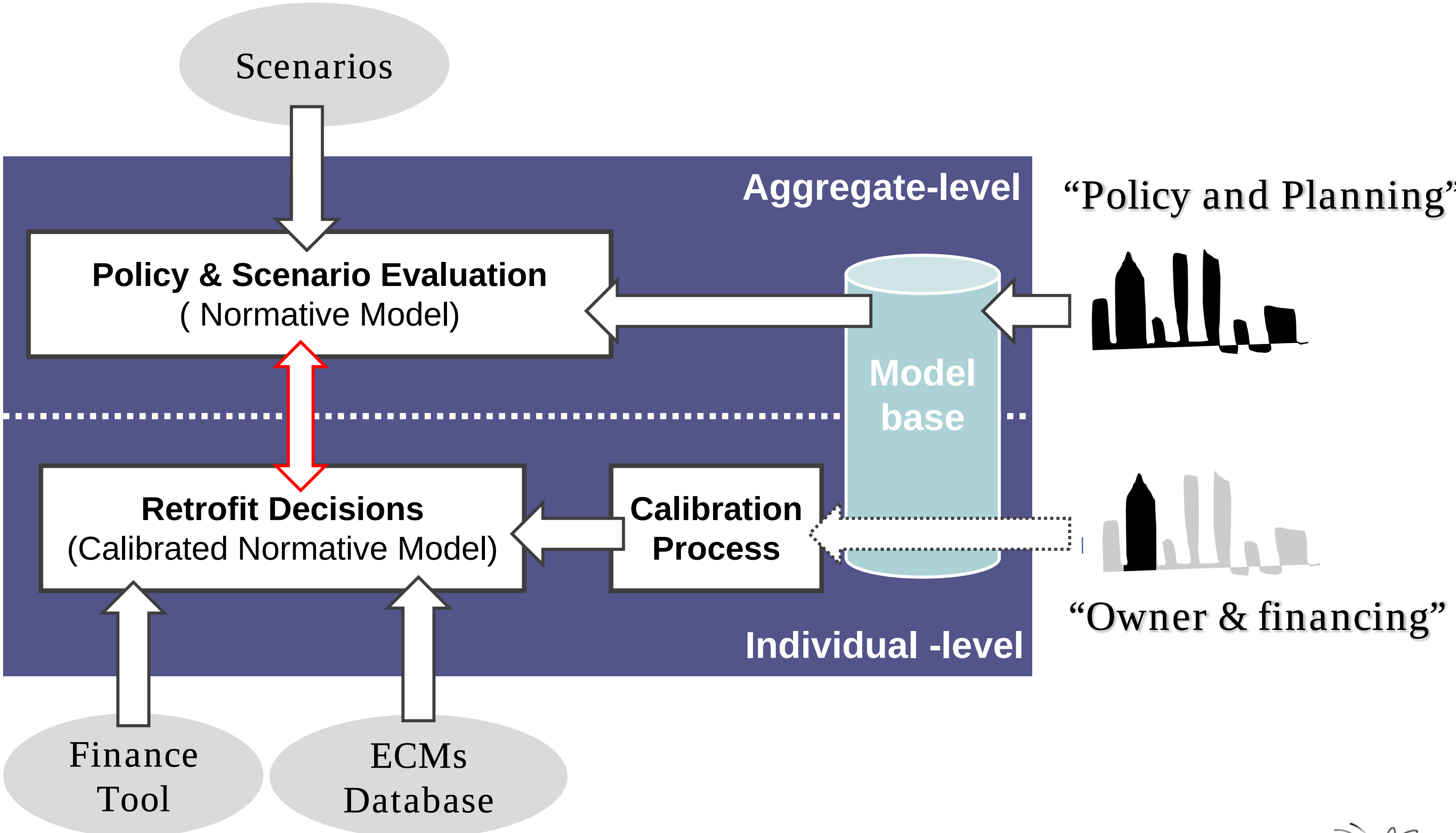
1. Chicago lab retrofit
2. A campus model
3. Microgrid optimization
4. The London Westminster model
5. The Manhattan model
6. Resilient communities with multi-layered intelligence

1. Chicago Loop retrofit



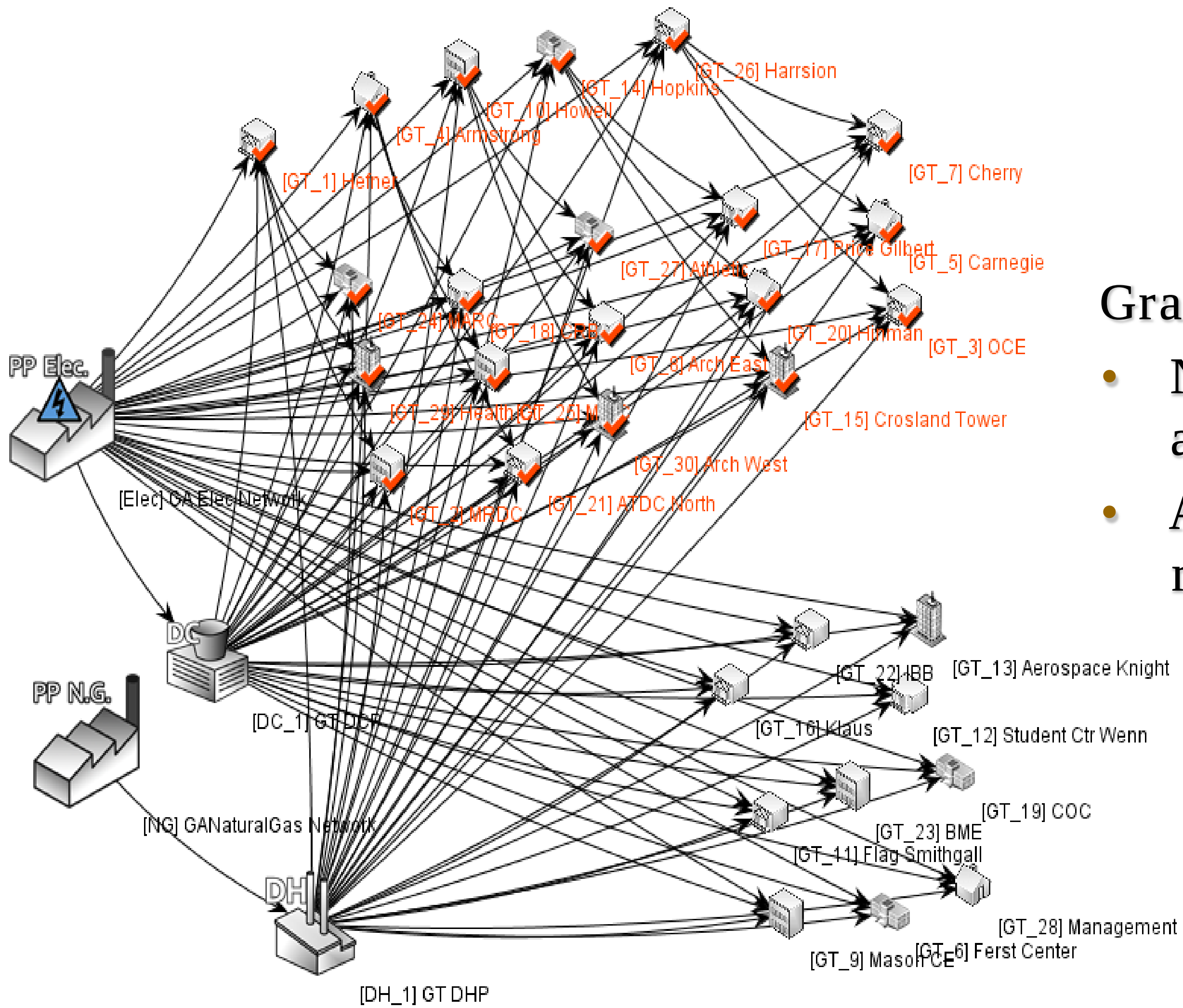


Heo Y.S., G. Augenbroe, D. Graziano, R.T. Muehleisen, L. Guzowski (2015). Scalable methodology for large scale building energy improvement: Relevance of calibration in model-based retrofit analysis. Building and Environment 87, 342-350



Heo Y.S., G. Augenbroe, D. Graziano, R.T. Muehleisen, L. Guzowski (2015). Scalable methodology for large scale building energy improvement: Relevance of calibration in model-based retrofit analysis. Building and Environment 87, 342-350

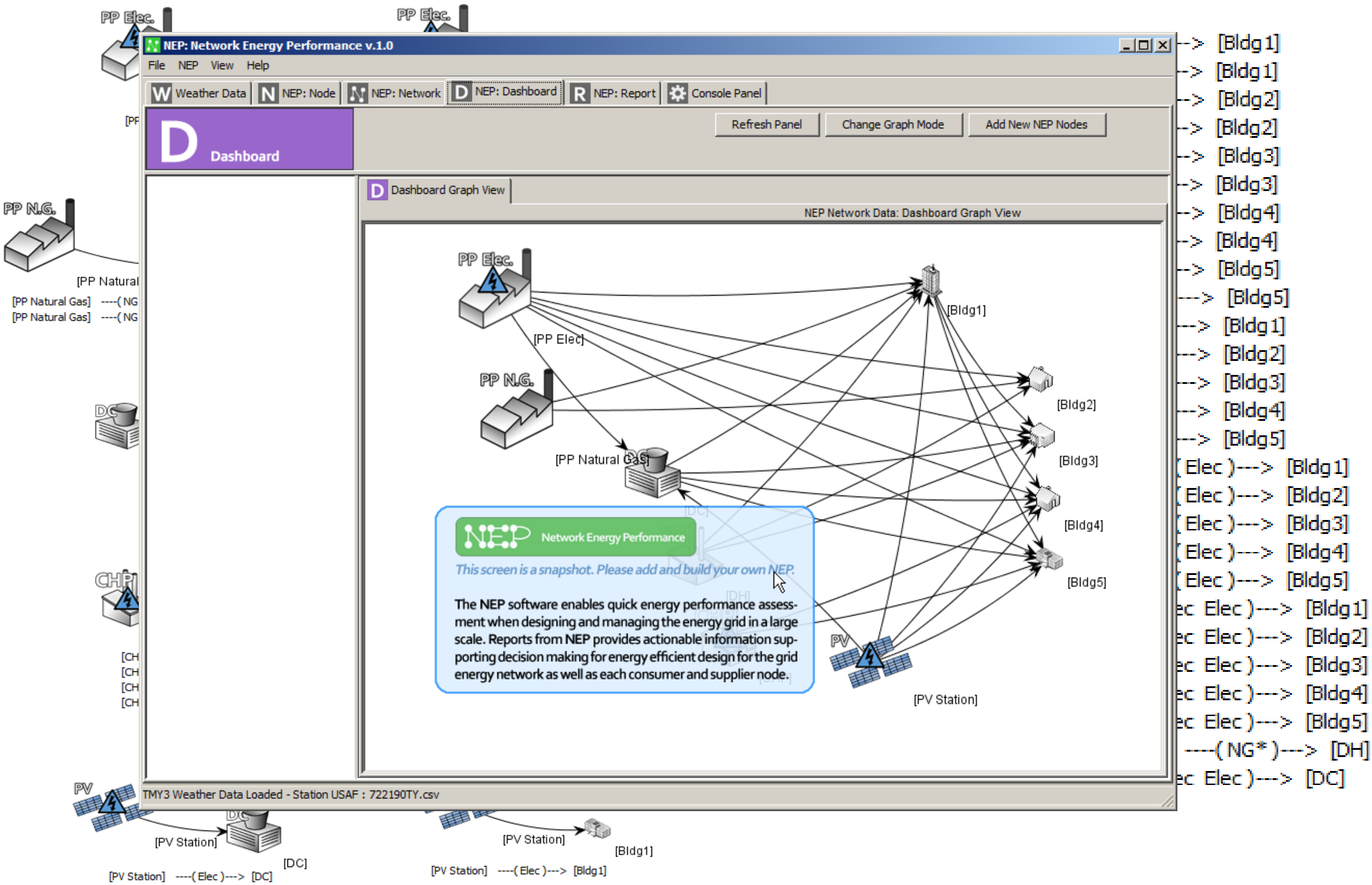
2. Campus network



Graph of:

