Distributed Stochastic Control Framework for Uncertain Multi-Agent Networks

(Large-Scale Complex Systems)

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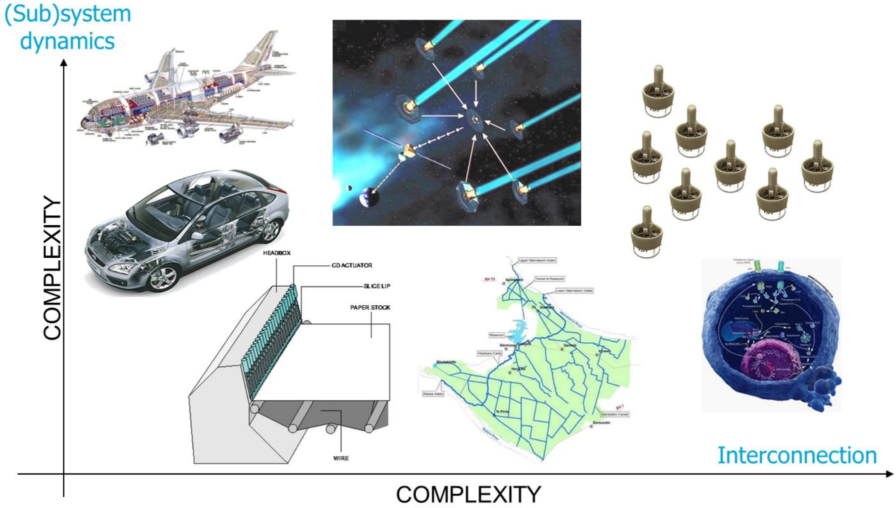
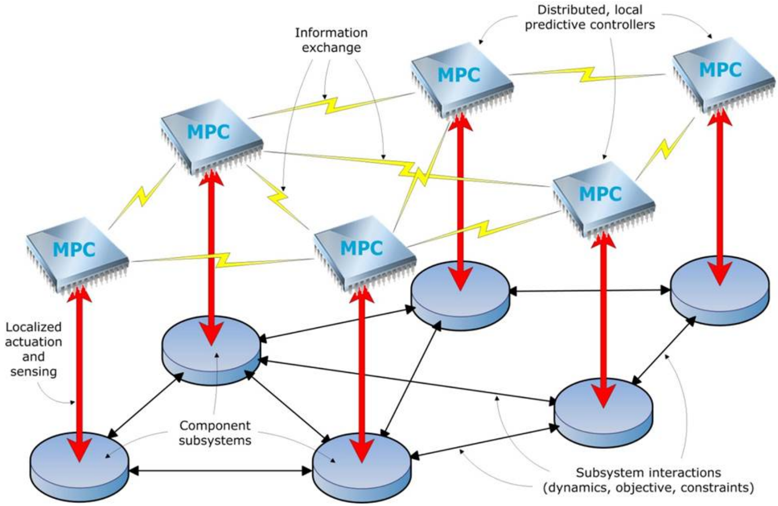
TUDelft

Large-Scale Complex Systems



Objective



Distributed, local
predictive controllers
Information
exchange
MPC
MPC
MPC
MPC
MPC
MPC
Localized
actuation
and
sensing
Component
subsystems
Subsystem interactions
(dynamics, objective, constraints)

Optimization and Team Decision Making

- How can we **distribute optimal team decision-making**?
- How can this work in a **real-time control system**?
- What **information should be exchanged**?
- How can we **deal with uncertainty sources** in networked systems?

Outline

1. Smart Thermal Grids
   Multi-Agent Networks with Private and Common Uncertainties
2. Smart Power Grids
   Large-Scale Complex Power System with Uncertain Generation
3. Pick an MSc project in Distributed Framework
   Smart Energy Management with Presence of Uncertainties (Risks)
4. Concluding Remarks

Outline

1. Smart Thermal Grids
   Multi-Agent Networks with Private and Common Uncertainties
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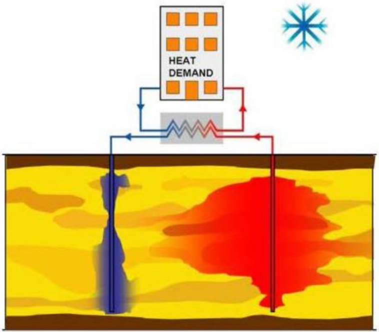
Smart Thermal Grids: Multi-Agent Network

Aquifer Thermal Energy Storage (ATES)

- A large-scale natural subsurface storage for thermal energy
- An innovative method for thermal energy balance in smart grids

Cold season:

- The building requests thermal energy for the heating purpose
- Water is injected into cold well and is taken from warm well
- The stored water contains cold thermal energy for next season

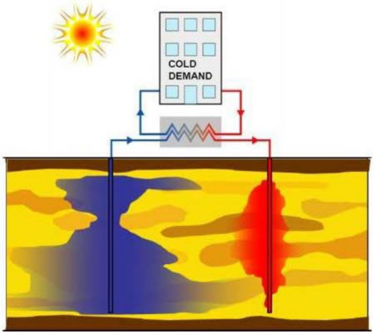


Aquifer Thermal Energy Storage (ATES)

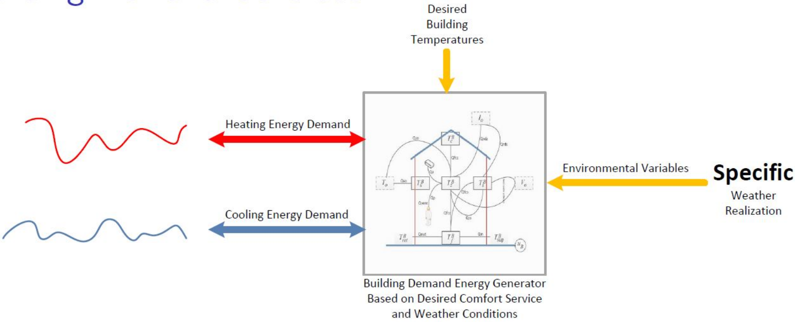
- A large-scale natural subsurface storage for thermal energy
- An innovative method for thermal energy balance in smart grids

Warm season:

- The building requests thermal energy for the cooling purpose
- Water is injected into warm well and is taken from cold well
- The stored water contains warm thermal energy for next season



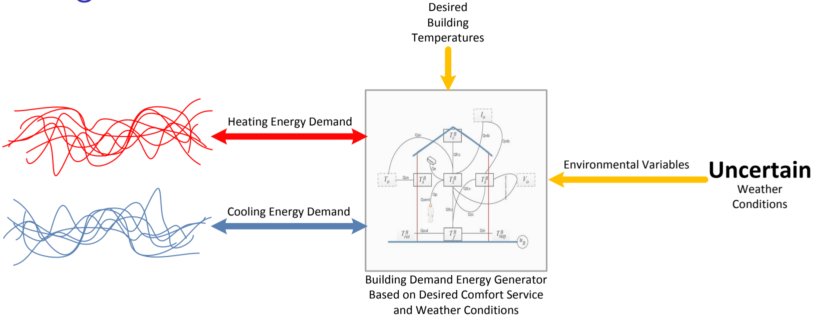
Building Demand Generator



Demand Profile Generator:

