Energy Efficient Control of a Smart Grid with Sustainable Homes based on Distributing Risk

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with support from Masahiro Ono, and Wesley Graybill

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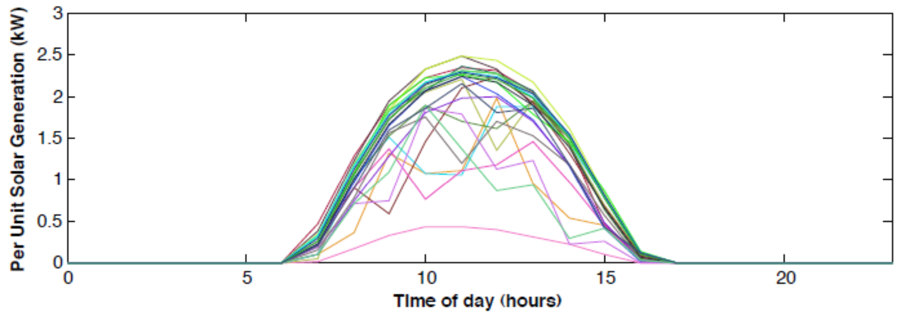
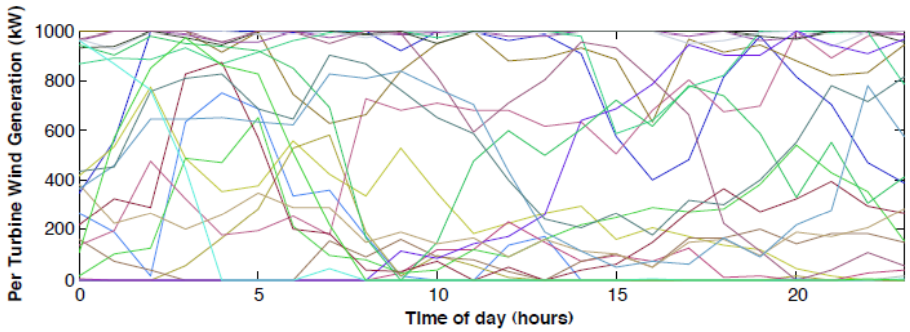
Massachusetts Institute of Technology

Motivation: High Penetration of Renewables

Electrical grid must prepare for high penetration of renewables.

Challenge: Wind and solar are undispatchable, intermittent, and unpredictable.





Key Elements of Approach

1. Increase controllability on demand side through
   – Flexible specifications of user needs and preferences, and
   – goal-directed optimal planning.
2. Improve robustness to uncertainty in supply and demand through
   – risk-constrained planning and
   – distributed risk markets.
3. Reduce labor, hence adoption barriers, by automating
   – Inference of expected user and environmental behavior, and
   – model acquisition of physical plant and customer behaviors.

Architecture: Risk-constrained, Goal-directed Grid Control

Key Technologies

Risk allocation
Goal-direction

Framework

Market-based Resource allocation

Non-dispatchable supply (solar, wind)

Dispatchable supply (Micro-CHP, biomass)

Demand

Contingent power dispatch

~24 hr time scale

Goal-directed demand response (buildings & E-cars)

Goal-directed Demand Response

- Today: Demand is inelastic, supply adapts.
- Goal: introduce flexibility in meeting demand.
- Approach:
  - Acquire descriptions of the consumer's intended activities, constraints and preferences.
  - Exploit flexibility in activity descriptions to reduce
    - overall energy consumption,
    - peak demand, and
    - risk of failing to support important consumer activities.

Testbed: Connected Sustainable Home

Federico Casalegno (PI), MIT Mobile Experience Lab

- Goal: Optimally control HVAC, window opacity, washer/dryer, e-car.
- Objective: Minimize energy cost.
- Uncertainty: Solar input, outside temp, energy supply, occupancy.
- Risk: Resident goals not satisfied; occupant uncomfortable.

Example Goals: Description of Resident Activities

"Maintain room temperature after waking up until I go to work. No temperature constraints while I'm at work, but when I get home, maintain room temperature until I go to sleep. Maintain a comfortable sleeping temperature while I sleep.

Example Goals: Description of Resident Activities

Also, dry my clothes before morning.

Example Goals: Description of Resident Activities

I need to use my car to drive to and from work, so make sure it is fully charged by morning.

Example Goals: Description of Resident Activities

*It's acceptable if my clothes aren't ready by morning or if the house is a couple degrees too cold, but my car **absolutely** needs to be ready to use before I leave for work."*

Example Goals: Description of Resident Activities

"Maintain room temperature after waking up until I go to work. No temperature constraints while I'm at work, but when I get home, maintain room temperature until I go to sleep. Maintain a comfortable sleeping temperature while I sleep. Also, dry my clothes before morning. I need to use my car to drive to and from work, so make sure it is fully charged by morning. It's acceptable if my clothes aren't ready by morning or if the house is a couple degrees too cold, but my car absolutely needs to be ready to use before I leave for work."

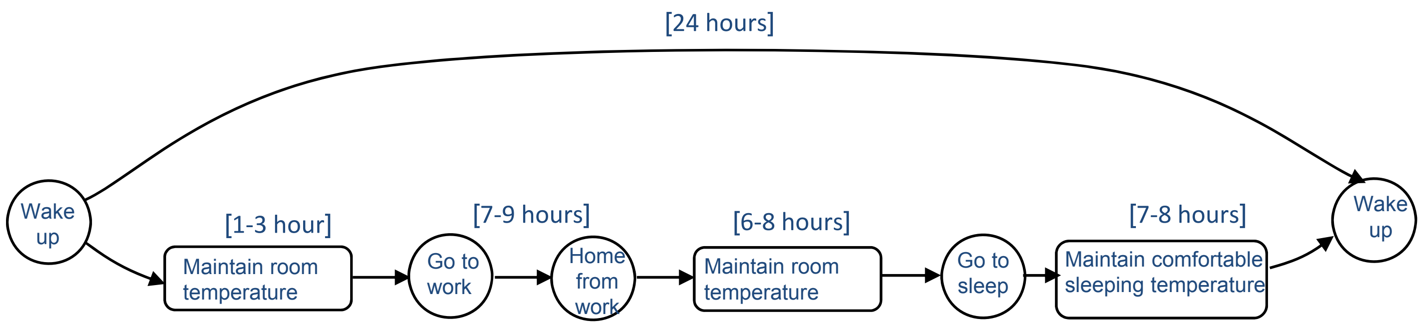
Flexibility Available to Control

- When activities are performed.

- When to charge/discharge batteries.

- Which activities to shed (when supply is low).

Encoding: Qualitative State Plan (QSP)



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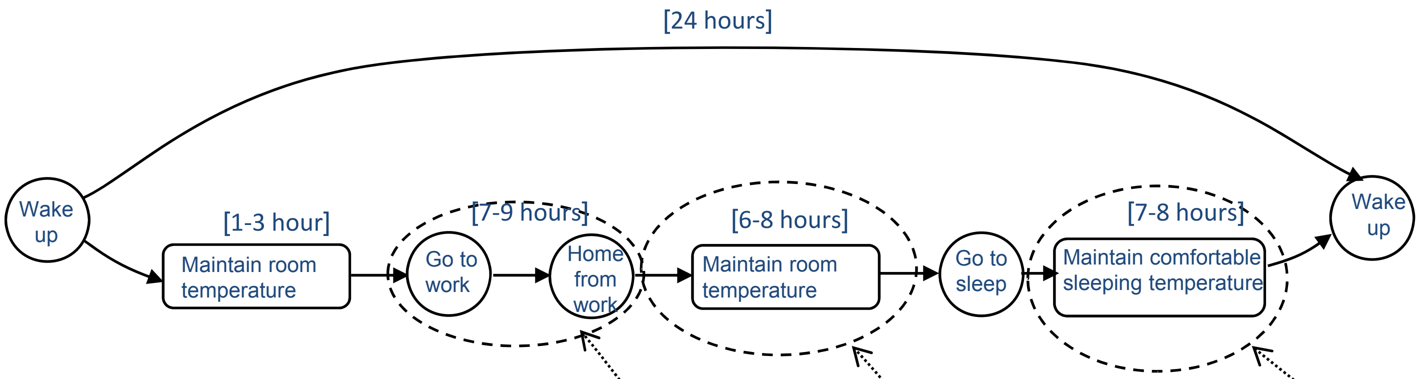
Encoding: Qualitative State Plan (QSP)



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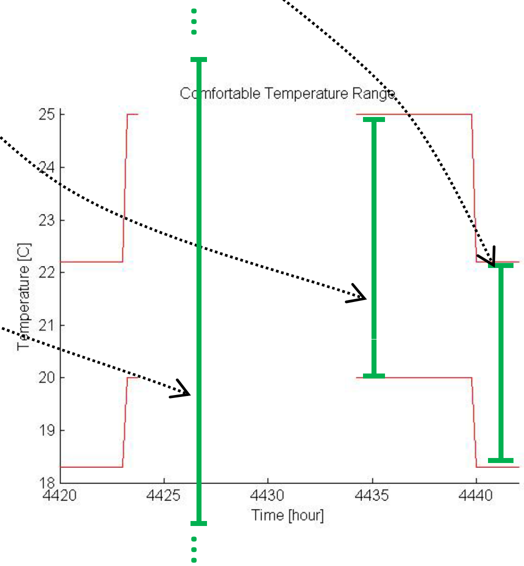