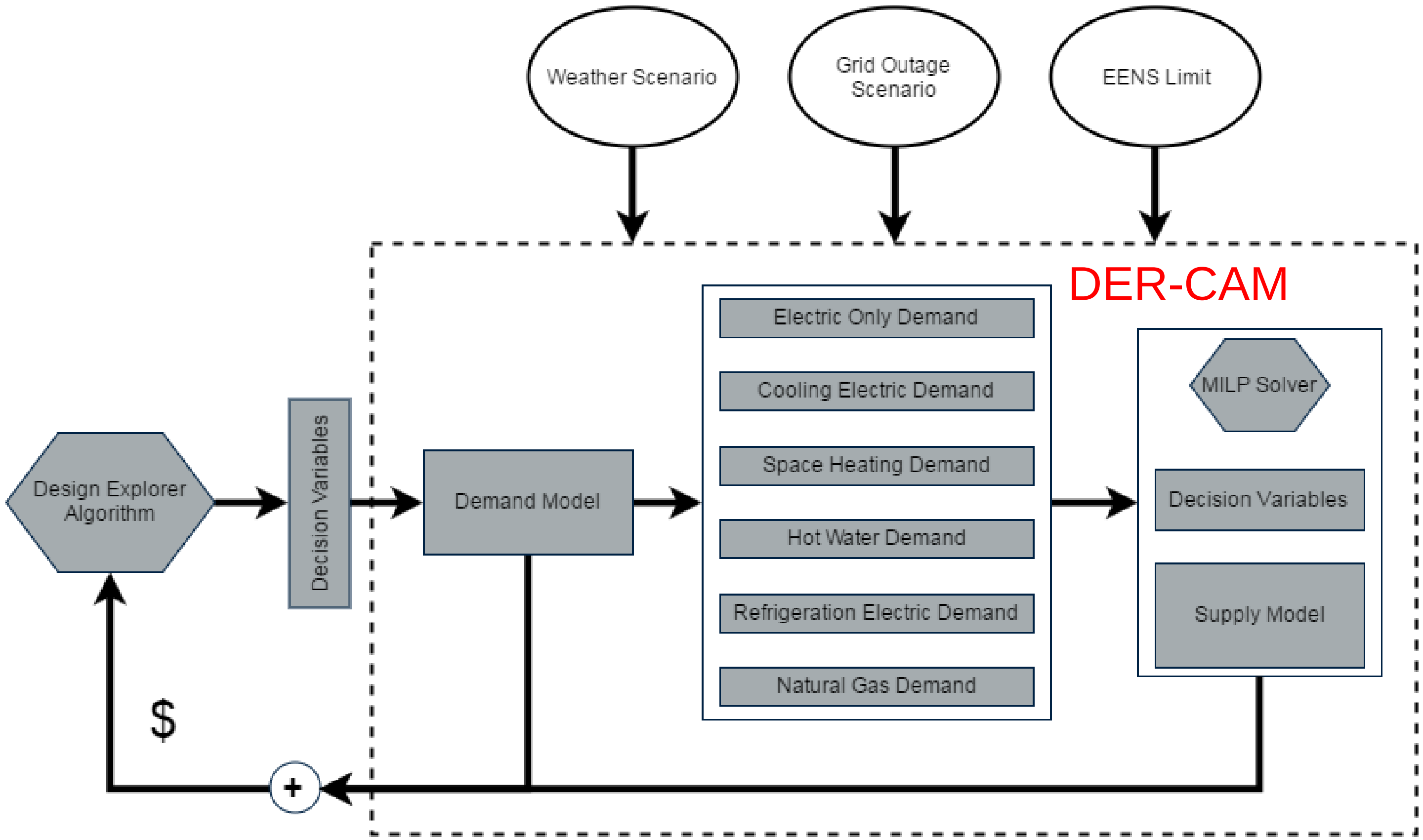
- Nodes: energy consumers and suppliers
- Arcs: exchange/sharing modes

Lee, sang Hoon (2012). Campus scale energy planning and management. PhD thesis Ga Tech.



Lee, sang Hoon (2012). Campus scale energy planning and management. PhD thesis Ga tech.

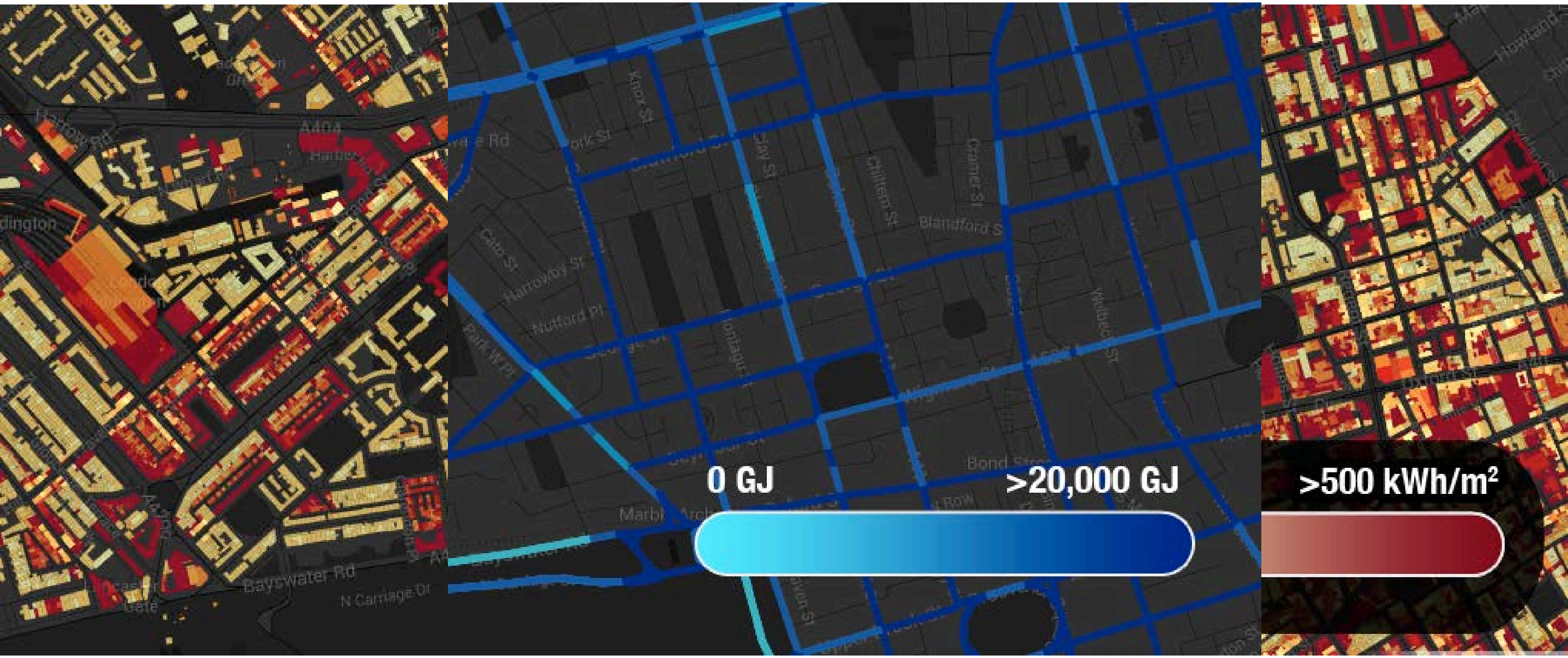
3. Microgrid optimization



Overview of the integrated optimization framework. DEA searches the decision variable space of the demand model, which interacts with the supply model through six exchange variables. A decision maker defines the weather, grid outage and EEMS scenario.

Michael Street (2016), Integrated performance based design of communities and distributed generation. PhD Dissertation Georgia Tech, 2016.