- Complete and detailed building dynamical model
- Desired building temperature (local controller unit)
- In a specific weather realization, deterministic demand profiles are generated

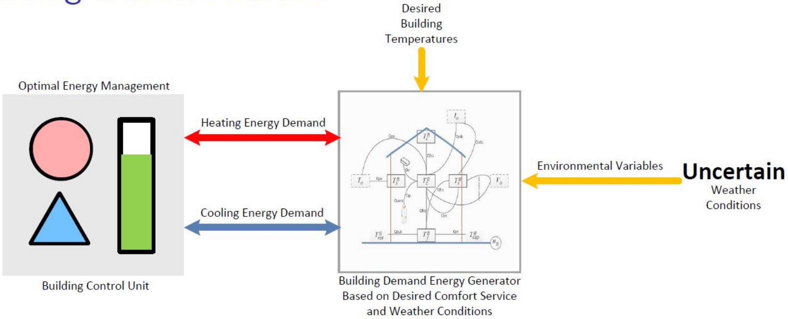
Building Demand Generator



Demand Profile Generator:

- Complete and detailed building dynamical model
- Desired building temperature (local controller unit)
- In uncertain weather conditions, uncertain demand profiles are generated

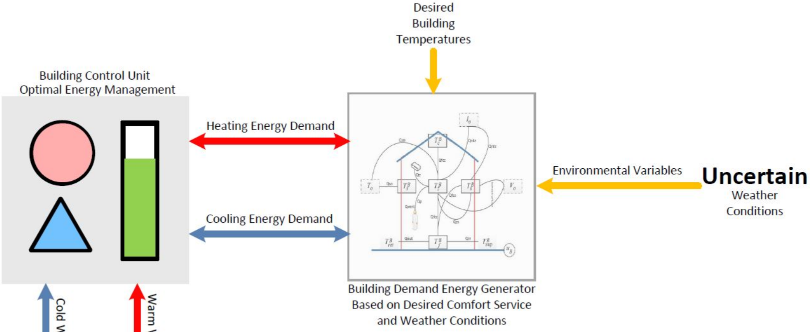
Building Comfort Service

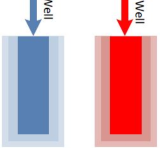


Building Control Unit:

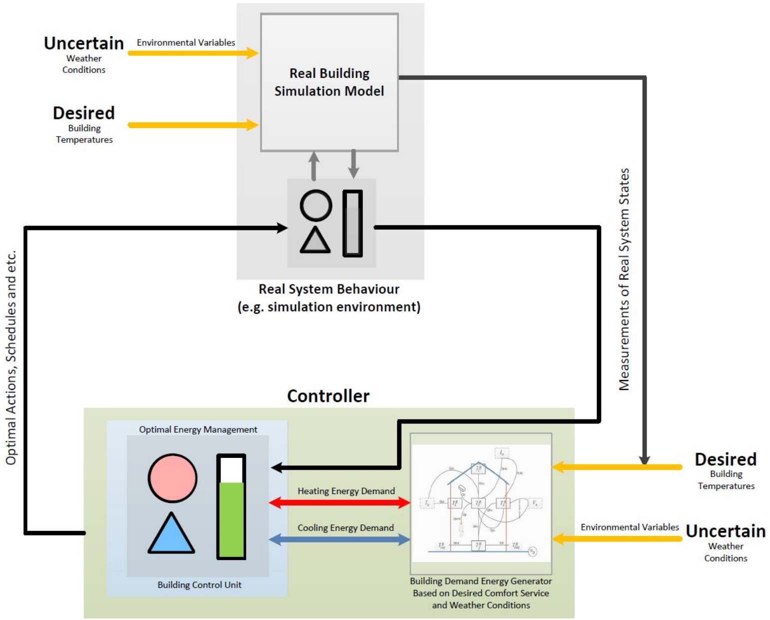
- Main components: Boiler, HP, HE, micro-CHP, Buffer Storage
- **ON/OFF status** together with **production schedule** as decisions
- Thermal **energy balance** for dynamical systems

Next Steps: ATES Systems



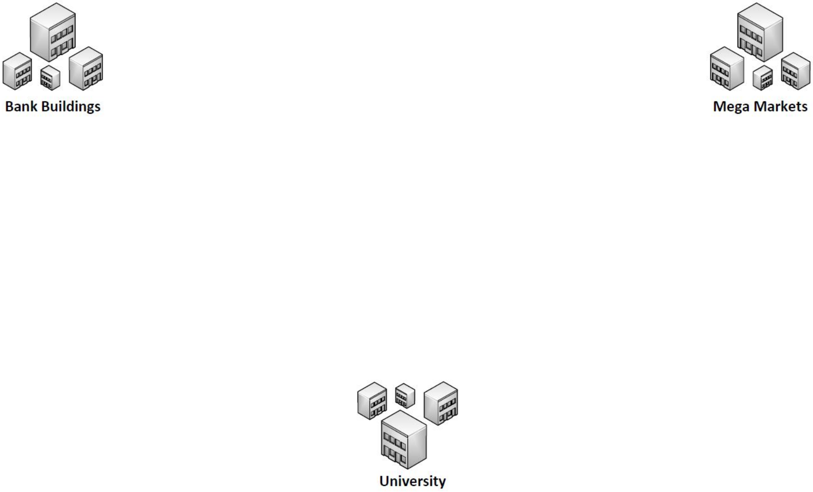


- **Incorporate ATES System**
- **Interaction between components**
- **Different operational time scale**
- **Additional degrees of freedom**

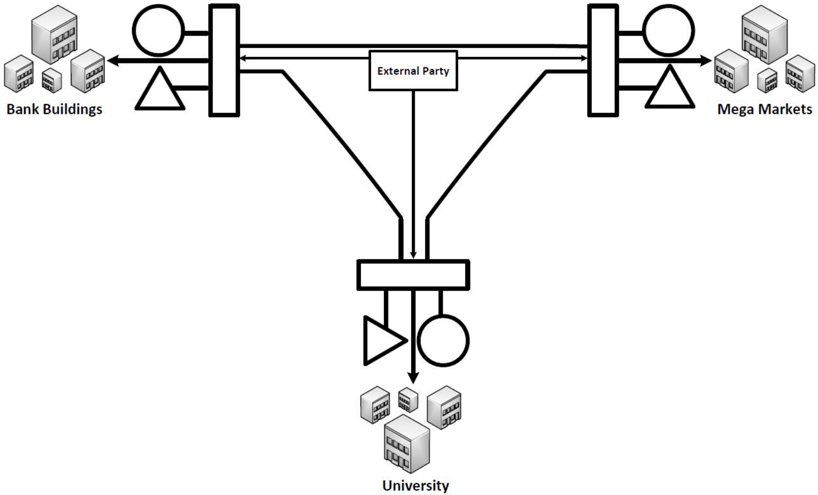


Uncertain
Environmental Variables
Weather
Conditions
Desired
Building
Temperatures
Real Building
Simulation Model
Real System Behaviour
(e.g. simulation environment)
Measurements of Real System States
Optimal Actions, Schedules and etc.
Controller
Optimal Energy Management
Heating Energy Demand
Cooling Energy Demand
Building Control Unit
Building Demand Energy Generator
Based on Desired Comfort Service
and Weather Conditions
Desired
Building
Temperatures
Environmental Variables
Uncertain
Weather
Conditions