Encode the Qualitative State Plan and Dynamics within a Model-Predictive Controller

$$\min_{\mathbf{U}} J(\mathbf{X},\mathbf{U}) + H(x_T)$$

Cost function (e.g. fuel consumption)

$$s.t.$$

Dynamics
(Discrete time)

$$\forall_{0 \le t \le T-1} \; x_{t+1} = Ax_t + Bu_t$$

Constraints

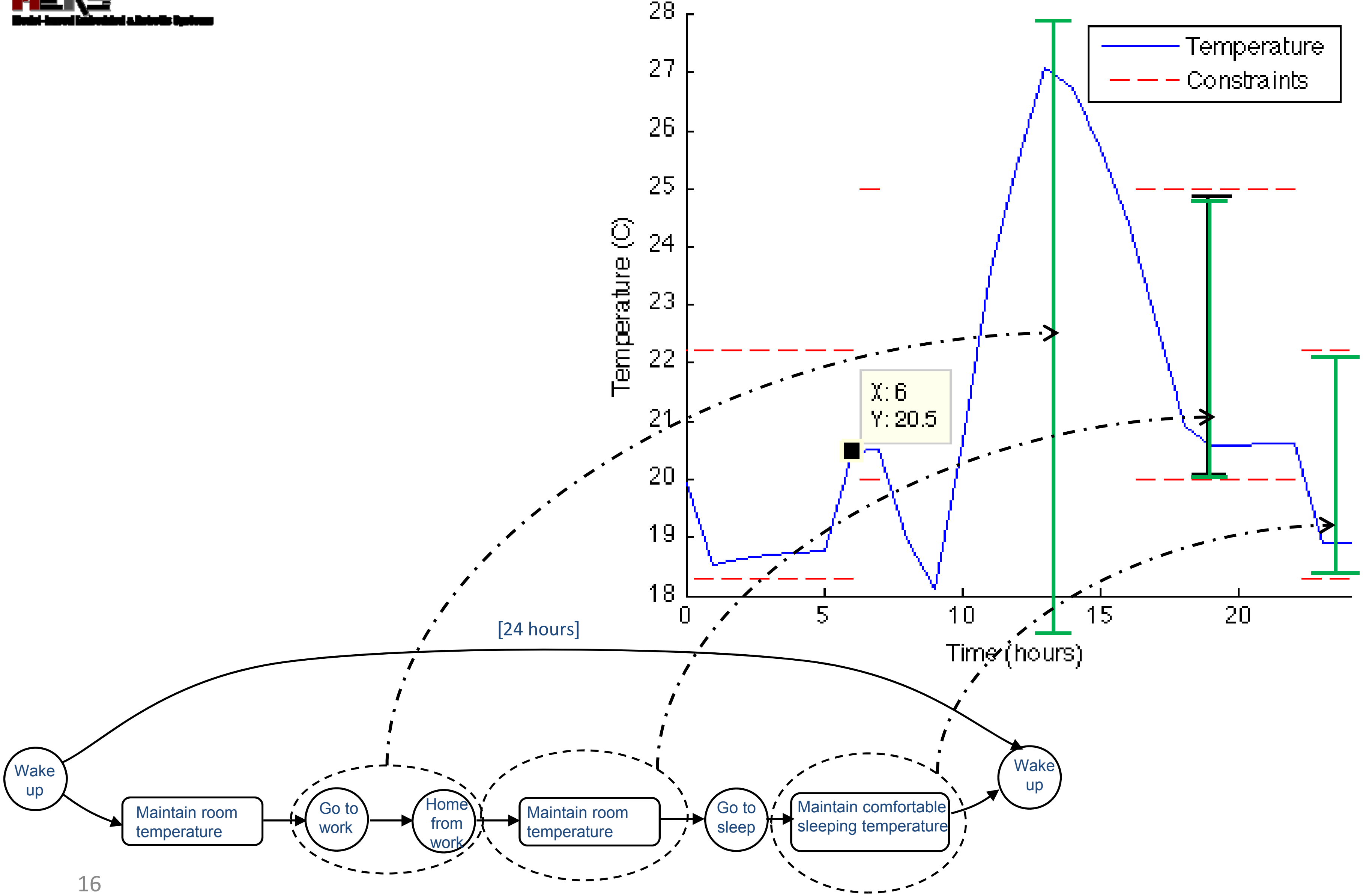
$$\bigwedge_{t=0}^{T} \bigwedge_{i=0}^{N} \bigvee_{j=0}^{M} h_t^{iT} x_t \le g_t^{ij}$$

Mixed Logic or Integer

$\mathbf{X} = \left[x_0 \cdots x_t\right]^T$ State vector (e.g. position of vehicle)

$\mathbf{U} = \left[u_0 \cdots u_{t-1}\right]^T$ Control inputs

pSulu Results



Energy Savings: Optimal Control

	Winter		Summer	
	Energy	Violation Rate	Energy	Violation Rate
p-Sulu	1.9379×10^4	0.000	3.4729×10^4	0
Sulu	1.6506×10^4	0.297	–	–
PID	3.9783×10^4	0	4.1731×10^4	0

	Spring		Autumn	
	Energy	Violation Rate	Energy	Violation Rate
p-Sulu	3.3707×10^4	0	3.8181×10^4	0
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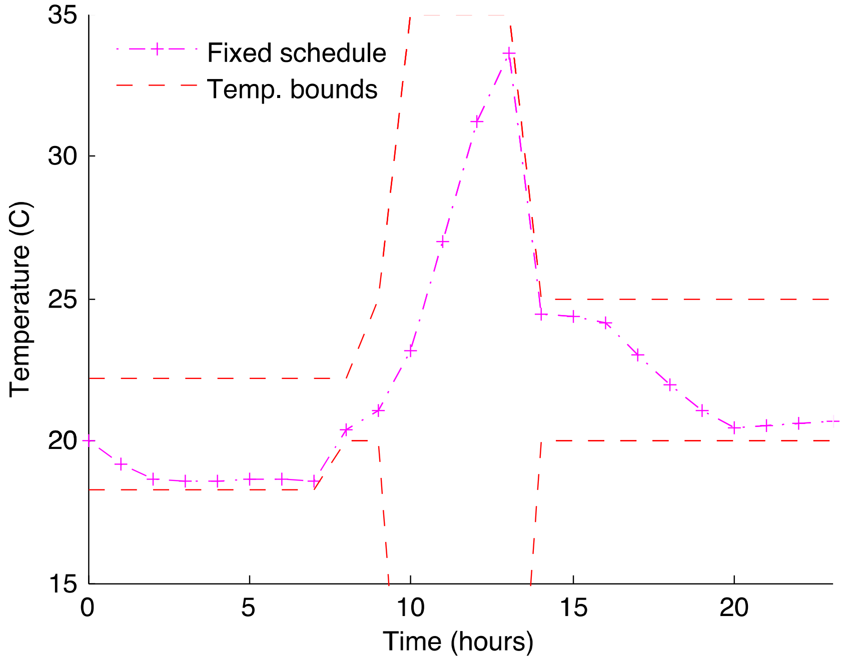
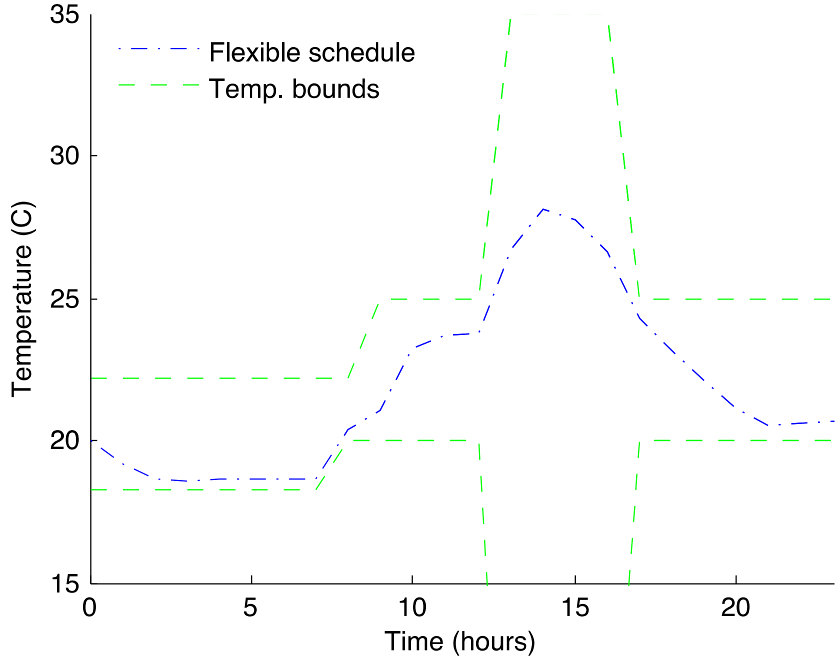
PID	3.9816×10^4	0	3.9955×10^4	0

- 42.8% savings in winter over PID
- 15.3%, 16.8%, and 4.4% in spring, summer, autumn

Energy Savings: Flexibility





- Reduction in energy consumption by considering resident flexibility.
- 10.4%, 1.6%, 1.6%, and 0.7% in the winter, spring, summer, and autumn.

Testbed: Connected Sustainable Home

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- Objective: Minimize energy cost.
- Uncertainty: Solar input, outside temp, energy supply, occupancy.
- Risk: Resident goals not satisfied; occupant uncomfortable.

Managing Uncertainty and Risk

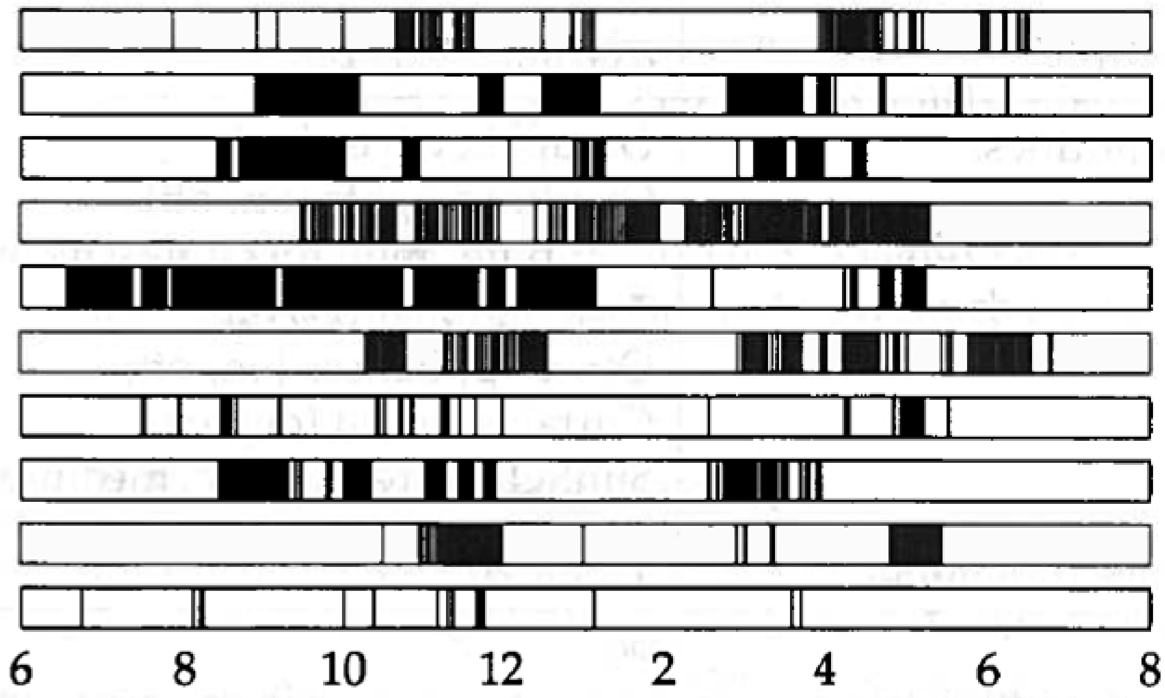
- 20% usage rate – Xerox PARC Responsive Environment study, 1993.
- Each room has a different occupancy profile.