4. London Westminster: 1000+



- EECi project at Un. Cambridge: Combined building and traffic emission model in urban canopy dispersion model

5. Very large scale urban models 10,000

- Urban heat island (UHI) effect: larger ambient temperature fluctuations in urban area
- UHI model used, following Sun and Augenbroe (2014):
  - The Town Energy Budget (TEB) model (Masson 2000)
  - The Interaction Soil–Biosphere–Atmosphere (ISBA) model (Noilhan and Planton 1989; Noilhan and Mahfouf 1996)

Detected GIS morphology → Simplified into → **Urban parameters** → Feed into → **TEB-ISBA UHI model** → Boundary condition of → **Energy model**

Detailed GIS morphology
- Individual building geometry

Urban parameters
- Urban canyon height
- Urban canyon aspect ratio
- Coverage of vegetation area
- Coverage of built area

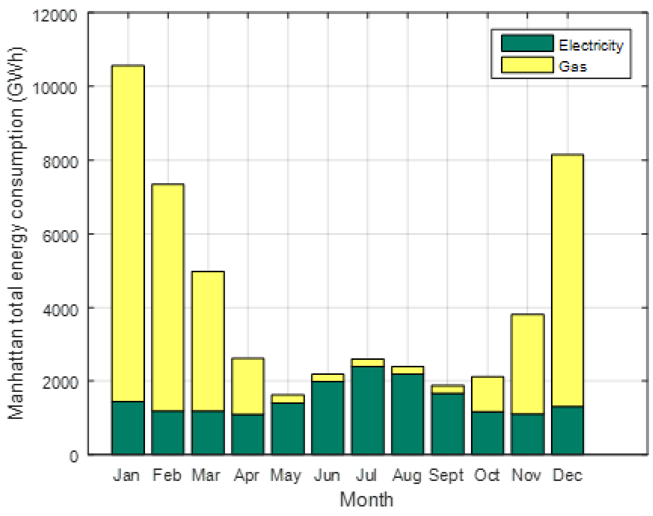
TEB-ISBA UHI model
- Calculated hourly actual ambient temperature

Energy model
- Adjusted energy consumption under UHI effect

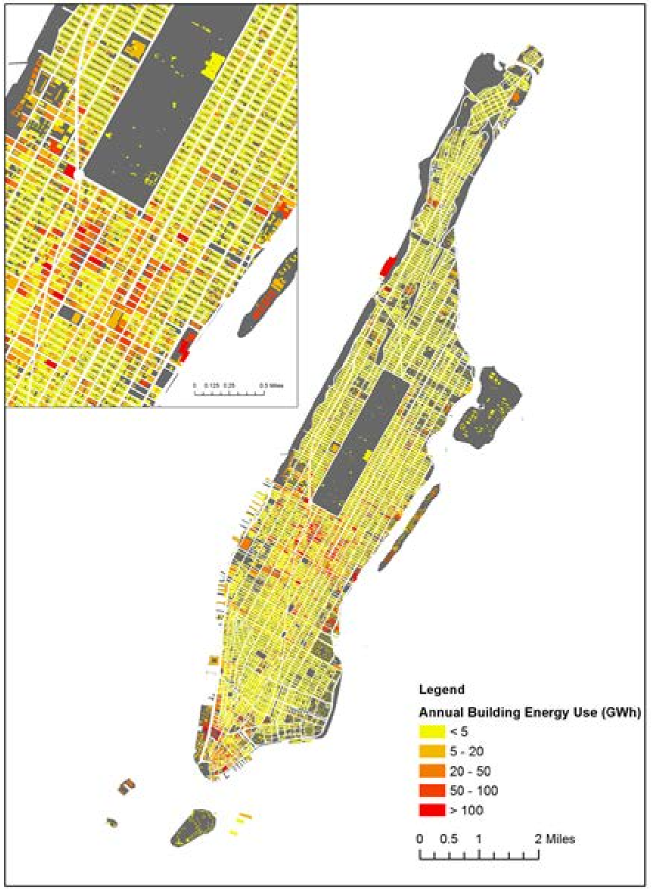
Quan, S.J., Li, Q., Augenbroe, G., Brown, J., & Yang, P.-J. (2015). Urban Data and Building Energy Modeling: A GIS-Based Urban Building Energy Modeling System Using the Urban-EPC Engine (Ch 24). In S. Geertman, J. Ferreira Joseph, R. Goodspeed, & J. Stillwell (Eds.), Planning Support Systems and Smart Cities SE - 24 (pp. 447–469).

Urban outcomes

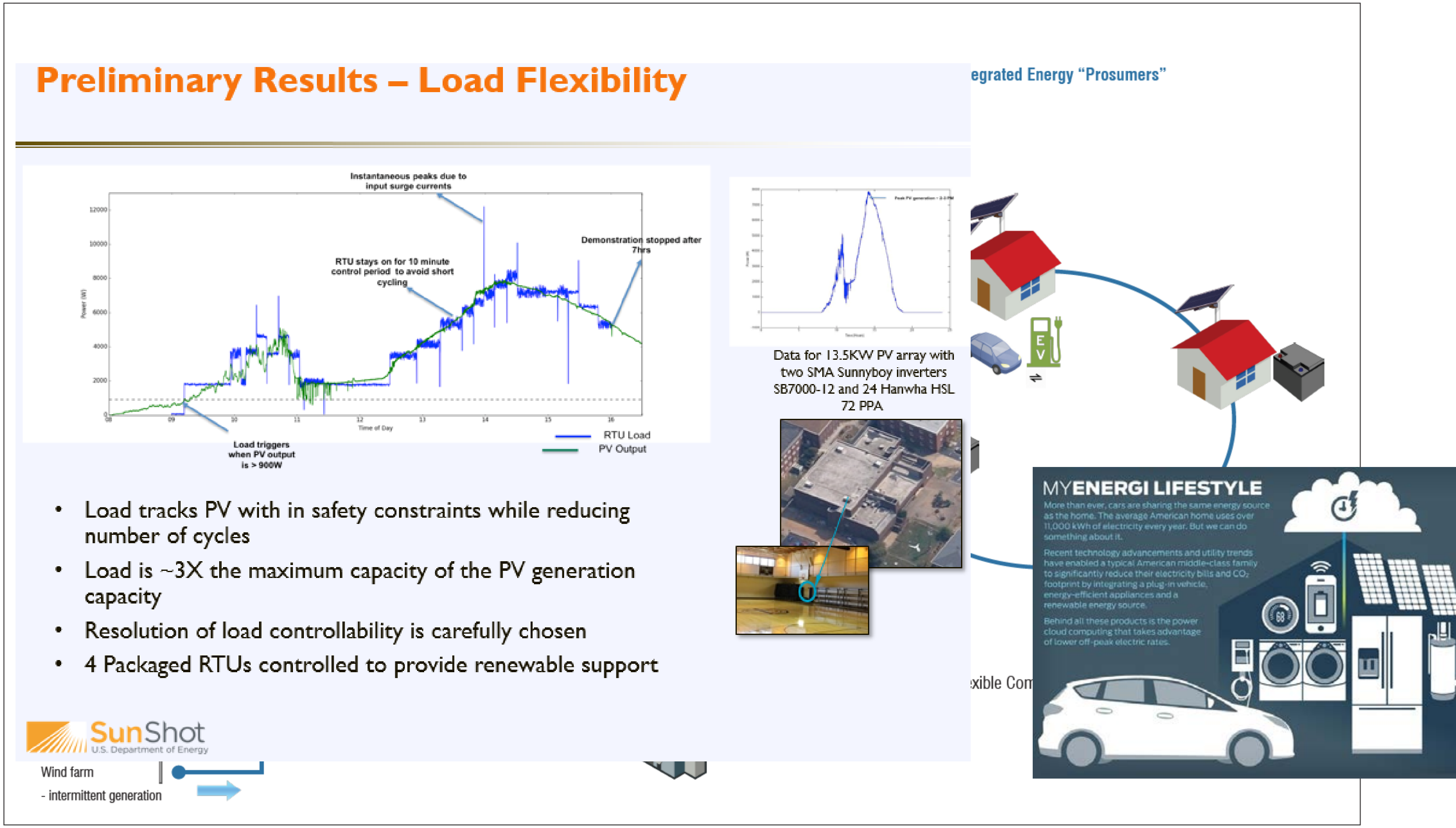
- Temporal and spatial characteristics of urban-scale building energy



Above: monthly total building energy consumption of Manhattan
Right: spatial building total energy consumption across Manhattan



6. Connected, resilient communities



Gustavo Carneiro (2017), Integration of buildings and DER in neighborhood energy models Georgia Tech PhD thesis

The consensus road forward

Step 1: Automatic generation of synthetic environments from

- GIS
- BIM
- Census (PUMS)
- Other…..

Step 2: Population of building energy models

Step 3: Add urban climate parameters

Step 4: Add “light touch”” calibration based on smart meter data

One question is usually avoided!

The unanswered question

What model fidelity is adequate for the individual building nodes?

Typical choices:

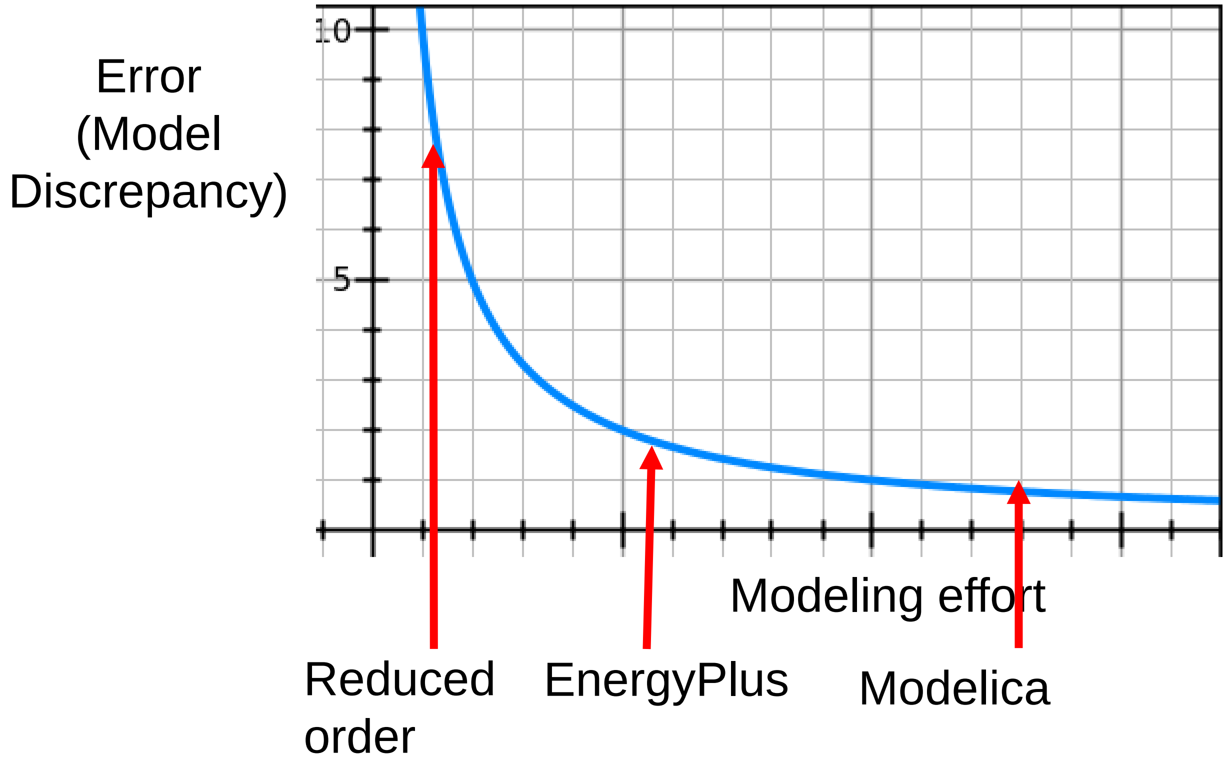
- Statistical (Regression, Surrogate, Gaussian Process)
- Reduced order (aggregate model with zonal mass-nodes): EPC
- Fully dynamic, from retail (IES, EnergyPlus) to customized
- Research (Modelica)

Ramifications:

- How to handle p2p dynamics (co-simulation)
- At what scale does the individual still matter

Obviously "it all depends what you want to achieve"!