Smart Thermal Grids: Conceptual Representation



Smart Thermal Grids: Conceptual Representation



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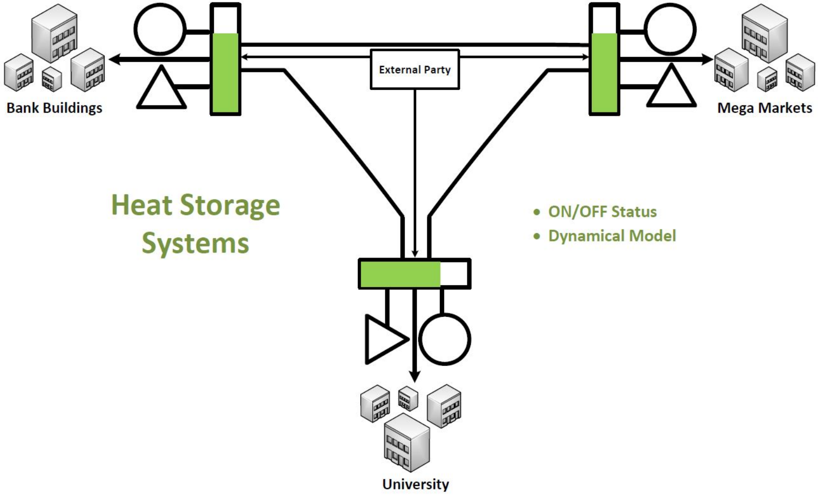

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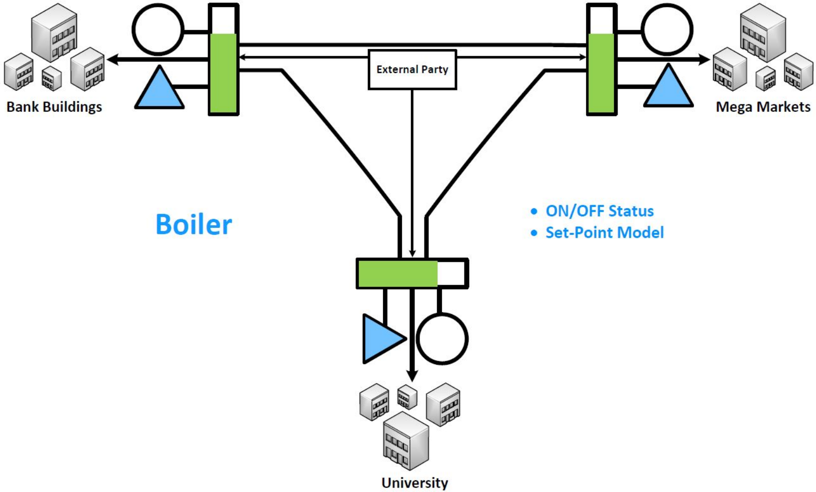

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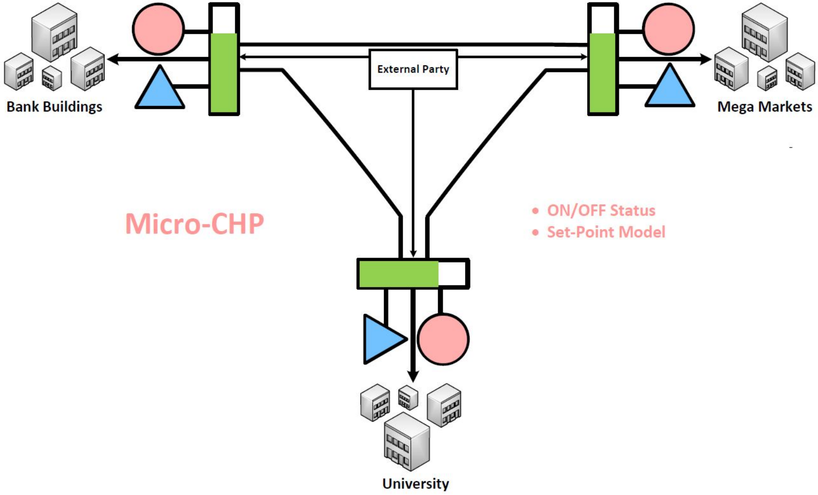

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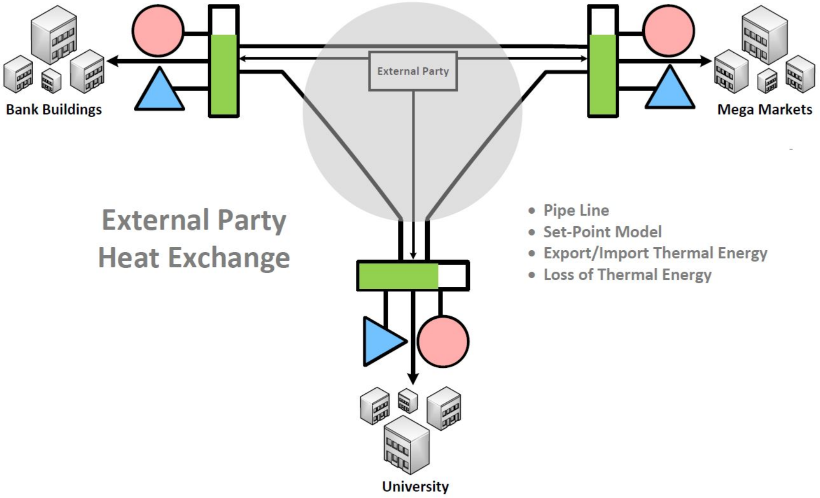
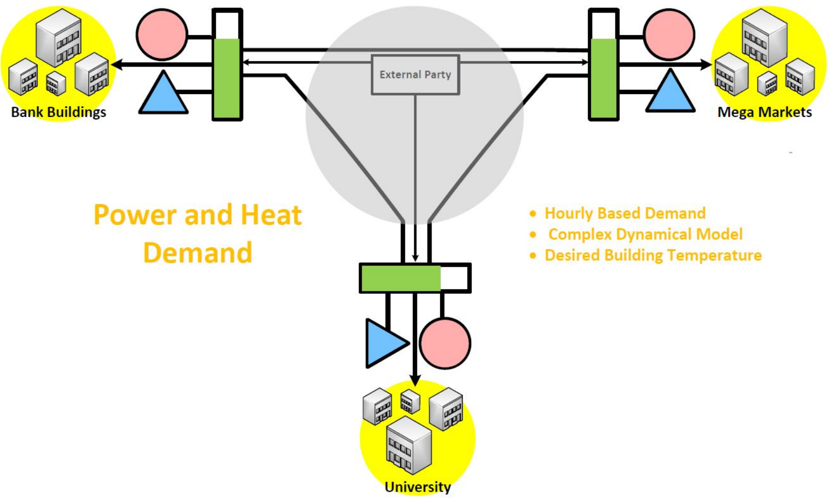