Occupancy is Uncertain ⇒ Controller must take risk.

Occu

1

Cra



12am

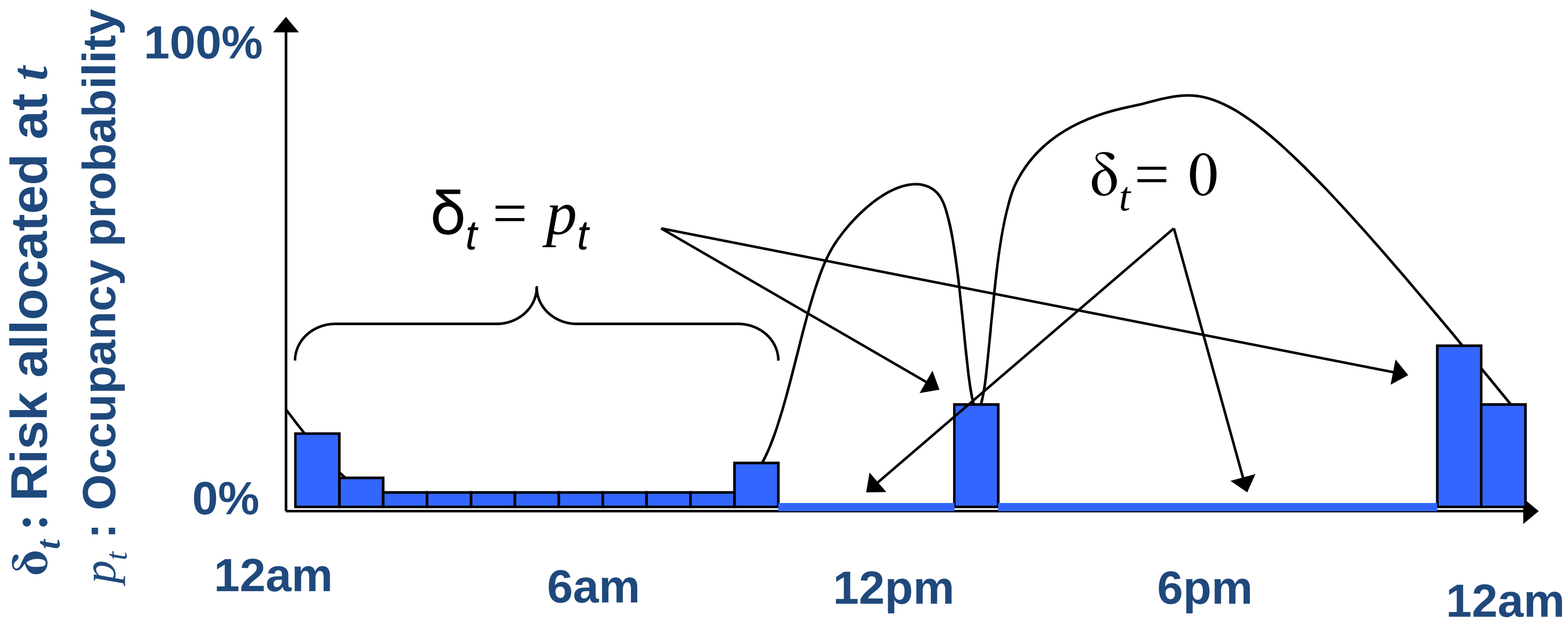
Figure 2: Occupancy data for ten different offices over the course of a single day. Each bar is shaded when the corresponding office is occupied and blank when the office is vacant.

Control Decisions Imply Risk

- ***When should a controller take risk?***
  - Risk at time t : δ_t
  - Acceptable risk over time horizon: Δ

$$\delta_t = 0 \quad \text{or } p_t$$

$$\sum_{t=1}^{T} \delta_t \leq \Delta$$



Approach: Risk Allocation with Masahiro Ono

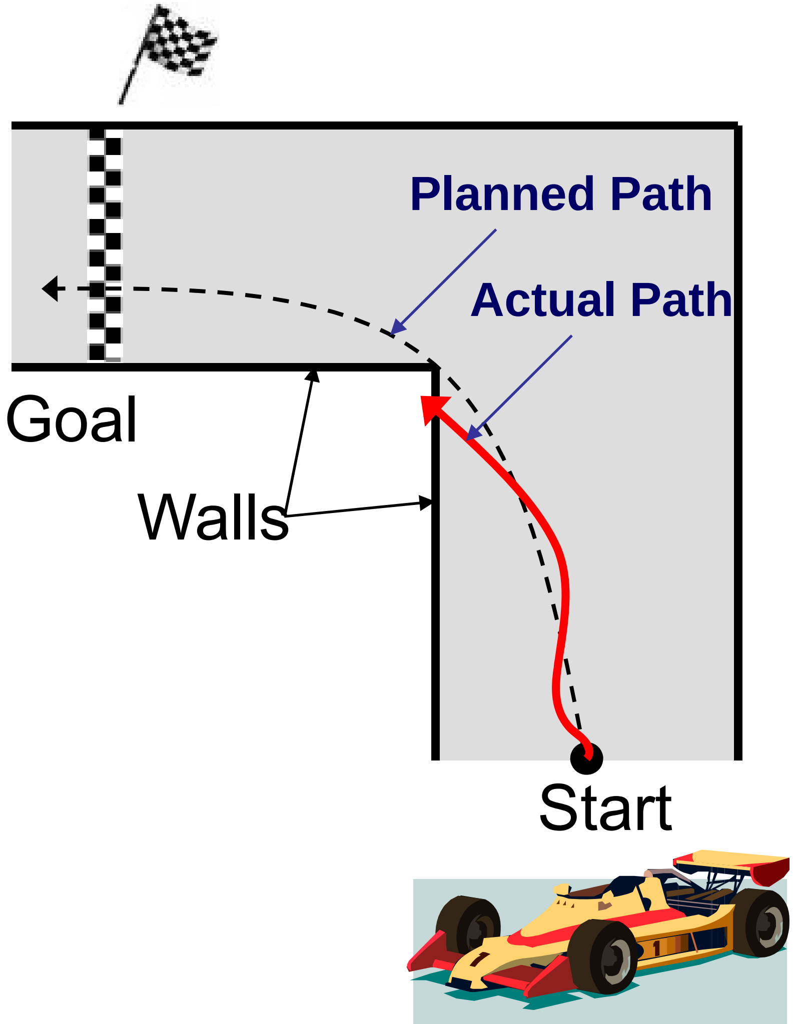
Framework :

- **Chance-constrained Stochastic Optimization.**

Methods:

- **Iterative Risk Allocation (IRA) algorithm.**
- **Market-based Iterative Risk Allocation (MIRA) algorithm.**

Example: Race Car Path Planning



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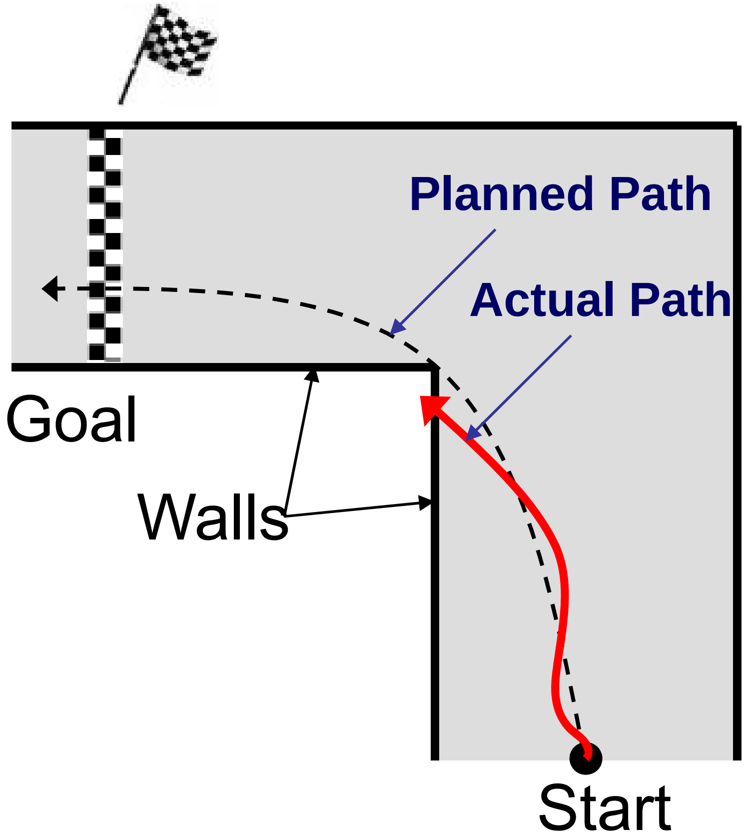


- Cannot guarantee 100% safety.
- Driver wants a probabilistic guarantee:

  P(crash) < 0.1%

Chance constraint.

Chance-Constrained Optimal Planning

$$\min_{u_{1:T} \in \mathbf{U}^T} J(u_{1:T})$$

Convex function

Cost function (e.g. fuel consumption)

s.t.