The question is relevant



"Lazy modeling leads to oversizing"

"Over-engineered models have no pay back"

Question: How does urban scale modeling amplify these issues?

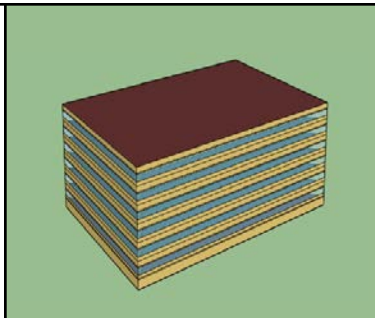
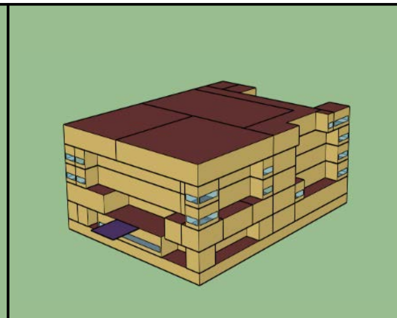
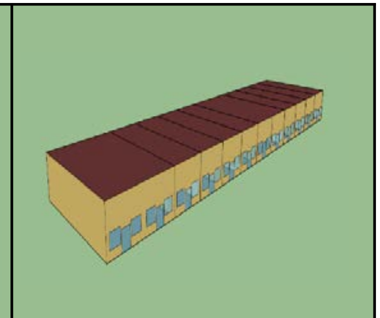
Let's address this question in a study

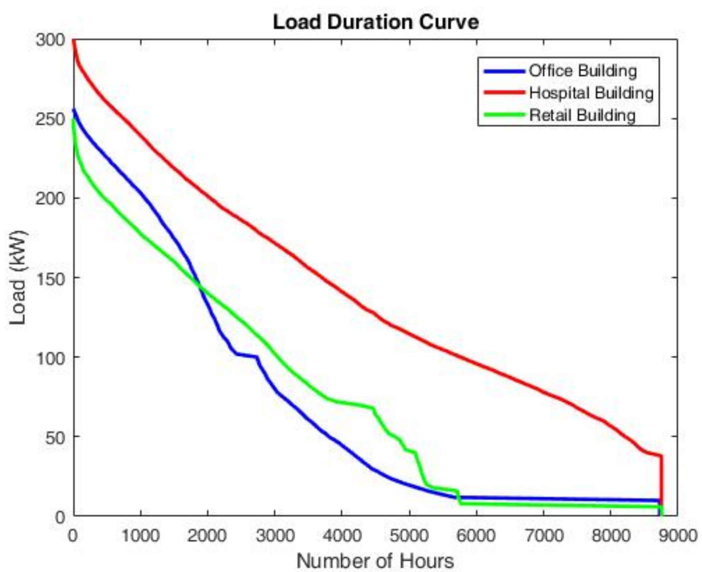
Goal of study: Select optimal set of measures that reduce electricity cost
FOR ONE BUILDING AT A TIME

- With special attention on: demand charges (DC)
- In different DC rate structures (by local utilities)

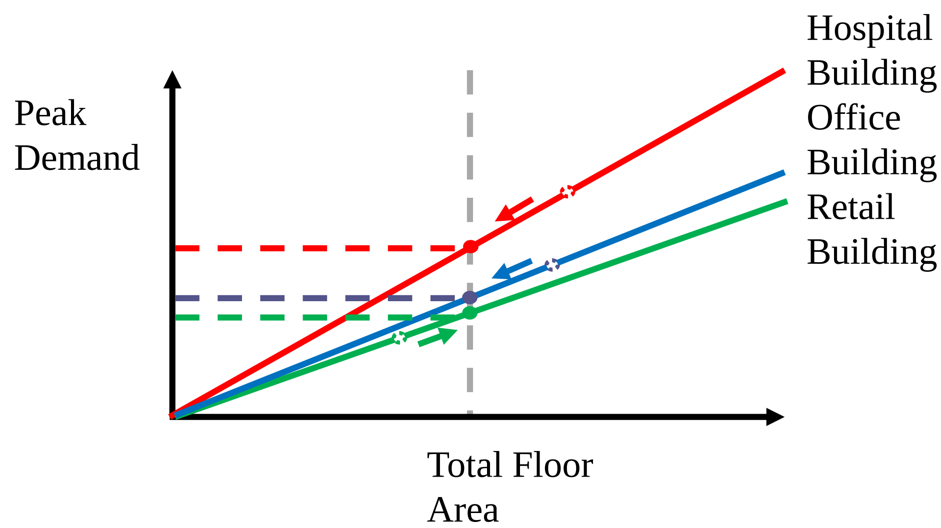
Yuna Zhang, Optimal strategies for demand charge reduction by commercial building operators. PhD dissertation Georgia Tech, June 2017

Application cases

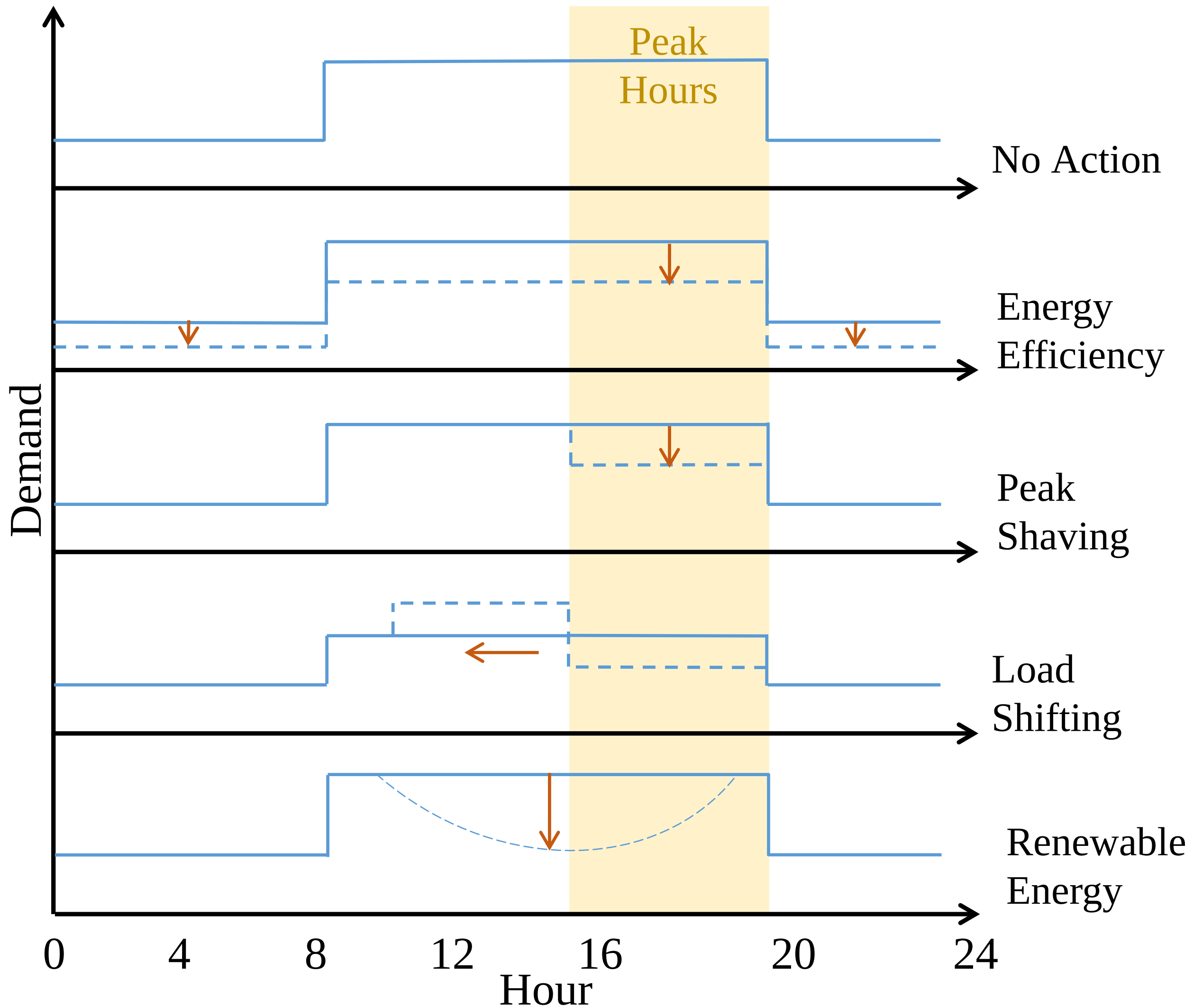
Building Model			
Building Type	Office	Hospital	Retail
Floor Area	3000 m^2	3000 m^2	3000 m^2