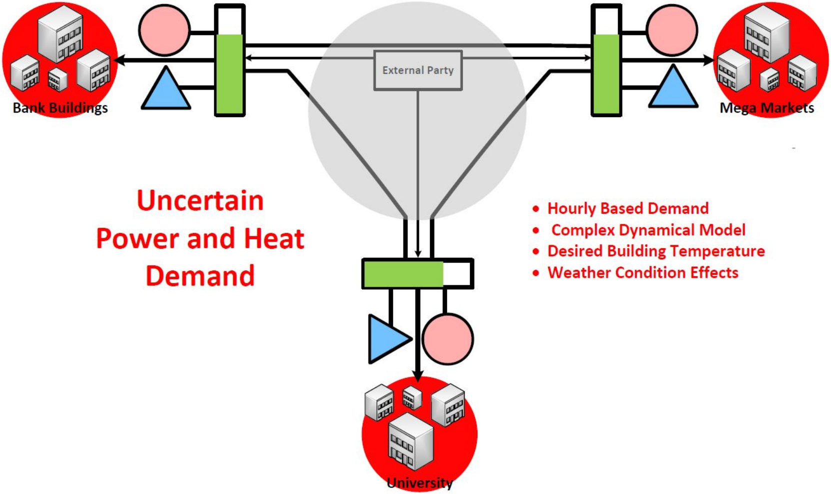
External Party
Heat Exchange

- Pipe Line
- Set-Point Model
- Export/Import Thermal Energy
- Loss of Thermal Energy

Smart Thermal Grids: Conceptual Representation



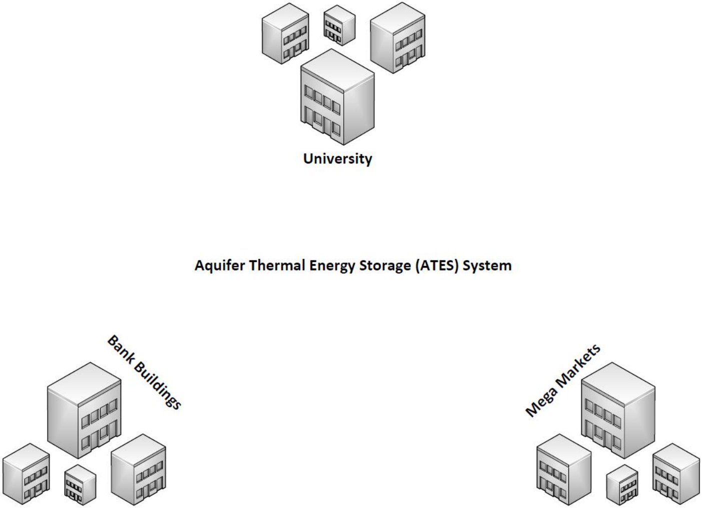
Smart Thermal Grids: Conceptual Representation



Uncertain Power and Heat Demand

- Hourly Based Demand
- Complex Dynamical Model
- Desired Building Temperature
- Weather Condition Effects

Smart Thermal Grids: ATES Systems



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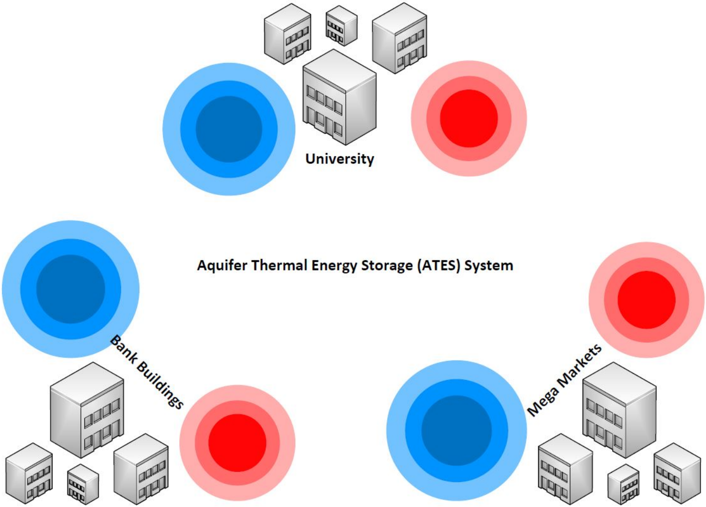

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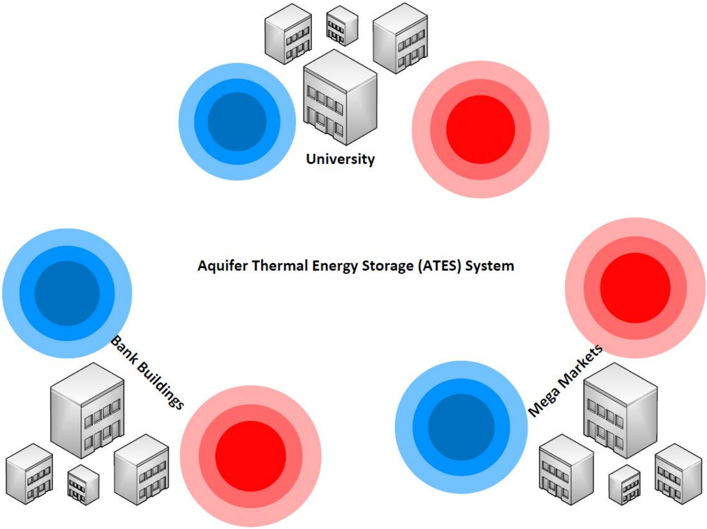

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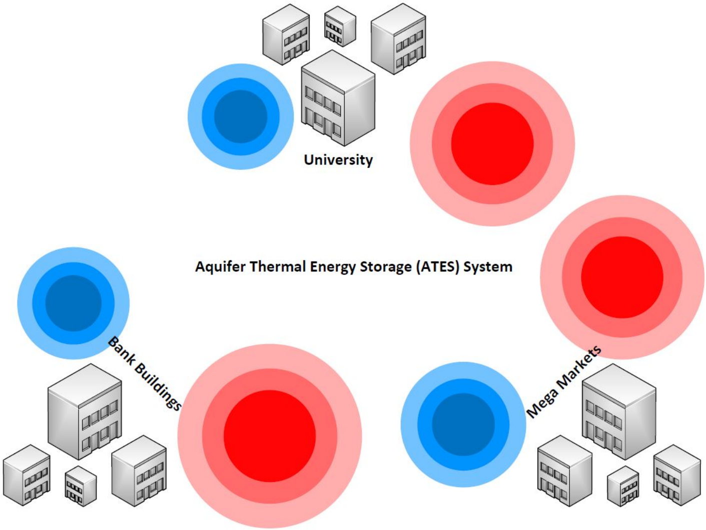