Stochastic dynamics

$$\bigwedge_{t=0}^{T-1} x_{t+1} = Ax_t + Bu_t + w_t$$

$$w_t \sim N(0, \Sigma_t)$$

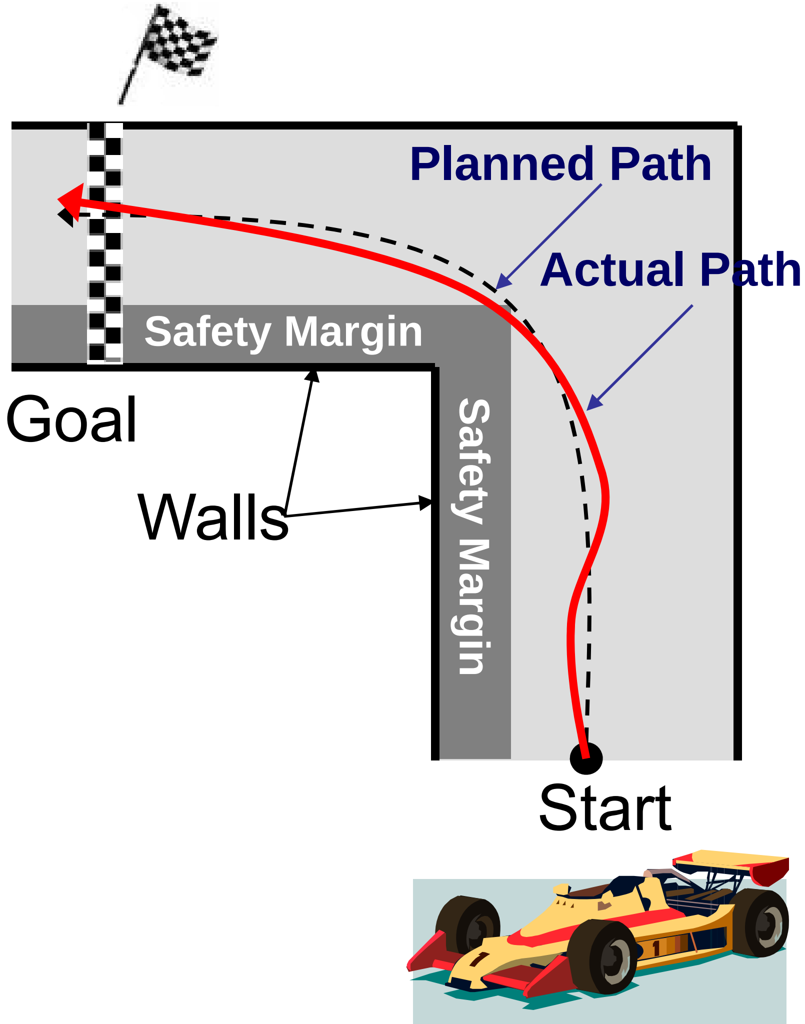
$$x_0 \sim N(\bar{x}_0, \Sigma_{x,0})$$

Risk bound
(Upper bound of the probability of failure)
Assumption: $\Delta < 0.5$

Chance constraint

$$\Pr\left[\bigwedge_{t=1}^{T} \bigwedge_{i=1}^{N} h_t^{iT} x_t \leq g_t^i\right] \geq 1 - \Delta$$

Example: Race Car Path Planning



- Cannot guarantee 100% safety.
- Driver wants a probabilistic guarantee:

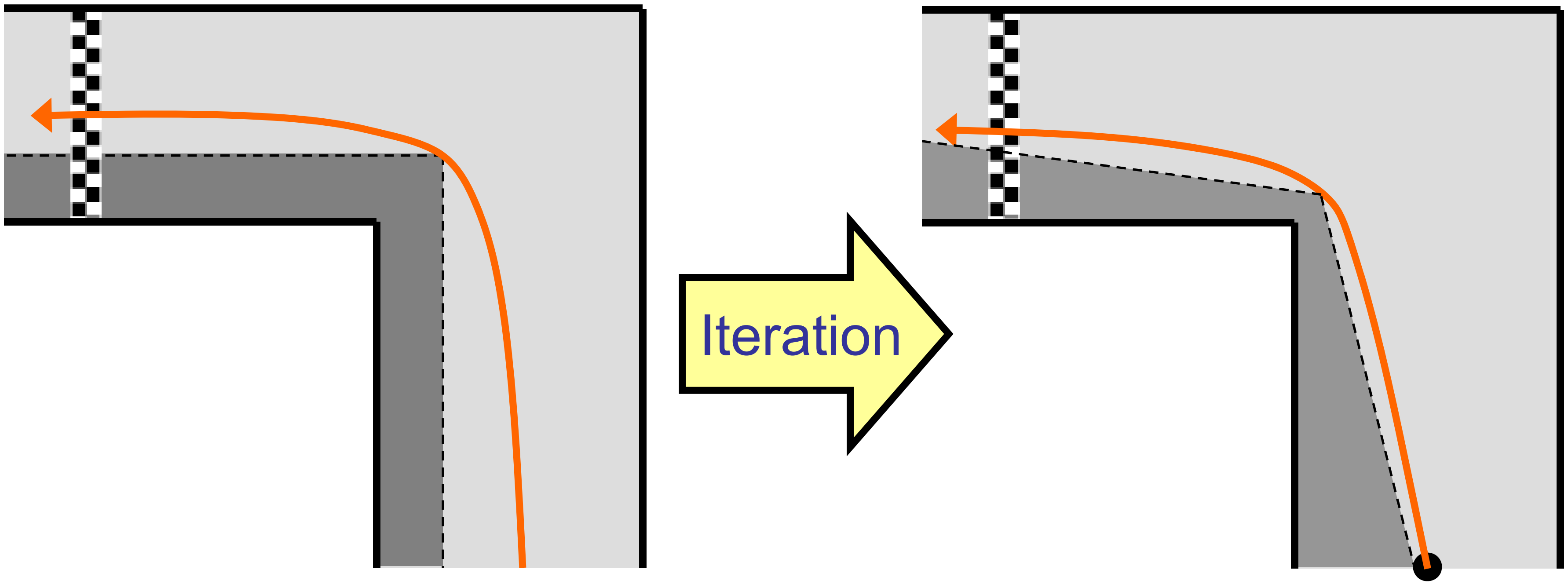
  $P(\text{crash}) < 0.1\%$

  Chance constraint.

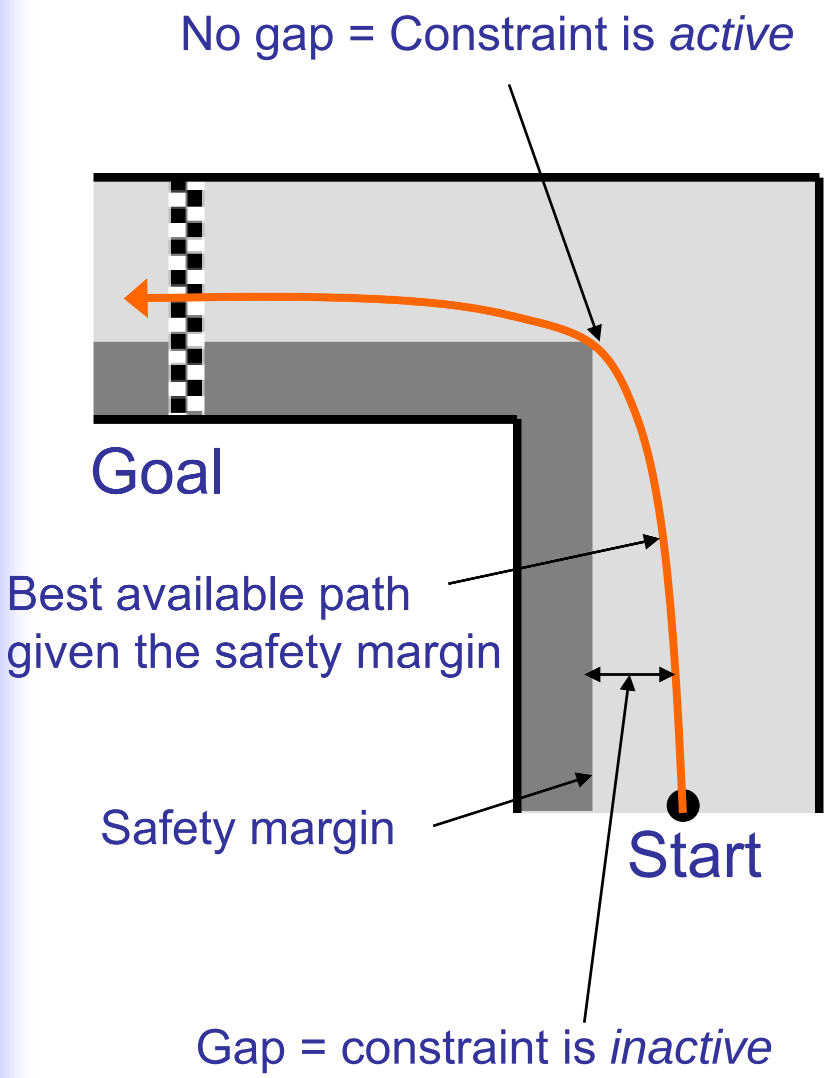
- Approach: design safety margin.

Iterative Risk Allocation (IRA) Algorithm

- Starts from a suboptimal risk allocation.
- Improves the risk allocation through iteration.