Load Duration Curve



Methods To Reduce Demand Charges



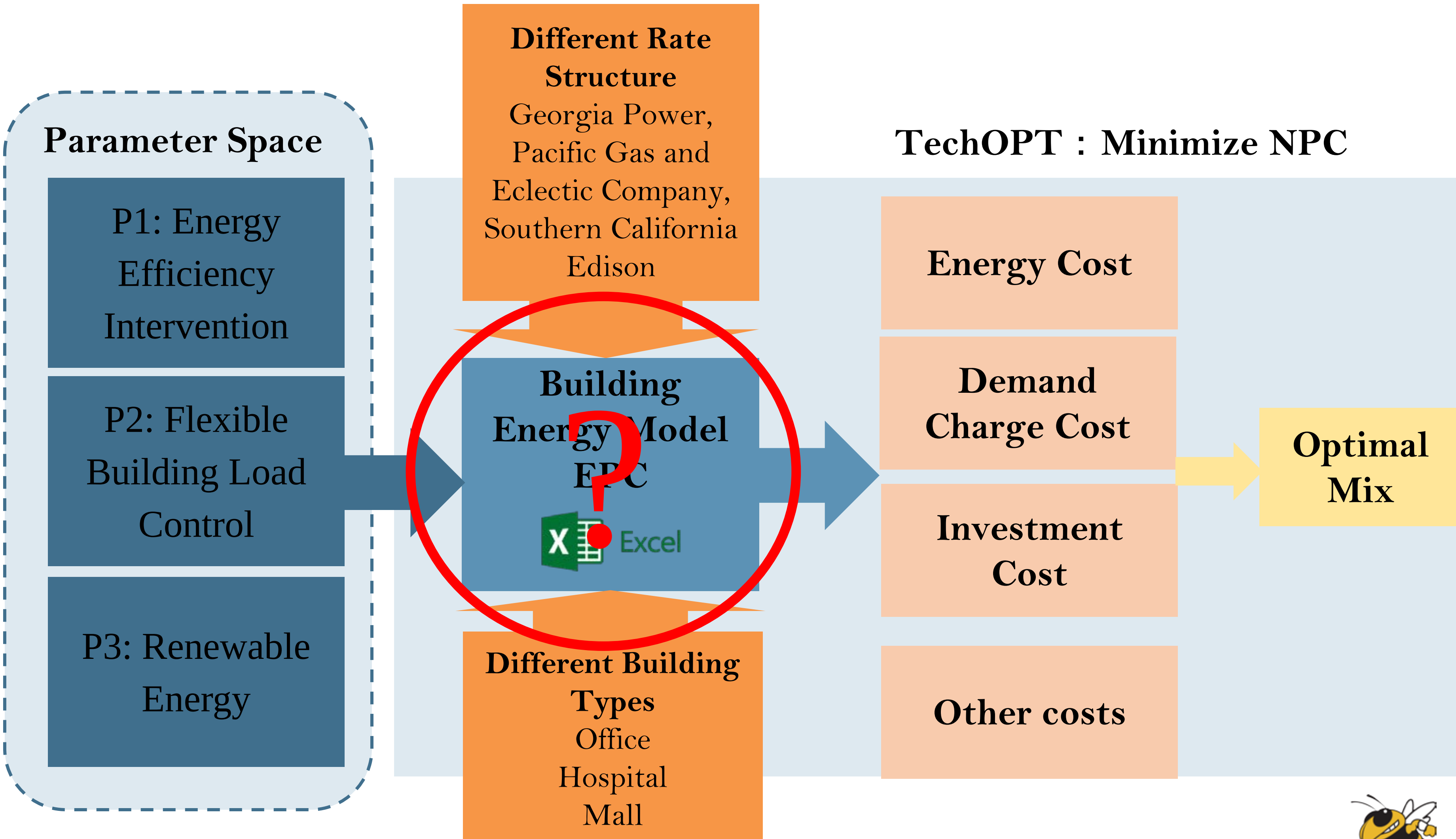
EEM and EFM (parameterizations)

	Building Parameters	Value		Cost
		Min	Max	
Energy Efficiency Intervention (EEM)	Infiltration Rate($m^3/h/m^2$)	0.2	0.8	\$4-\$10/m
	Wall Insulation Thickness (mm)	0	100	\$10-\$17/m^2
	Emissivity of Roof	0.4	0.9	\$10-\$22/m^2
	Solar Reduction Factor	0.8	1	\$45-\$65/each window
	Window SHGC	0.25	0.8	\$450-\$650/each window
Energy Flexibility Intervention (EFM)	Temperature Control	0	2.5	Productivity loss
	Lighting Dimmer	0	30	\$300/each dimmer
	Voltage Throttling	0	1	Productivity loss
	Schedule Adjustment	0	1	\$0
	Area of the PV System (m^2)	0	200	\$520 per m^2

Goal: select EEM+EFM set with highest NPV

- For given building type in given location
- Under given specific electricity rate structure

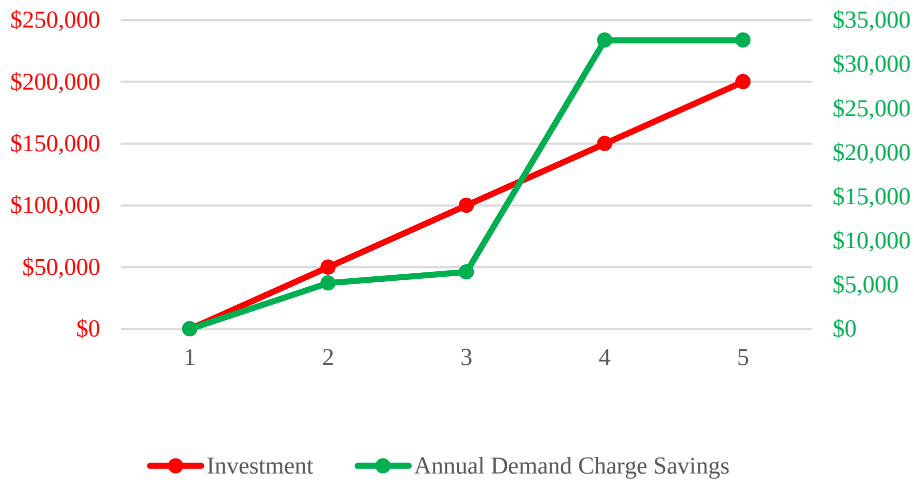
Deterministic Optimization

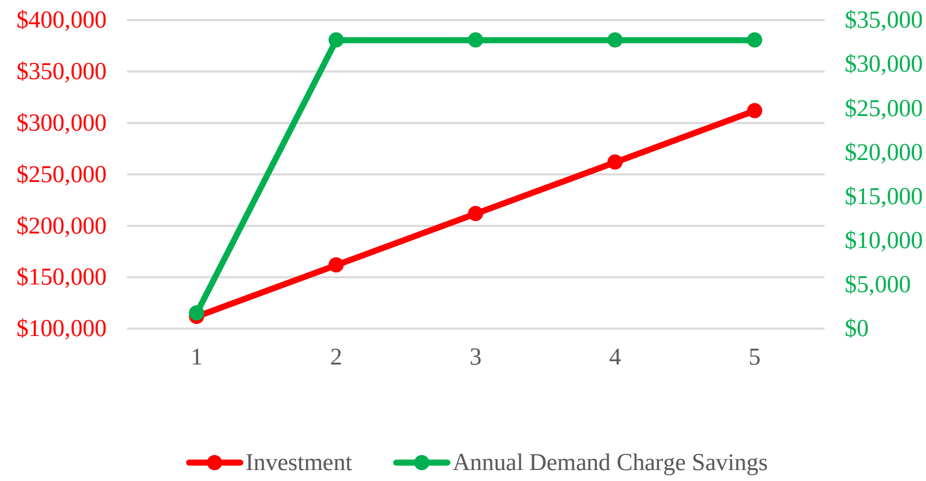


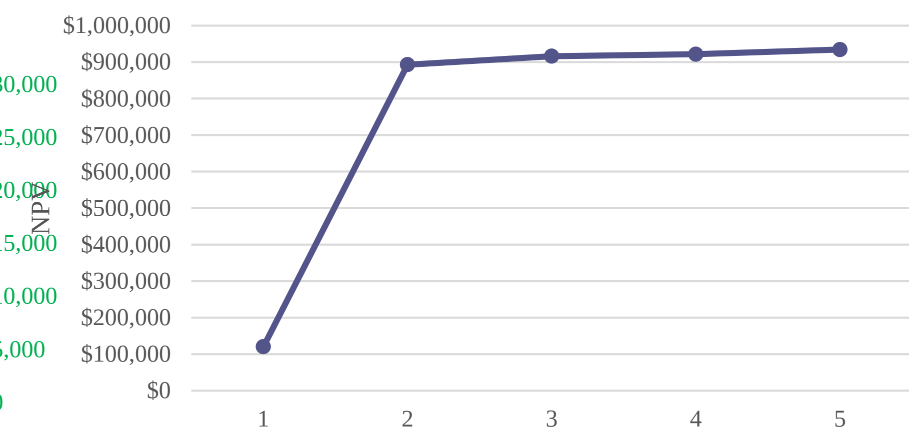
Five electricity rate structures (cases)

<table>
<tr><th rowspan="2"></th><th rowspan="2">Rate Structure</th><th rowspan="2">DC Threshold (kW)</th><th colspan="2">Demand Charge Rate ($/kW)</th><th colspan="2">Energy Rate ($/kWh)</th><th rowspan="2">Coincident Peak</th><th rowspan="2">TOU</th><th rowspan="2">DR</th></tr>
<tr><th>Summer</th><th>Winter</th><th>Summer</th><th>Winter</th></tr>
<tr><td>Case 1</td><td>GP PLM-11</td><td>35-500</td><td colspan="2">8.24</td><td colspan="2">Table 4.1</td><td>No</td><td>No</td><td>No</td></tr>
<tr><td rowspan="2">Case 2</td><td>PGE A-10 Non TOU</td><td>200-499</td><td>16.78</td><td>9.45</td><td>0.16492</td><td>0.12832</td><td rowspan="2">No</td><td rowspan="2">No</td><td rowspan="2">No</td></tr>
<tr><td>PGE A-1 Non TOU</td><td>75-200</td><td colspan="2">0</td><td>0.16492</td><td>0.12832</td></tr>
<tr><td rowspan="2">Case 3</td><td>PGE A-10 TOU</td><td>200-499</td><td>16.78</td><td>9.45</td><td colspan="2" rowspan="2">Table 4.3</td><td rowspan="2">No</td><td rowspan="2">Yes</td><td rowspan="2">Yes</td></tr>
<tr><td>PGE A-1 TOU</td><td>75-200</td><td colspan="2">0</td></tr>
<tr><td rowspan="2">Case 4</td><td>SCE TOU-GS-3 Option A</td><td>200-500</td><td>17.81</td><td>17.81</td><td colspan="2" rowspan="4">Table 4.4</td><td rowspan="2">No</td><td rowspan="2">Yes</td><td rowspan="2">No</td></tr>
<tr><td>SCE TOU-GS-2 Option A</td><td>20-200</td><td>15.48</td><td>15.48</td></tr>
<tr><td rowspan="2">Case 5</td><td>SCE TOU-GS-3 Option B</td><td>200-500</td><td>17.81+17.42+3.43</td><td>17.81</td><td rowspan="2">Yes</td><td rowspan="2">Yes</td><td rowspan="2">Yes</td></tr>
<tr><td>SCE TOU-GS-2 Option B</td><td>20 -200</td><td>15.48+17.32+3.38</td><td>15.48</td></tr>
</table>

Some results







Some inspections and consequences

How do we know whether the results are valid?

Will a higher fidelity model lead to different optimal sets of measures??

One answer: rebuild the model with a higher fidelity tool and compare

Better answer: test the influence of the model discrepancy on outcomes.

Even better answer: test the influence of the model discrepancy on decisions.