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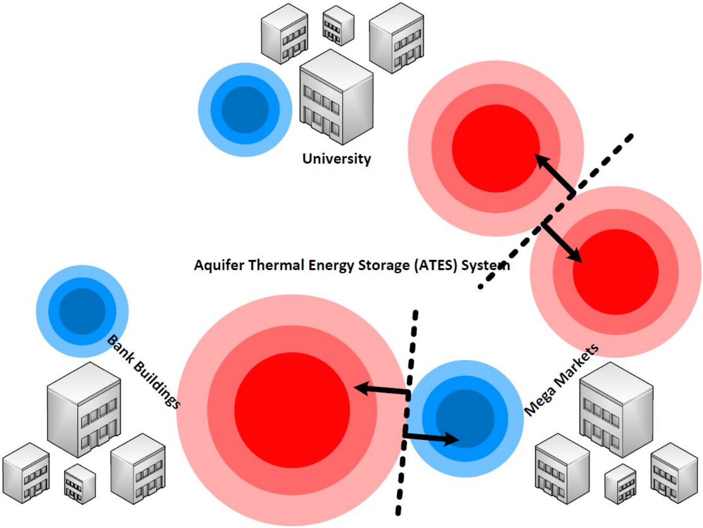
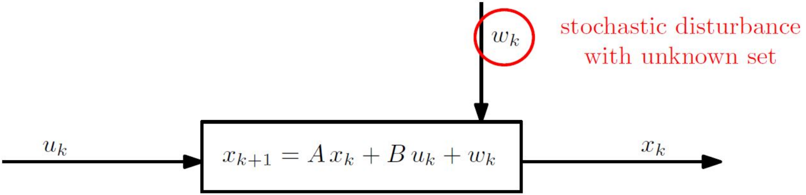


Mathematical Model

Define x_k to be the imbalance error between demand and production level. This yields the following dynamical model for imbalance error:



Our objective: design a state feedback control policy that minimizes the energy consumption of buildings, while keeping room temperatures between comfortable limits, despite *uncertain weather conditions*, and subject to the operational constraints

Stochastic Optimization Problems

Optimization problems under uncertainty:

- **Robust Programs:** provide a guaranteed level of performance for all admissible values of the uncertain parameters equally likely:

$$\begin{cases} \min\limits_{x} & c(x) \\ \text{s.t.} & g(x,\delta) \le 0, \quad \forall \delta \in \Delta \\ & x \in \mathcal{X} \end{cases} \qquad \textbf{(RPs)}$$

  - Tractability issue occurs in many control problems
  - Very conservative since all uncertainty realizations are treated equally

Stochastic Optimization Problems

Optimization problems under uncertainty:

- **Chance Constrained Programs:** the relaxed version of RPs that allow constraint violation with a low probability $\varepsilon \in [0, 1]$:

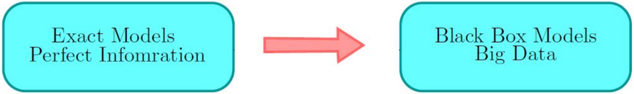
$$\begin{cases} \min\limits_{x} & c(x) \\ \text{s.t.} & \mathbb{P}\left[g(x, \delta) \leq 0\right] \geq 1 - \varepsilon \\ & x \in \mathcal{X} \end{cases} \qquad \textbf{(CPs)}$$

  - Accessibility of the probability distribution $\mathbb{P}$
  - Intractable optimization problem and in general nonconvex
  - Probability associated with the chance constraints can be hard to compute since it requires a multi-dimensional integral

Stochastic Optimization Problems

Optimization problems under uncertainty:

- **Big Data Programs:** We see a definite transition from a classical exact model to a data driven approach in the age of big data:



- How we deal with optimization and or control problems to reflect this transition?
  - We do not know the model information exactly: $\mathbb{P}$, $g(\cdot)$
  - Only a finite amount of data is available $\{\, g_k(\cdot) \mid k = 1, 2, \cdots, N \,\}$
- How much information is really required to make meaningful estimates or informed decisions?

Stochastic Optimization Problems

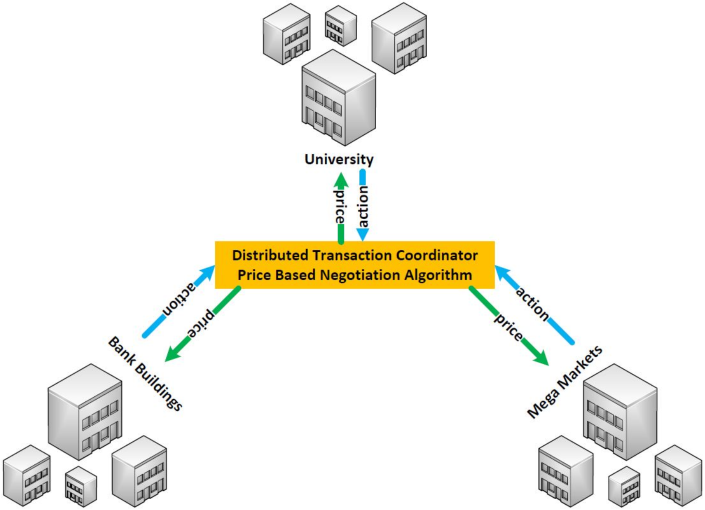
Optimization problems under uncertainty:

- **Scenario Programs:** Computationally tractable approximations of CPs in which only finitely many uncertainty scenarios are considered:

$$\begin{cases} \min\limits_{x} & c(x) \\ \text{s.t.} & g(x, \delta_i) \leq 0, \quad \forall i \in \{1, \cdots, N\} \\ & x \in \mathcal{X} \end{cases} \qquad \textbf{(SPs)}$$

  - δ_i, for $i = 1, \cdots, N$, are N independent and identically distributed scenarios drawn according to the probability measure $\mathbb{P}$
  - Based on generating a large number N of stochastic scenarios, thus may lead to a very conservative solution
  - E.g., convex problem $N > 10^3$, and nonconvex problem $N > 10^4$

Next Steps: Price Based Negotiation Algorithm



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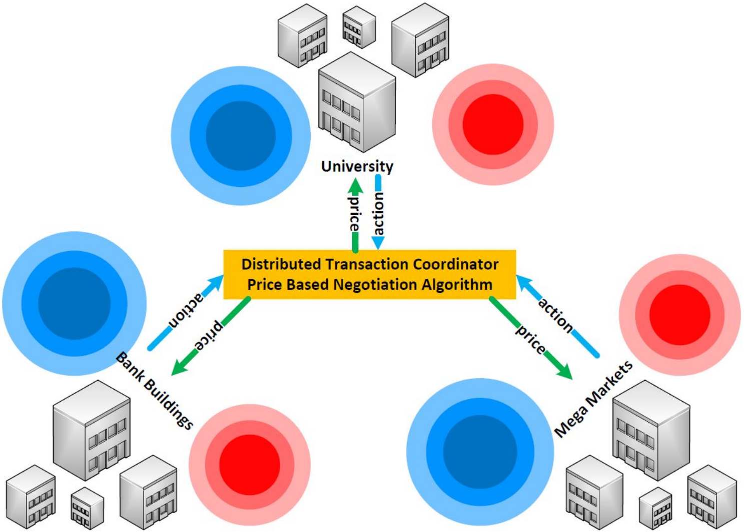