Iterative Risk Allocation Algorithm



Algorithm IRA

1 Initialize with arbitrary risk allocation.

2 Loop

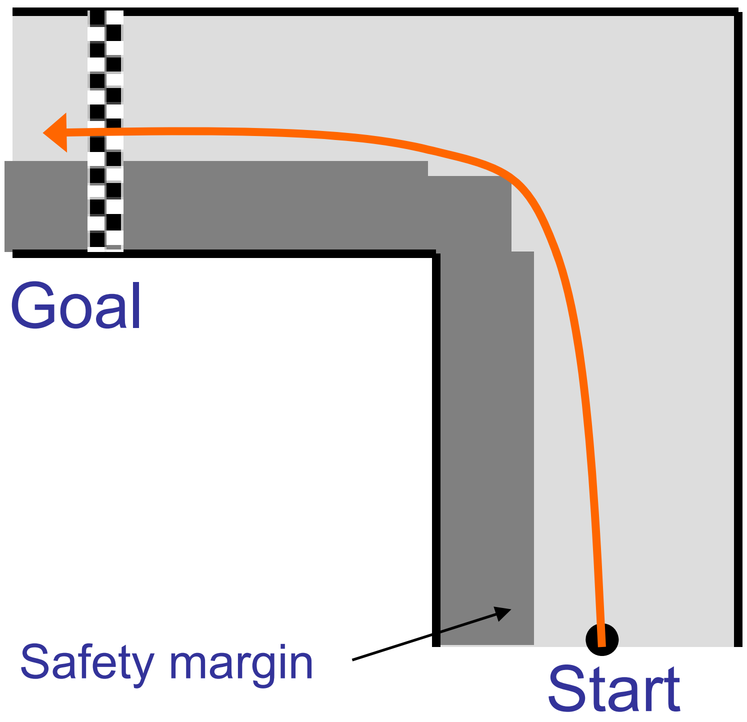
3 Compute the best path for the current risk allocation.

4 Decrease risk where a constraint is inactive.

5 Increase risk where a constraint is active.

6 End loop

Iterative Risk Allocation Algorithm



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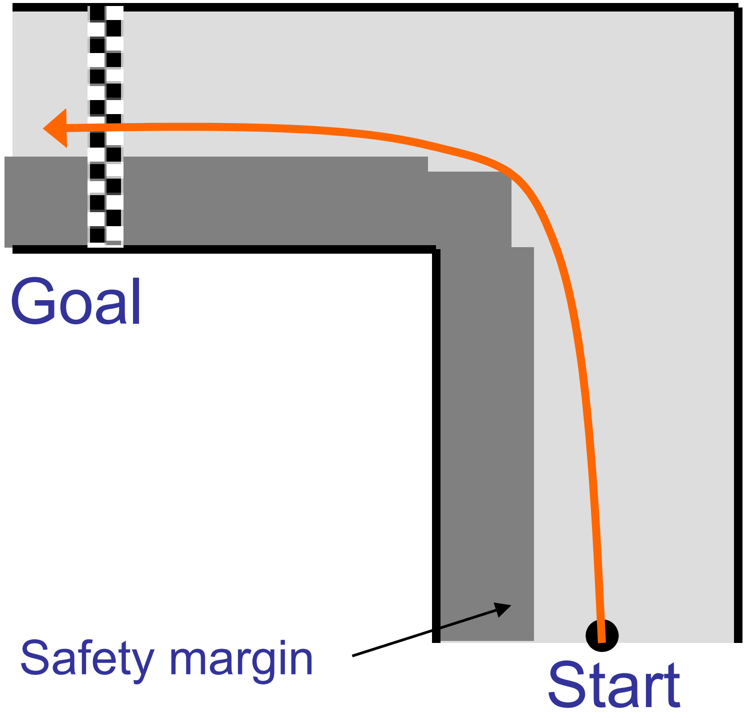
Iterative Risk Allocation Algorithm



Algorithm IRA

1 Initialize with arbitrary risk allocation.
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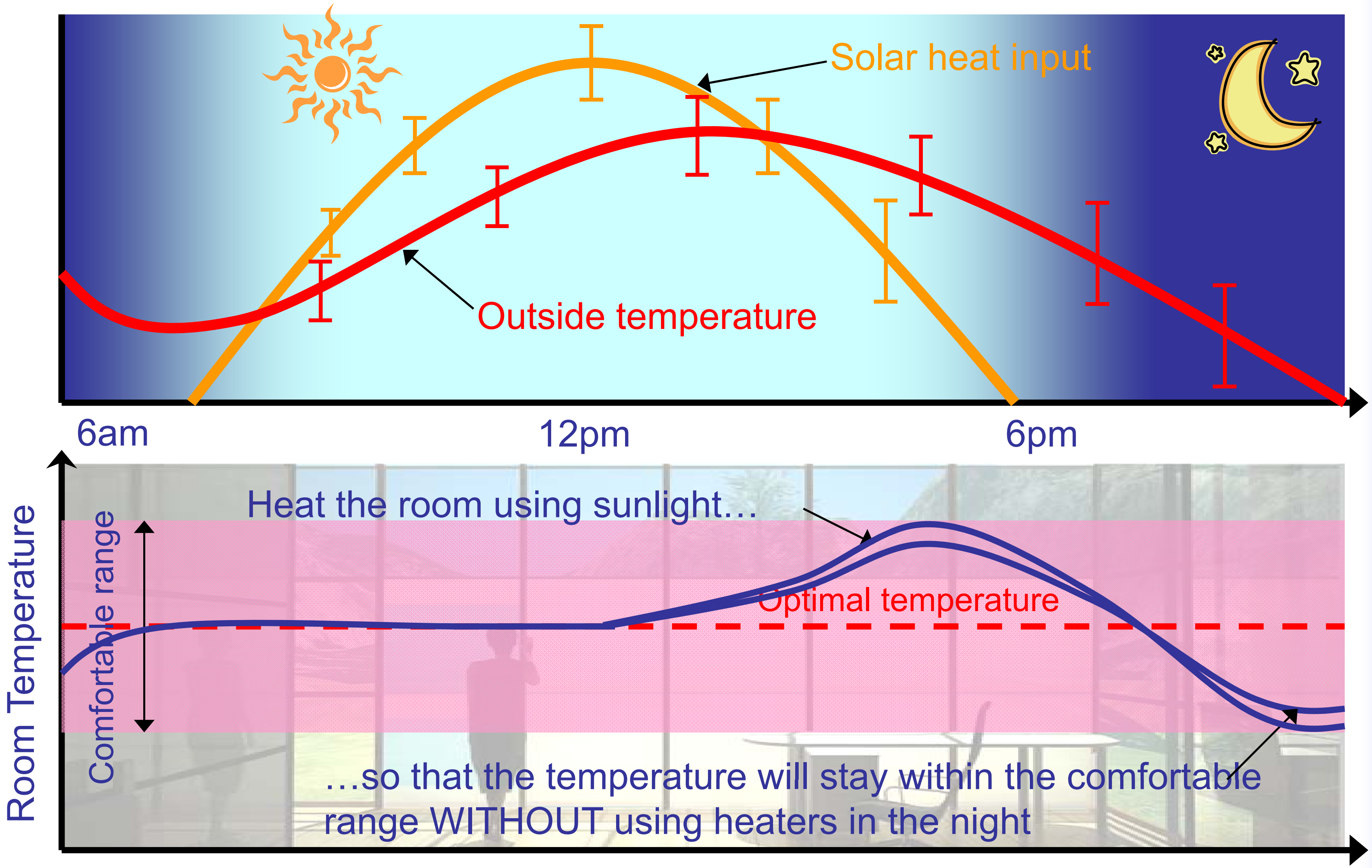
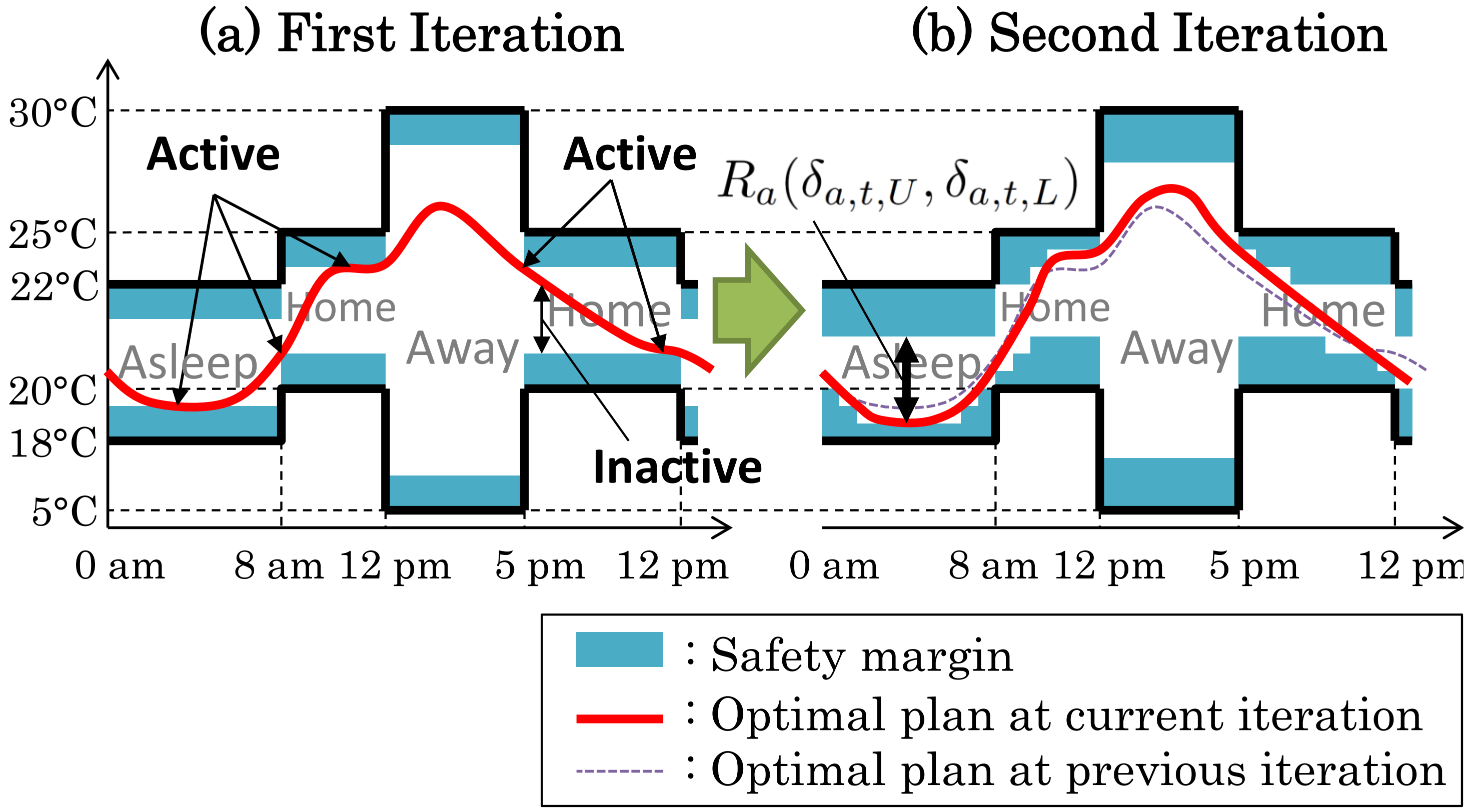
Robust-IRA- MPC for Dynamic Window