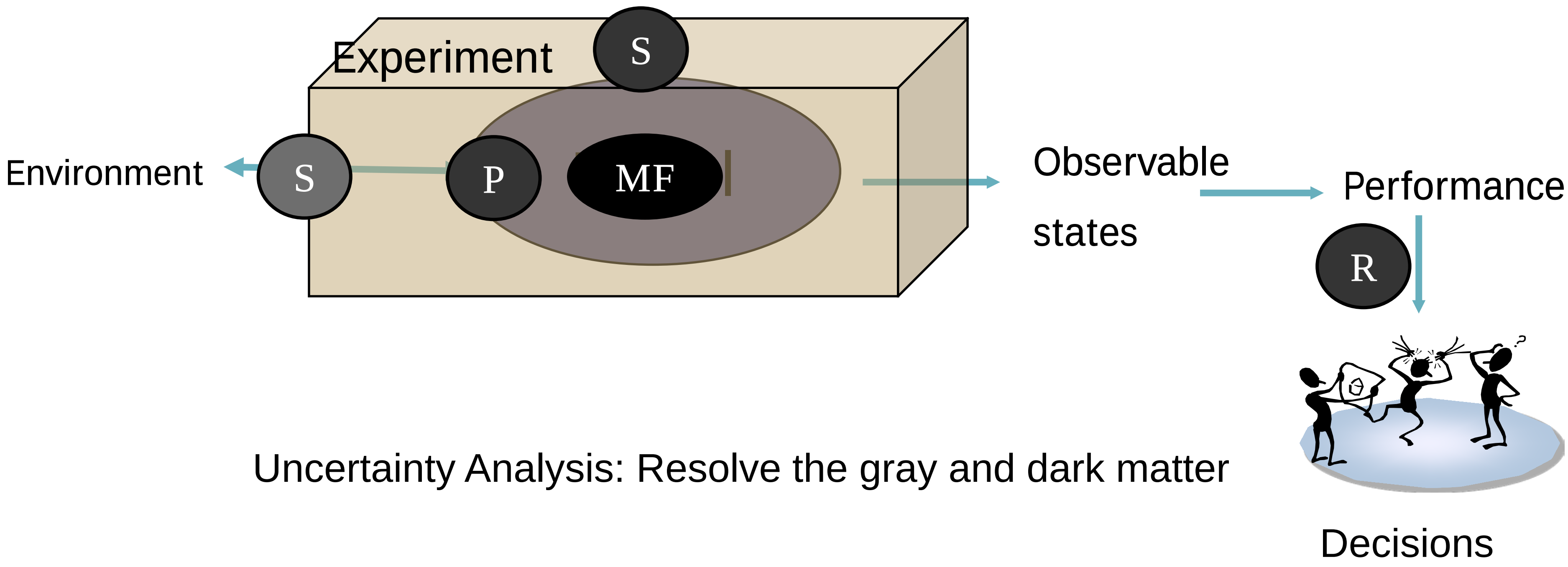
This requires:

- Develop risk criteria in the decision making; develop the measures
- Determine how model discrepancy affects risk measures

Consequence: we need to recognize uncertainties in parameters AND model

A view on simulation

Definition: Perform an experiment on a virtual or real artifact

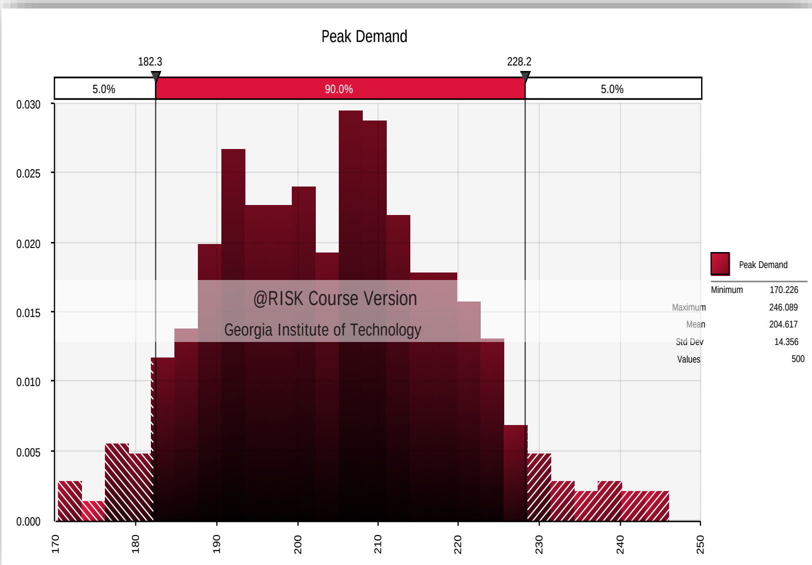


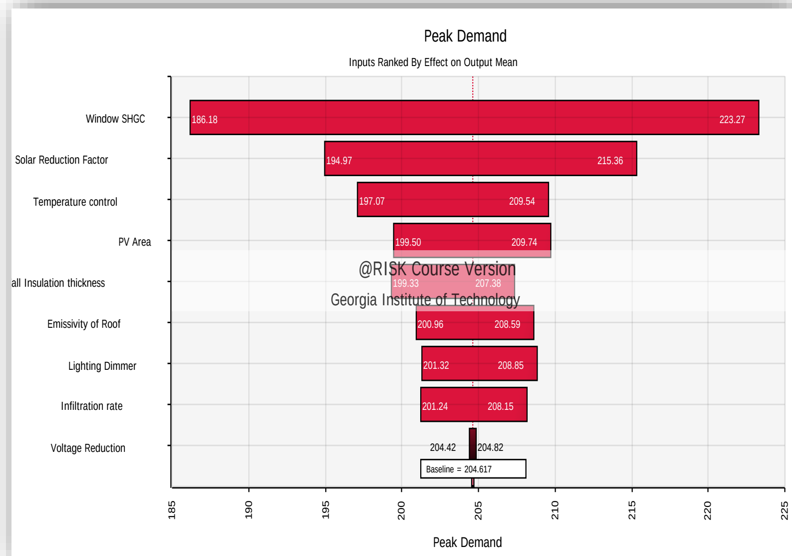
Parameter and Scenario uncertainties

	Uncertainty Parameter	Range
Energy Model Parameter	U-value of Wall	-10% ~ +10%
	U-value of Window	-10% ~ +10%
	Infiltration Rate	-10% ~ +10%
Scenario Parameters	Occupancy Density	-20% ~ +20%
	Appliance Density	-20% ~ +20%
Cost Factors	Productivity Loss	Bivariate Kernel Density
	Product Cost	-10% ~ +10%
	Future Demand Charge Rate	-2% ~ +2%