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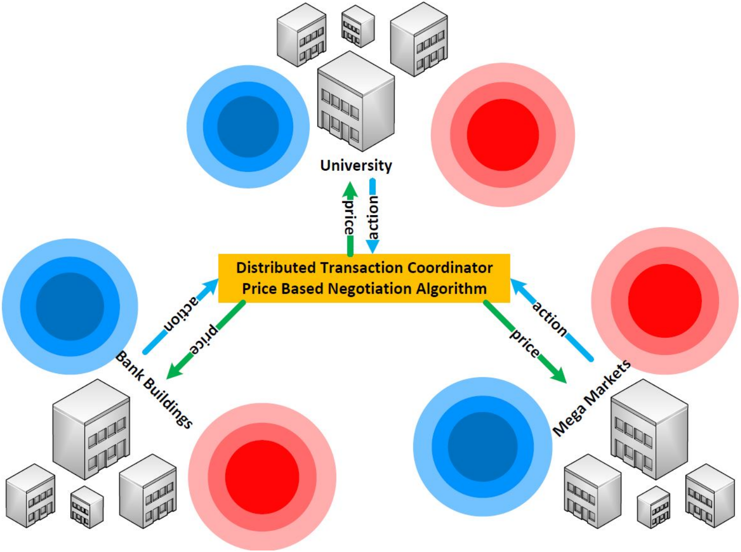

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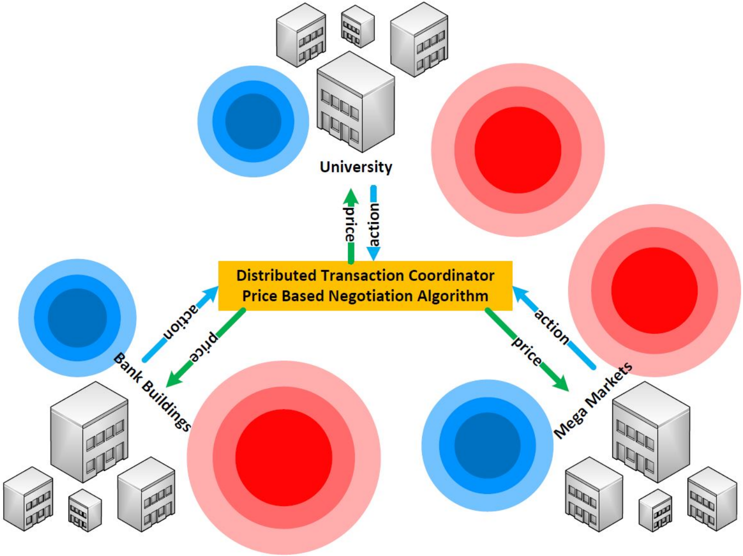

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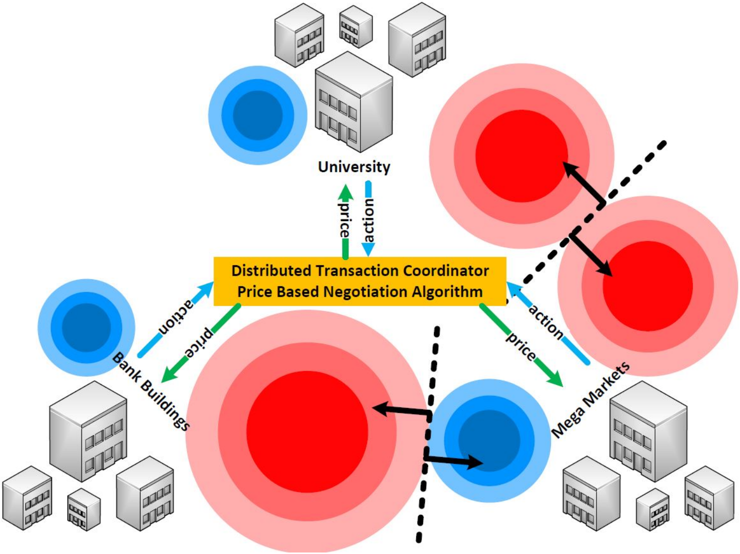
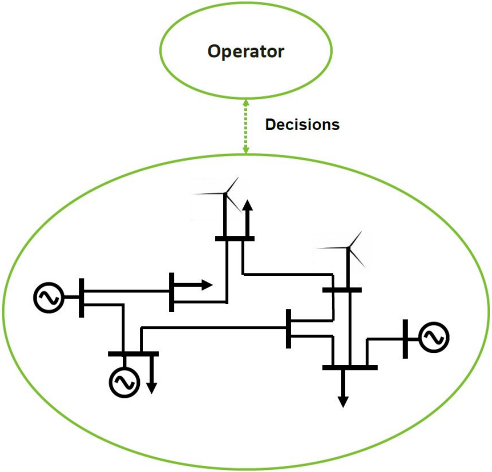


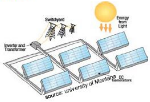
Outline

Smart Power Grids Under Uncertainty

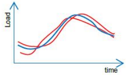


Wind power

PV power



Demand



Contingencies

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Decision Making Under Uncertainty

Main tasks of the Transmission System Operator (TSO):

1. Ensure ''N-1 security''

N-1 security criterion:

No operational limit violation after any single component outage

[Maria Vrakopoulou, FERC conference June 23-25, 2014]

Decision Making Under Uncertainty

Main tasks of the Transmission System Operator (TSO):

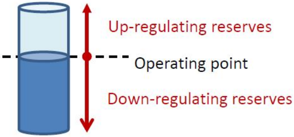
1. Ensure "N-1 security"

N-1 security criterion:

No operational limit violation after any single component outage

2. Maintain power balance

Generation active power capacity



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Decision Making Under Uncertainty

Main tasks of the Transmission System Operator (TSO):

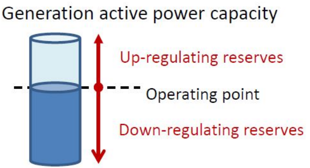
1. Ensure ''N-1 security''

N-1 security criterion:

No operational limit violation after any single component outage

Optimal component setpoints
for *preventive* and *corrective* control

2. Maintain power balance



Optimal reserve capacity and allocation

..but an optimal and secure operation under **uncertainty** is a challenging problem!

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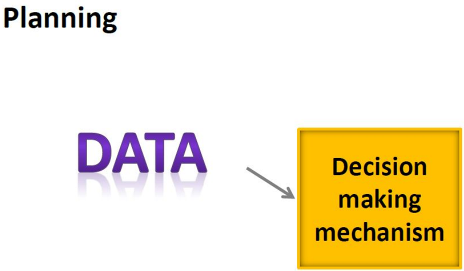
Decision Making Mechanism Under Uncertainty



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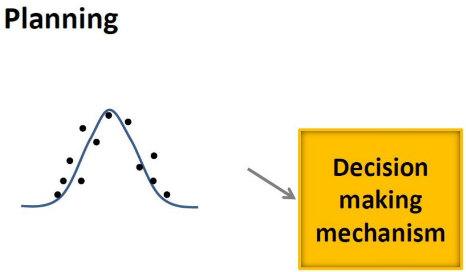
Decision Making Mechanism Under Uncertainty



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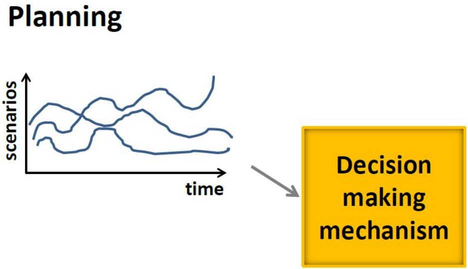
Decision Making Mechanism Under Uncertainty