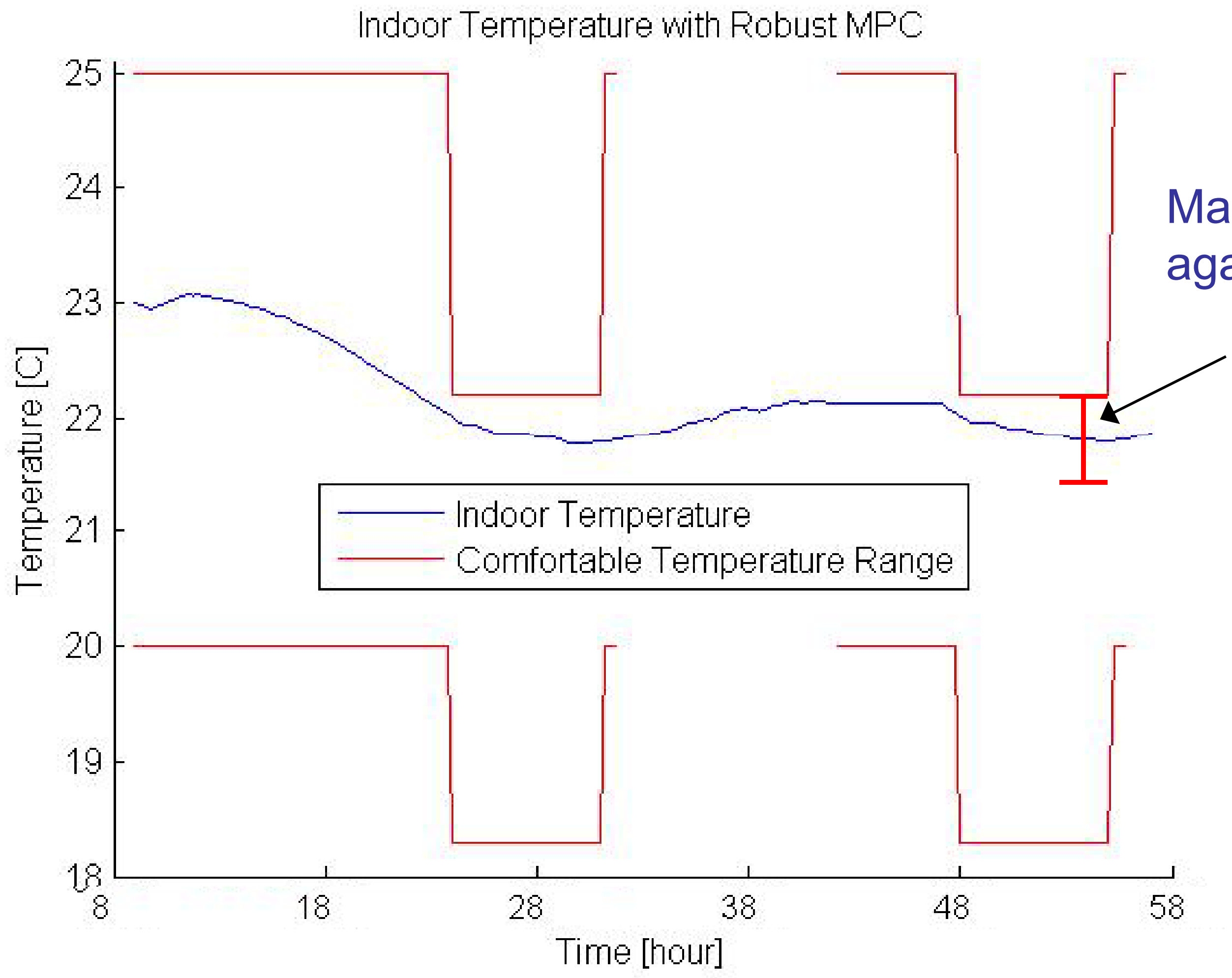


Application: Building Control



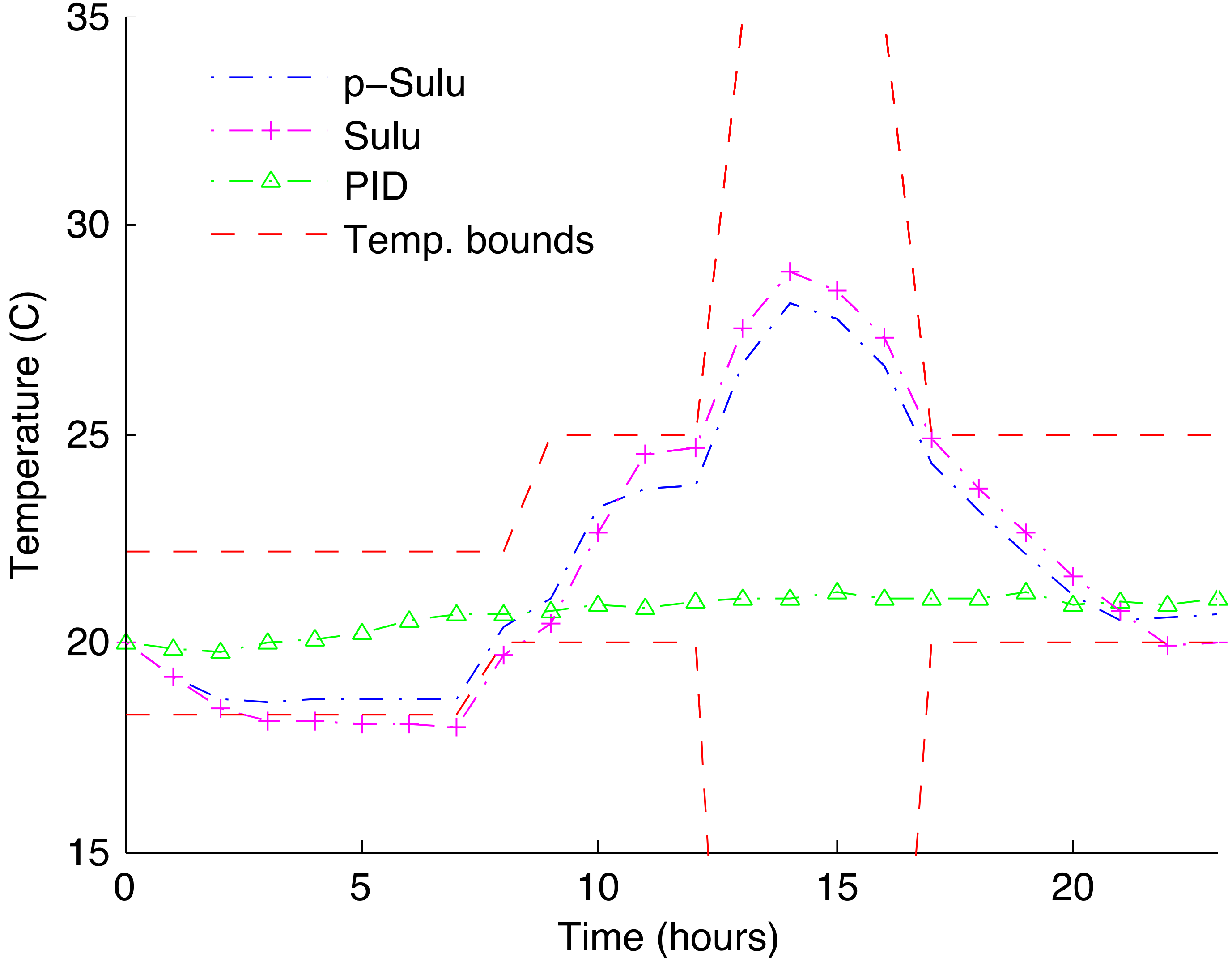
Take risk of violating resident constraints where largest energy savings are possible.

Robust-IRA-MPC Results



Margin protects against uncertainty

Results



p–Sulu
Sulu
PID
Temp. bounds
Temperature (C)
Time (hours)
35
30
25
20
15
0
5
10
15
20