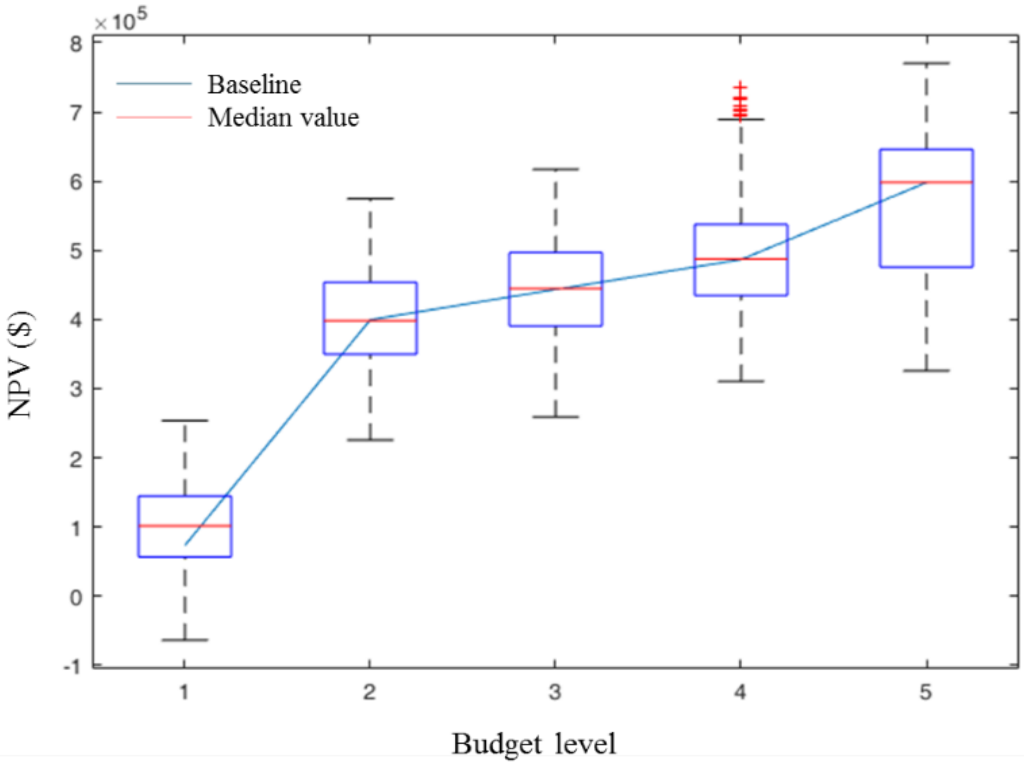
Uncertainty analysis

UA and SA of Peak Demand



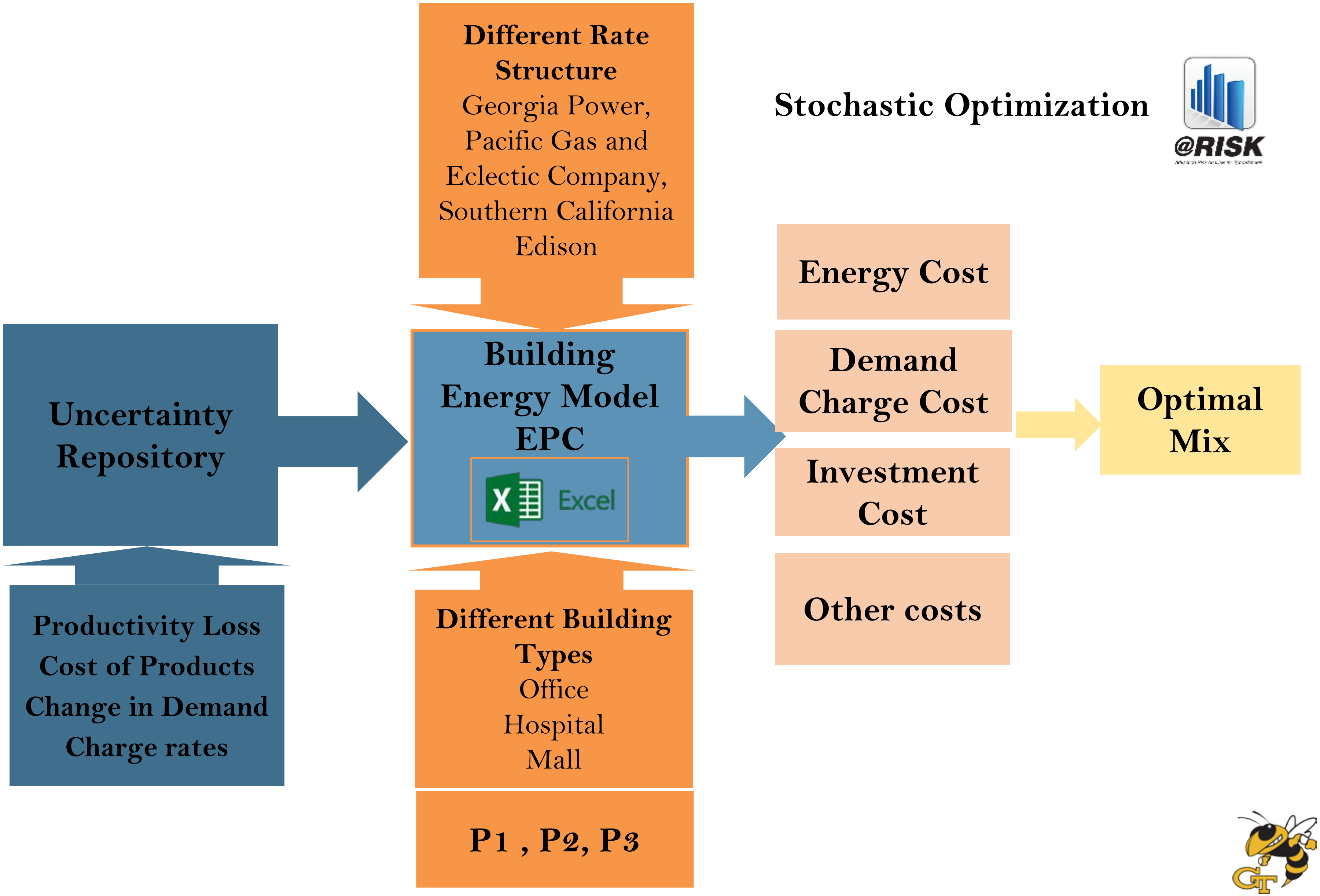


Uncertainty analysis of NPV



NPV results of optimal EEM and EFM under uncertainty for the office building case 5

Stochastic Optimization



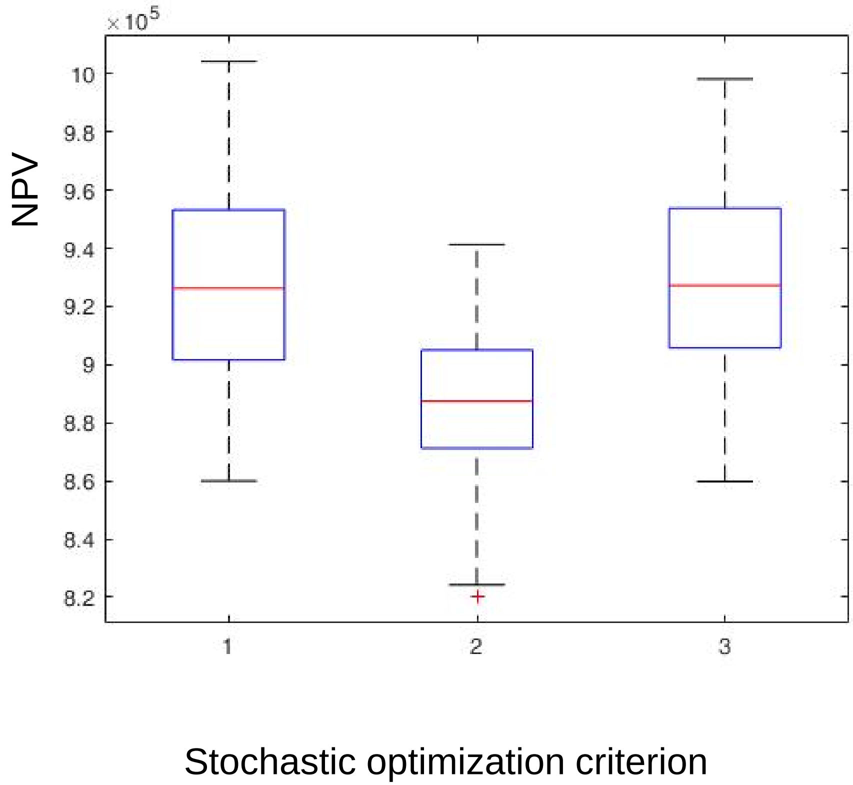
Optimization criteria

$$(1)\ \boldsymbol{\theta}^* = \arg\max_{\theta\in\Theta} \mathrm{E}\{\mathrm{NPV}(\boldsymbol{\theta}, \boldsymbol{\xi})\}$$

$$(2)\ \boldsymbol{\theta}^* = \arg\max_{\theta\in\Theta} E\{NPV(\boldsymbol{\theta}, \boldsymbol{\xi})\}\ \&\ \sigma\{NPV(\boldsymbol{\theta}, \boldsymbol{\xi})\} \le V_{limit}$$

$$(3)\ \boldsymbol{\theta}^* = \arg\max_{\theta\in\Theta} NPV(\boldsymbol{\theta}, \boldsymbol{\xi})\ \&\ Prob\{NPV(\boldsymbol{\theta}, \boldsymbol{\xi}) \ge V_{limit}\} > Prob_{limit}$$

Result with the three criteria



Back to the major question

How do we validate the building energy model (for our research purpose)?

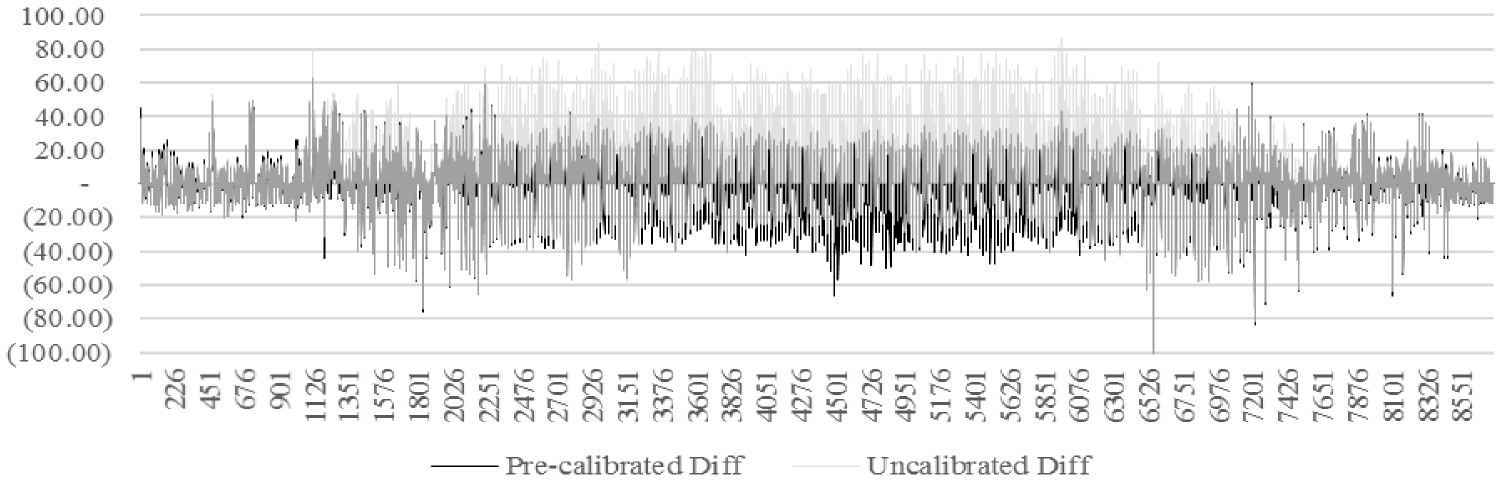
- Focus on MFU
- Relate to other relevant uncertainties

Validity question: will stakeholder decisions be influenced by model fidelity, i.e. do the risk measures change such that stakeholder will make other decision.

In our case we proceed as follows to answer this question:

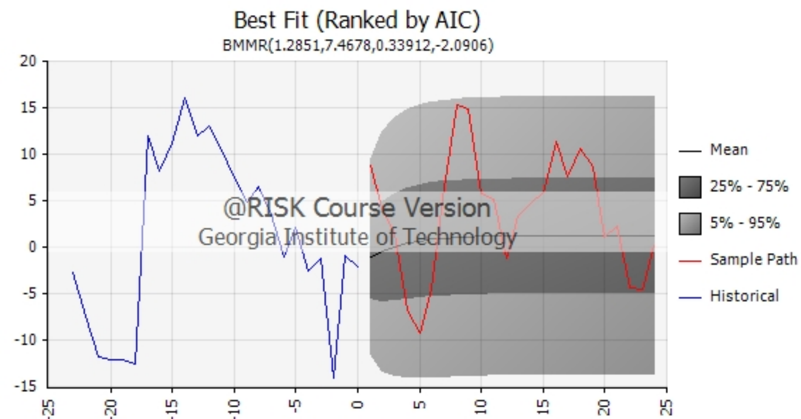
- We start from the low fidelity tool
- Quantify MFU by comparing to high fidelity model: “delta” in power(t)
- Develop a statistical model of delta (time series) and add to our model
- Redo the stochastic optimization
- Inspect the impact on the relevant risk measures

The result for delta(t)



Delta [kW] between EPC and EnergyPlus

Two steps:
Step 1: without tuning → delta
Step 2: after tuning → $delta^{C}$

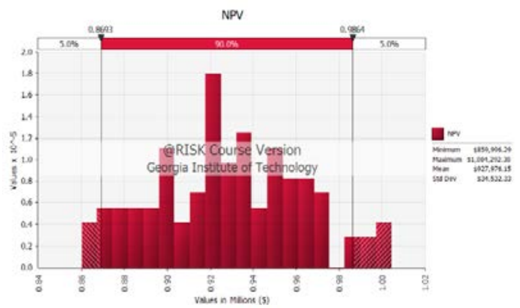


Time series fit of delta (t)

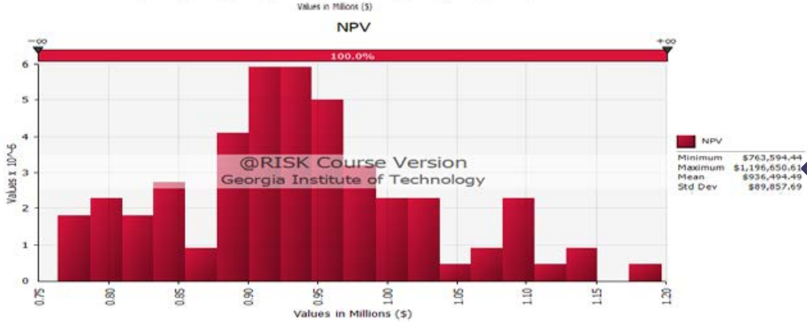
Repeat stochastic optimization

Findings:

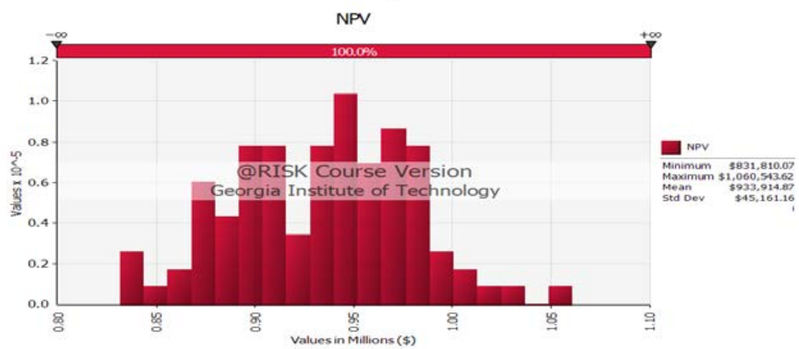
- With delta, in some cases different optimum
- With delta^{C}, in all cases same optimum (when using criterion 1)



Distribution with delta=0 (original case)



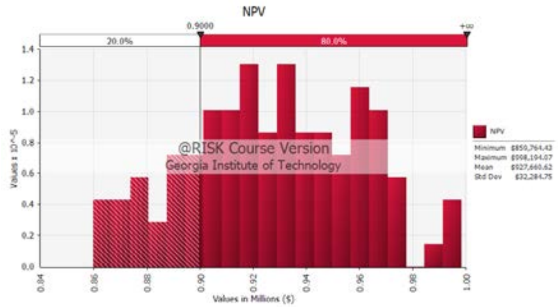
Distribution with delta



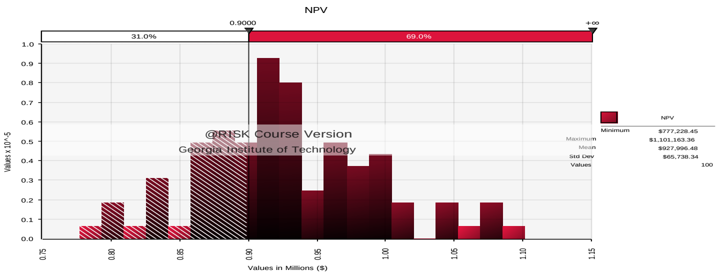
Distribution with delta^{C}

Impact of delta on risk measures

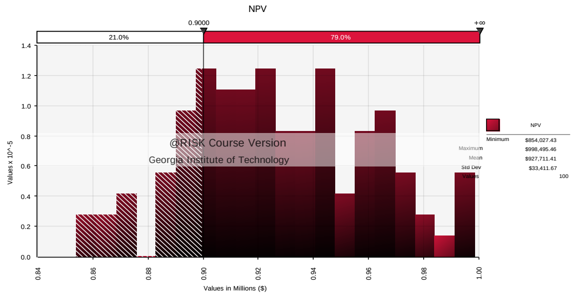
Question: will the added delta lead to rejecting an optimum set that was acceptable
Example criterion 3: P(NPV > 0.9M) > .8



Passes



Does not pass; P = 0.69



Almost passes: P =0.79

What does it all mean?

Work is continuing:

- SA used to rank delta and delta^{C} against other uncertainties
- Apply to more cases; draw general conclusions

For now the conclusions are:

- Our reduced-order model is valid for power studies
- Some fine tuning is sometimes necessary

We will apply the same technique to multi building nodes (each has its own delta)

Since the reduced order tool is simple but adequate, we are developing a do-it-yourself tool for building operators (totally Excel based)

General conclusions

Many urban energy model developments choose a BEM based on a hunch rather than on inspection of validity

Many current neighborhood energy models are over-engineered

If less is known about the buildings, the role of MFU becomes less important (rather self evident but now quantifiable)

The introduction of risk measures is necessary to conduct validity tests

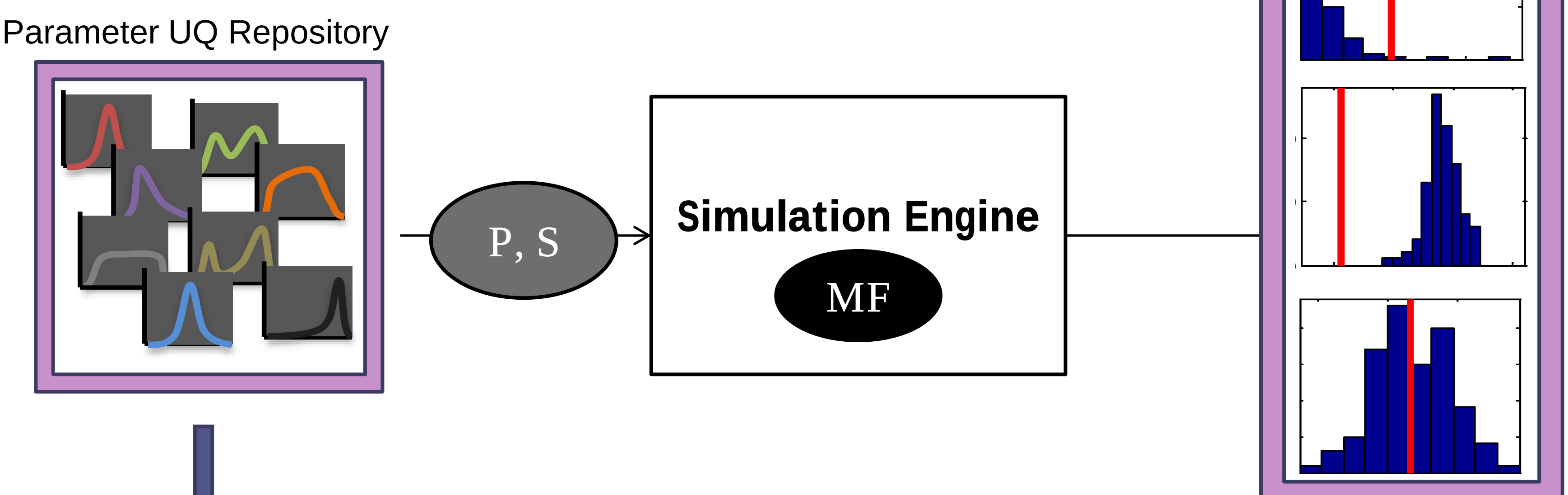
The DC reduction optimization can be packaged as a DIY tool

Thanks for your listening!

Fried@gatech.edu

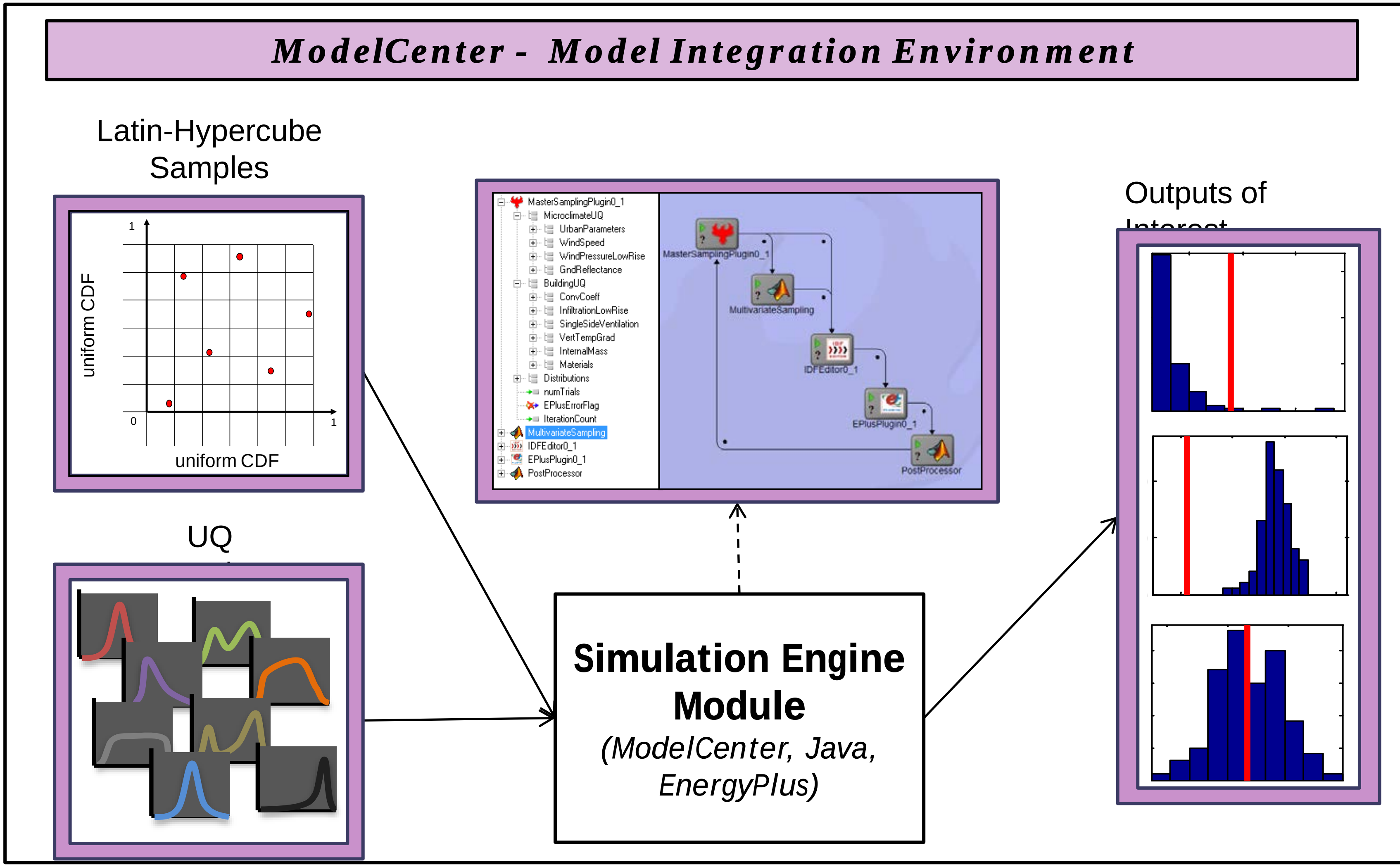
Uncertainty Analysis

Major development



gbXML schema extension: gbXML_uq

Scaled up to GURA-Workbench (EnergyPlus)



Augenbroe, G., Y. Zhang, J. Khazaii, Y. Sun, H. Su, B. D. Lee, and J. Wu, "Implications of the Uncoupling of Building and HVAC Simulation in the Presence of Parameter Uncertainties", *13th International Conference of the International Building Performance Simulation Association*, Chambery, France, 08/2013.

Lee, B. D., Y. Sun, G. Augenbroe, and C. J. J. Paredis, "Towards Better Prediction of Building Performance: A Workbench to Analyze Uncertainty in Building Simulation", *13th International Conference of the International Building Performance Simulation Association*, Chambery, France, 08/2013.