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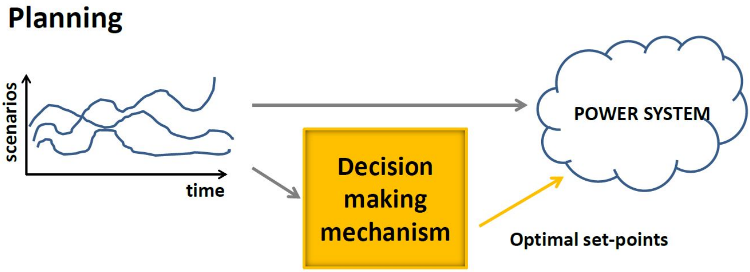

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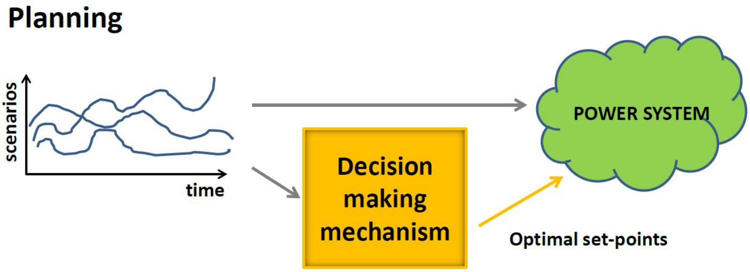

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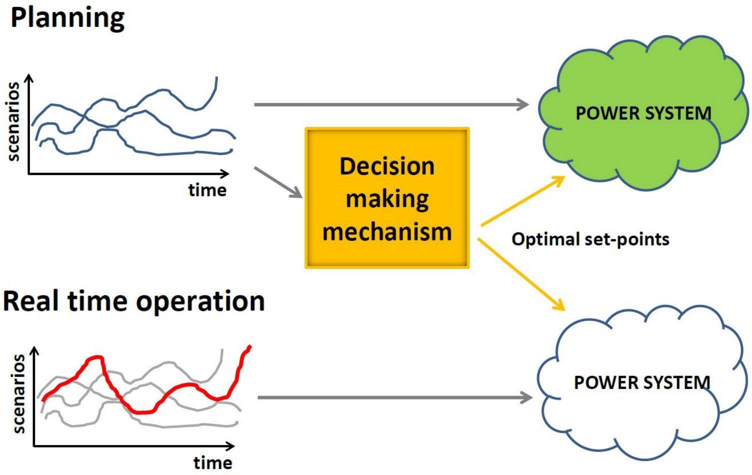
Decision Making Mechanism Under Uncertainty



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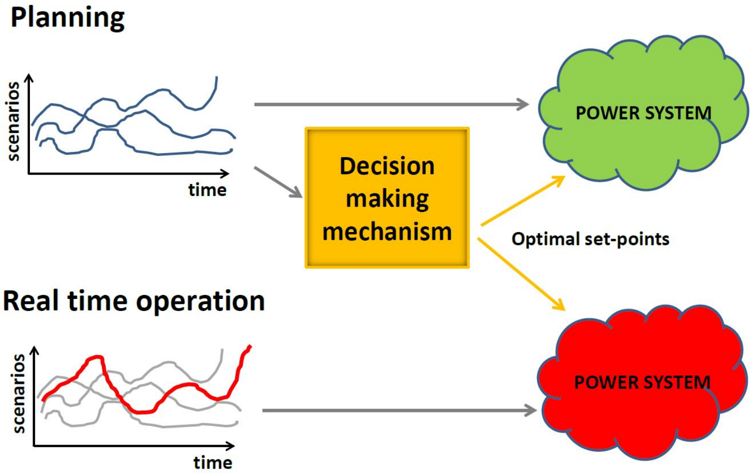

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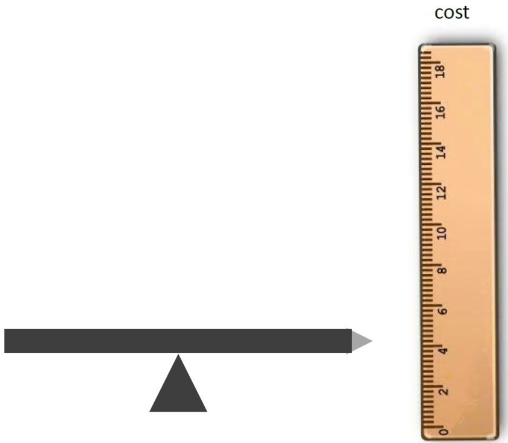
Optimal Energy Management Under Uncertainty

a) Operational costs



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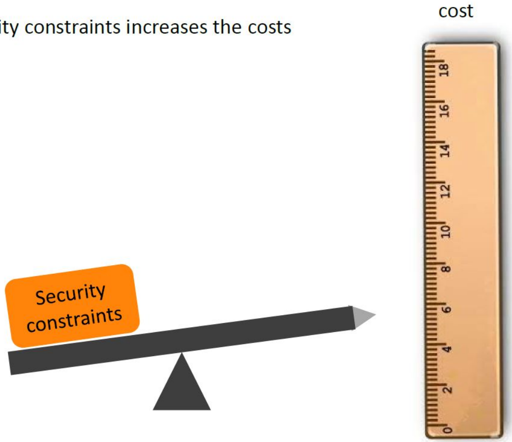
Optimal Energy Management Under Uncertainty

a) Operational costs

- Including security constraints increases the costs



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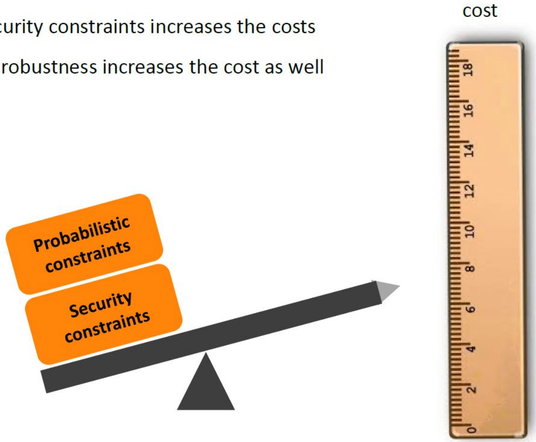
Optimal Energy Management Under Uncertainty

a) Operational costs

- Including security constraints increases the costs
- Probabilistic robustness increases the cost as well



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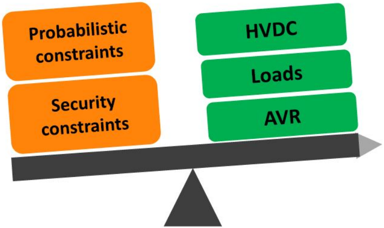
Optimal Energy Management Under Uncertainty

a) Operational costs - OPF

- Decrease cost by exploiting controllability of certain componets (e.g. AVR, HVDC, Loads)
- Model their post-disturbance set-point as a function of the uncertainty (e.g. affine policies)