Improvement in Comfort

	Winter		Summer	
	Energy	Violation Rate	Energy	Violation Rate
p-Sulu	1.9379×10^4	0.000	3.4729×10^4	0
Sulu	1.6506×10^4	0.297	–	–
PID	3.9783×10^4	0	4.1731×10^4	0
	Spring		**Autumn**	
	Energy	Violation Rate	Energy	Violation Rate
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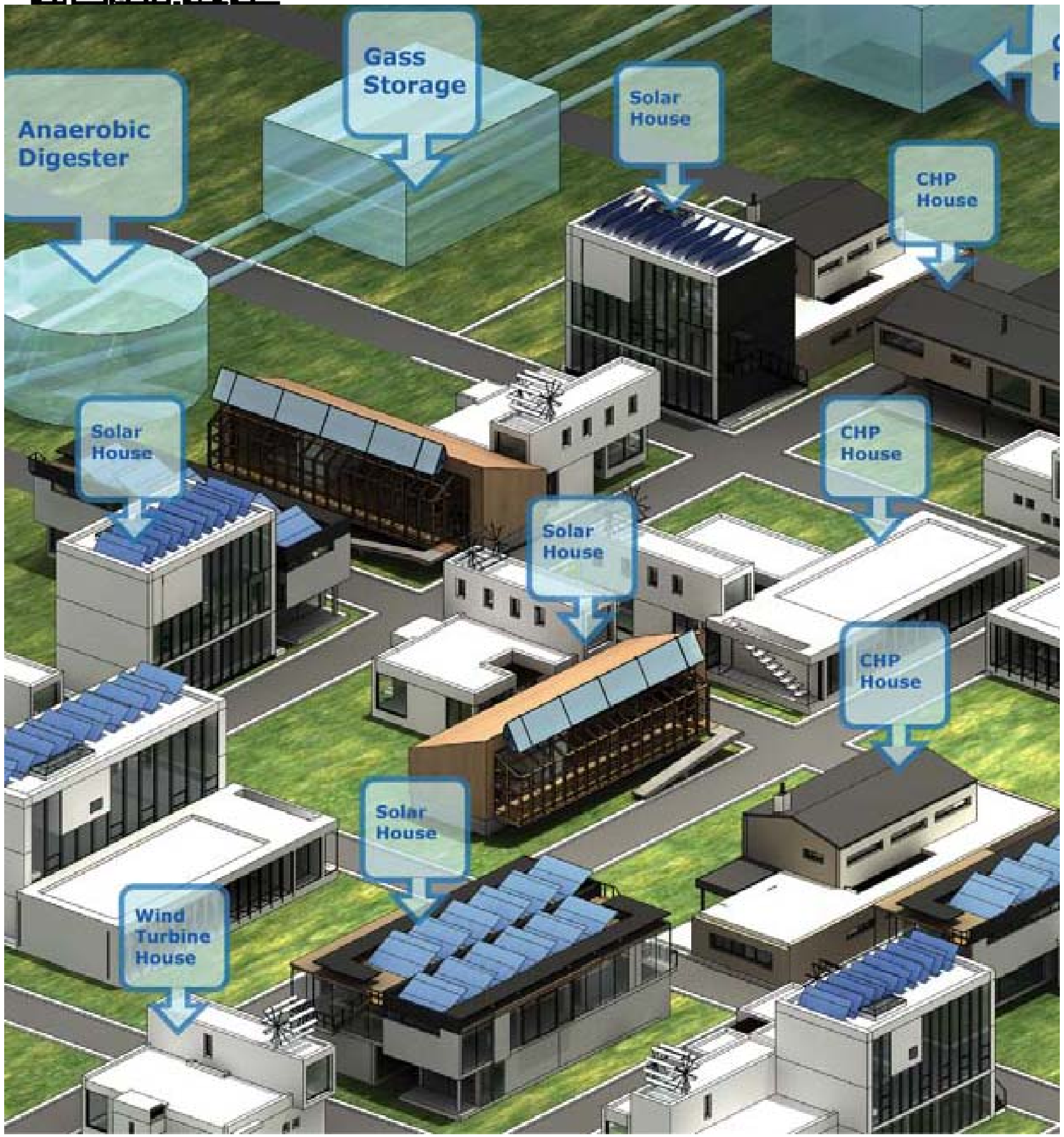
Sulu	3.0954×10^4	0.308	3.6780×10^4	0.334
PID	3.9816×10^4	0	3.9955×10^4	0

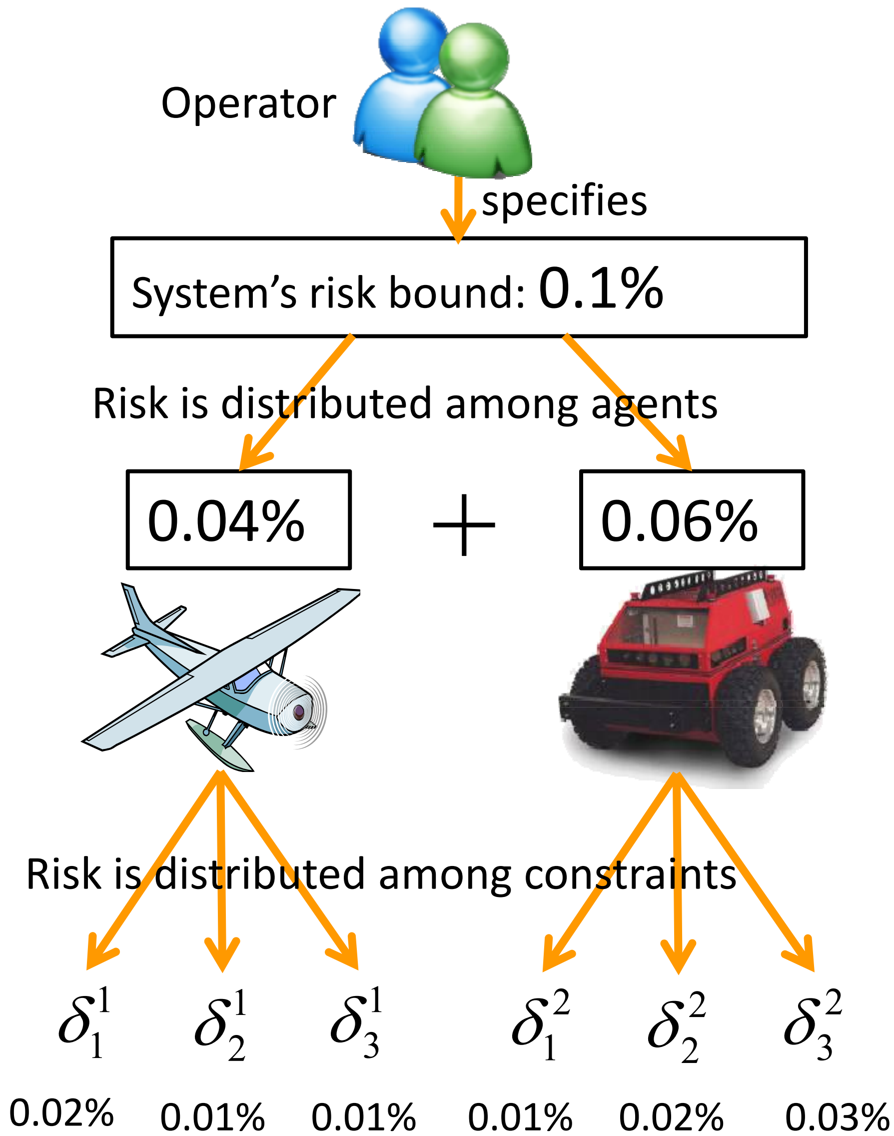
- Deterministic control (Sulu): 30% comfort violations.
- Risk-sensitive control (p-Sulu): near 0% violations.

(Sub)Urban Scale Sustainability



- Heterogeneous connected homes with different energy sources.
- Symmetric energy exchange between houses.
- Challenge:
  - How to distribute energy optimally,
  - while limiting the risk of an energy shortage,
  - without centralized control.

Allocation between Risk-coupled Agents



Multi-agent

$$\min_{U^{1:I} \in \mathbf{U}^{1:I}} \sum_{i=1}^{I} J^i(U^i)$$

$$s.t. \quad \Pr\left[\bigwedge_{i=1}^{I} \bigwedge_{n=1}^{N_i} h_n^{iT} X^i \le g_n^i \right] \ge 1 - \Delta$$

Decomposed, deterministic RA reformulation

$$\min_{U^{1:I} \in \mathbf{U}^{1:I}, \delta_{i:N}^{1:I}} \sum_{i=1}^{I} J^i(U^i)$$

$$s.t. \quad \bigwedge_i \bigwedge_n h_n^{iT} \bar{X}^i \le g_n^i - m_n^i\left(\delta_n^i\right)$$

$$\sum_{i=1}^{I} \sum_{n=1}^{N^i} \delta_n^i \le \Delta$$

Allocation between Risk-coupled Agents

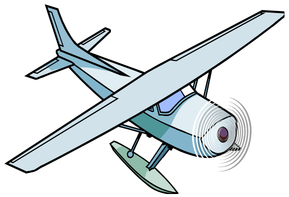
Operator

specifies

System's risk bound: 0.1%

Risk is distributed among agents

0.04% + 0.06%



- Need to optimize risk allocation between agents since they have different sensitivities to risk.

$$\sum \left(\begin{array}{l} \textit{Individual} \\ \textit{risk bounds} \end{array} \right) \leq \begin{array}{l} \textit{System's} \\ \textit{risk bound} \end{array}$$

Multi-agent

$$\min_{U^{1:I} \in \mathbf{U}^{1:I}} \sum_{i=1}^{I} J^i(U^i)$$

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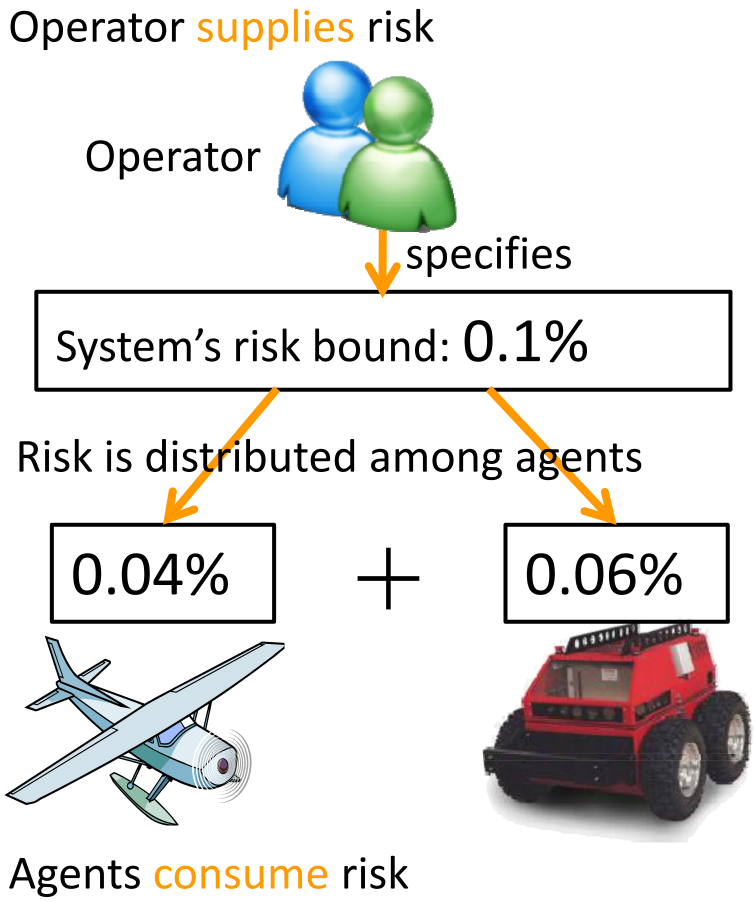
Market-based Iterative Risk Allocation



$$\sum \left(\textit{Demands for risk} \right) \leq \textit{Supply of risk}$$

- Treat each agent as an **independent** decision maker.
- Agents communicate through **market**.
- Find a globally optimal solution through **iteration.**
- Approach is **economically inspired** (*tâtonnement):*
  - **Risk is a resource** traded in a market.
  - Each agent has a *demand for risk* as a function of the price of risk.