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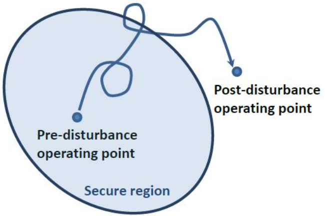
Probabilistic Energy Management Framework

a) Problem set-up

- DC power flow ⟶ linearized network equations
- Uncertainty: wind power P_w
- Preventive control: generation dispatch P_G
- Security for the post-disturbance steady state operating point after the Secondary Frequency Control



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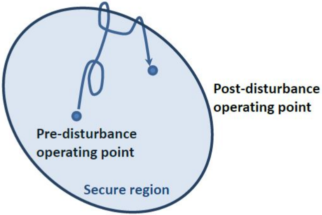

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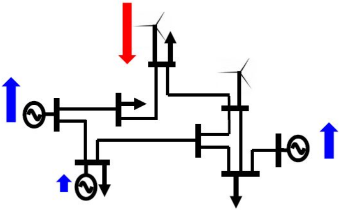
Generation-load mismatch $P_{mismatch}$ is compensated by the generators



$$P_{G,post} = P_G - d \cdot P_{mismatch}$$

$P_{mismatch}$: linear function of P_G and P_w

d: "distribution vector"

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Probabilistic Energy Management Framework

b) Optimization problem

Deterministic problem

$$\min_{\boldsymbol{x}} J(\boldsymbol{x})$$

subject to

$$F_{eq}\boldsymbol{x} + f_{eq} + H_{eq}\boldsymbol{\delta}^f = 0$$

$$F\boldsymbol{x} + f + H\boldsymbol{\delta}^f \leq 0$$

Decision variables: $\boldsymbol{x} = P_G$

Uncertain variables: $\boldsymbol{\delta} = P_w$

[Maria Vrakopoulou, FERC conference June 23-25, 2014]

Probabilistic Energy Management Framework

b) Optimization problem

Deterministic problem

$$\min_{x} J(x)$$

subject to

$$F_{eq}x + f_{eq} + H_{eq}\delta^f = 0$$

$$Fx + f + H\delta^f \leq 0$$

Chance constrained problem

$$\min_{x} J(x)$$

subject to

$$F_{eq}x + f_{eq} + H_{eq}\delta^f = 0$$

$$\mathbb{P}(Fx + f + H\delta \leq 0) \geq 1 - \varepsilon$$

Decision variables: $x = P_G$

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Probabilistic Energy Management Framework

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Decision variables: $x = P_G$

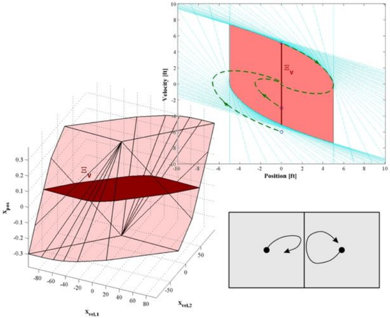
Uncertain variables: $\delta = P_w$

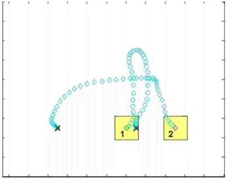
Trade-off between security and cost: $\varepsilon \in (0,1)$

[Maria Vrakopoulou, FERC conference June 23-25, 2014]

Outline

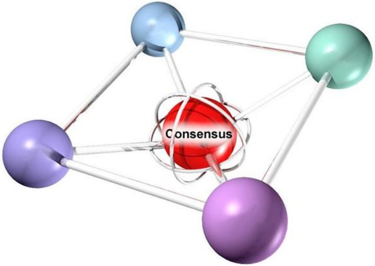
Distributed Constraint Fulfillment





- Design methods for coupled constraints (e.g. collision avoidance)
- Guaranteed feasibility in distributed MPC schemes
- Approximation schemes, controlled invariant sets and reachability
- Robust constraint fulfillment with negotiation
- Reducing conservativeness

Consensus in Distributed Predictive Control

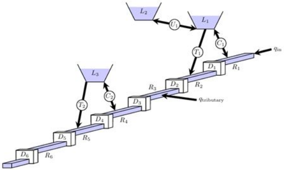


- Interplay between consensus seeking and MPC
- Incremental subgradient methods
- Optimal synchronization problems with constrained subsystem dynamics
- Application to multi-vehicle coordination, oscillator networks, etc.

Distributed Optimization and MPC for Large-Scale Infrastructures

MSc Project

Canal network

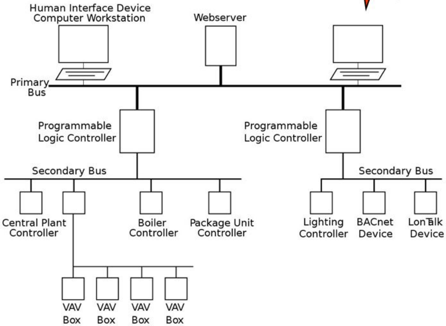


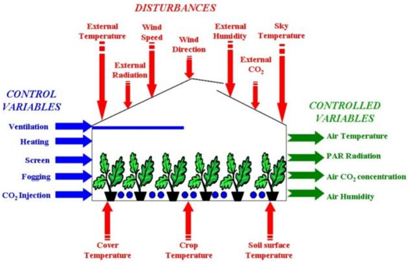
Hydro power network

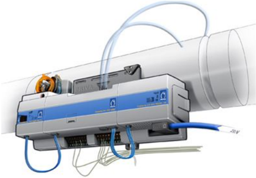
Traffic network

- Decomposition methods in optimization and dynamic programming
- Application to Distributed MPC schemes
- Study of performance versus uncertainty in DMPC schemes
- Achievable performance bounds

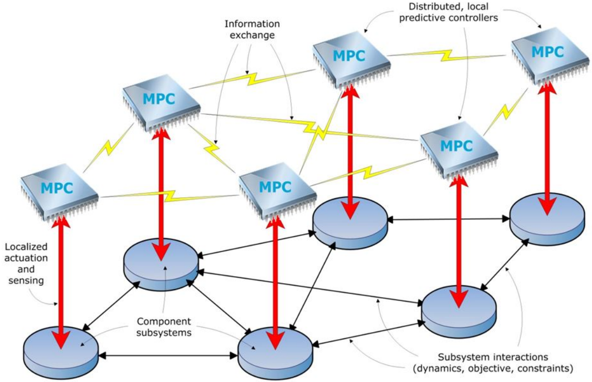
Distributed Optimization and MPC for High-Performance Buildings







Distributed Optimization and MPC for Large-Scale Infrastructures



- Decomposition methods in optimization and dynamic programming
- Application to Distributed MPC schemes
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Outline

Preparation for Control Theory Course

- **Refresh linear algebra knowledge**
  See material also on BlackBoard
- **Order textbook**
  Control System Design; An Introduction to State-Space Methods
  Author: B. Friedland
- **Do not forget to:**
  1. **Homework sets 0 and 1** have been posted check it in BlackBoard
  2. **First lecture on September 12** for more information
  3. **Deadline is September 15**

Thank you! Questions?

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Thank you! Questions?

Distributed Stochastic Control Framework for Uncertain Multi-Agent Networks

(Large-Scale Complex Systems)

Vahab Rostampour, Tamás Keviczky

Delft University of Technology
Deft Center of Systems and Control

September 8, 2016