Based on Dual Decomposition

Centralized Optimization

(decomposed, deterministic form)

$$\min_{U^{1:I} \in \mathbf{U}^{1:I}, \delta^{1:I}_{i:N}} \sum_{i=1}^{I} J^i(U^i)$$

$$s.t. \quad \bigwedge_{i=1}^{I} \bigwedge_{t=1}^{T} x^i_{t+1} = A^i \bar{x}^i_t + B^i u^i_t$$

$$\bigwedge_{i=1}^{I} \bigwedge_{n=1}^{N} h^{iT}_n \bar{X}^i \le g^i_n - m^i_n\left(\delta^i_n\right)$$

$$\sum_{i=1}^{I} \sum_{n=1}^{N^i} \delta^i_n \le \Delta$$

Convex optimization

Decentralized Optimization

Risk taken by the i'th agent

i'th agent: (Primal)

$$\min_{U^i \in \mathbf{U}^i, \delta^i_{1:N}} J^i(U^i) + p D^i$$

Dual variable = Price of risk

$$s.t. \quad \bigwedge_{t=1}^{T} x^i_{t+1} = A^i \bar{x}^i_t + B^i u^i_t$$

$$\bigwedge_{n=1}^{N} h^{iT}_n \bar{X}^i \le g^i_n - m^i_n\left(\delta^i_n\right)$$

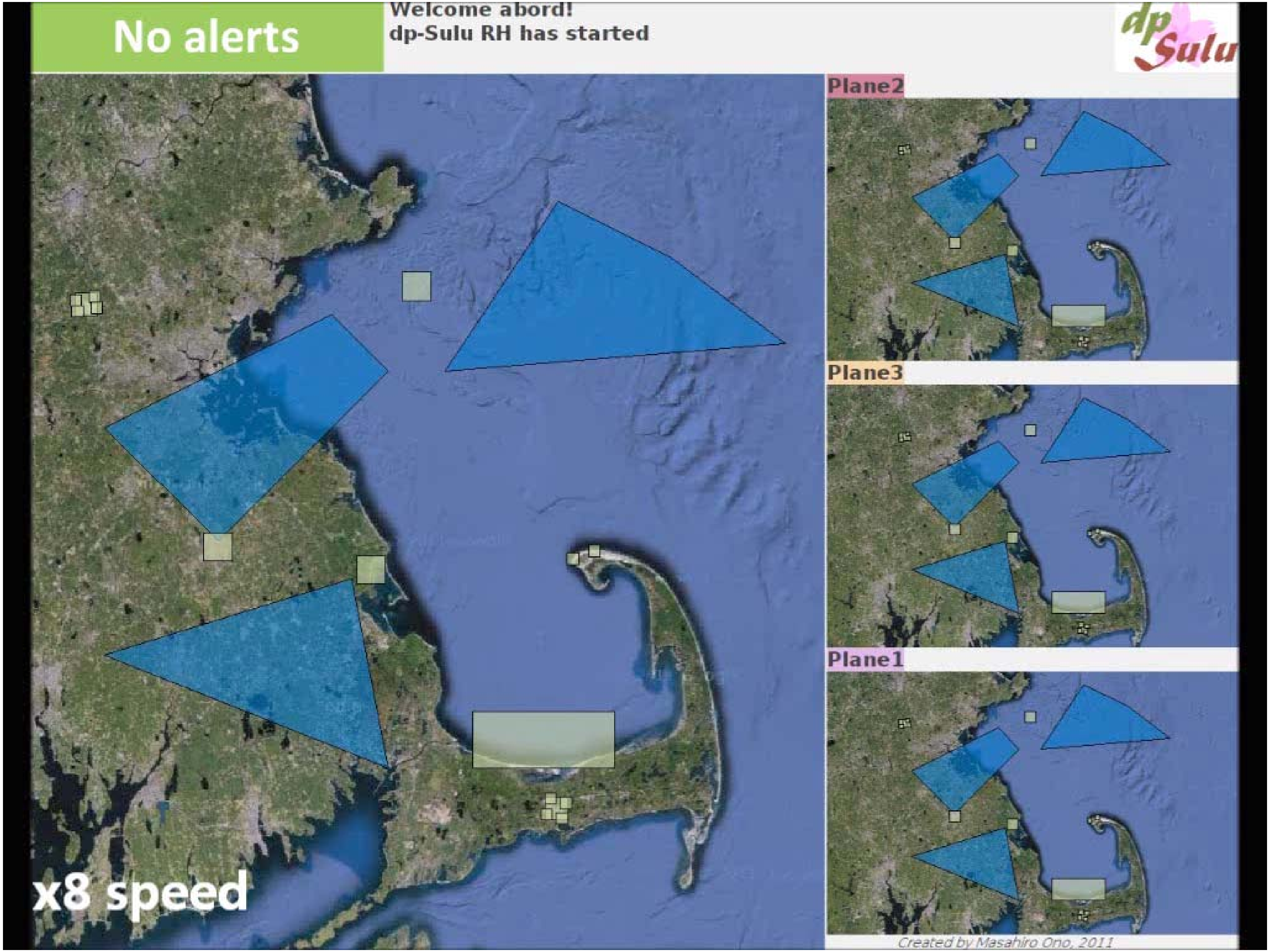
$$D^i = \sum_{n=1}^{N^i} \delta^i_n$$

Demand for risk from i'th agent

Market (Dual)

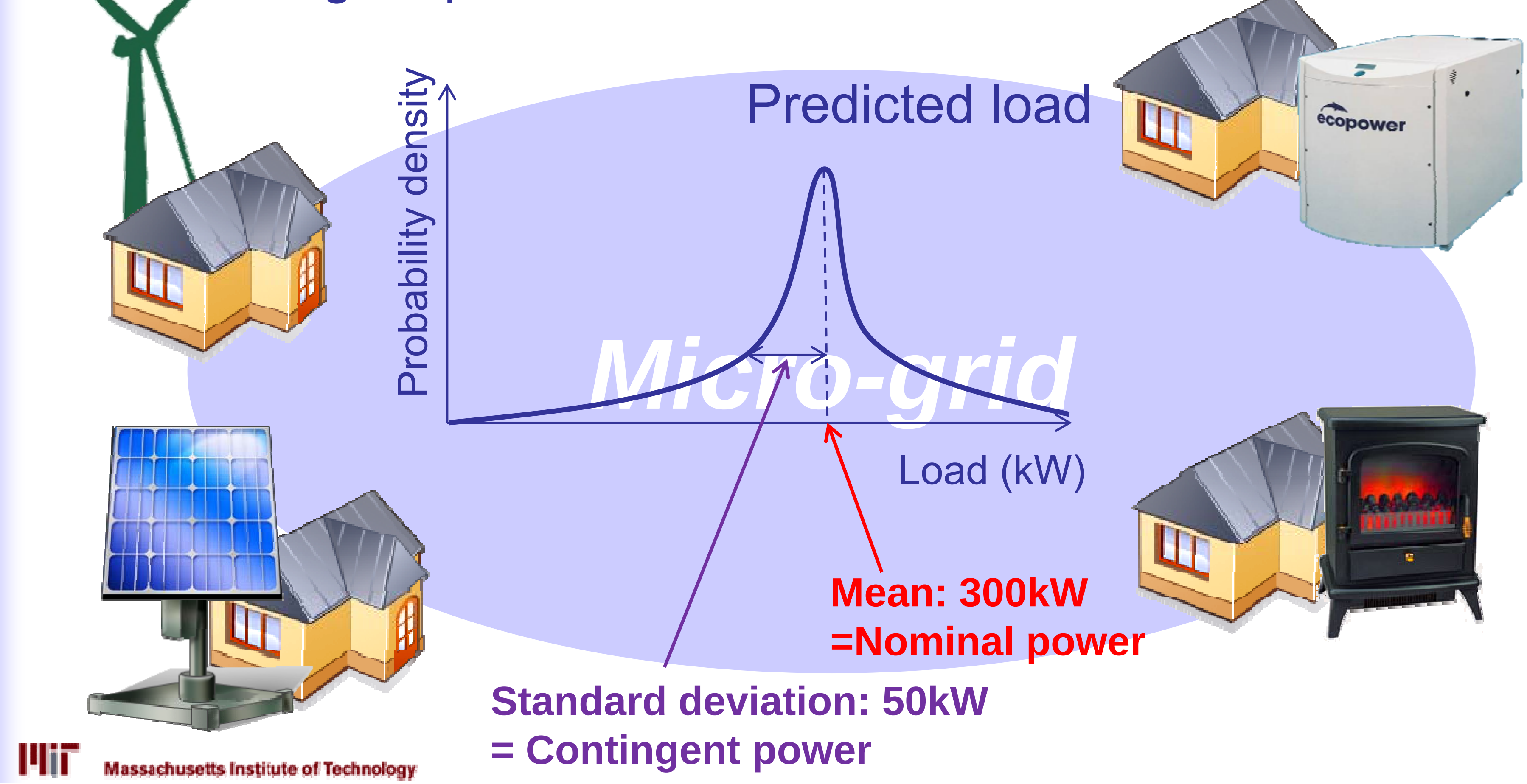
$$\sum_{i=1}^{I} D^{*i}(p) = \Delta$$

Root finding problem


No alerts
Welcome abord!
dp-Sulu RH has started
dp Sulu
Plane2
Plane3
Plane1
x8 speed
Created by Masahiro Ono, 2011

Market-based Contingent Power Dispatch

- Two kinds of energies are traded in a market:
  - Nominal power
  - Contingent power



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   - Inference of expected user behavior, and
   - Models of environment and plant.

Questions?