

Smart Power Systems of the Future: Foundations for Understanding Volatility and Improving Operational Reliability

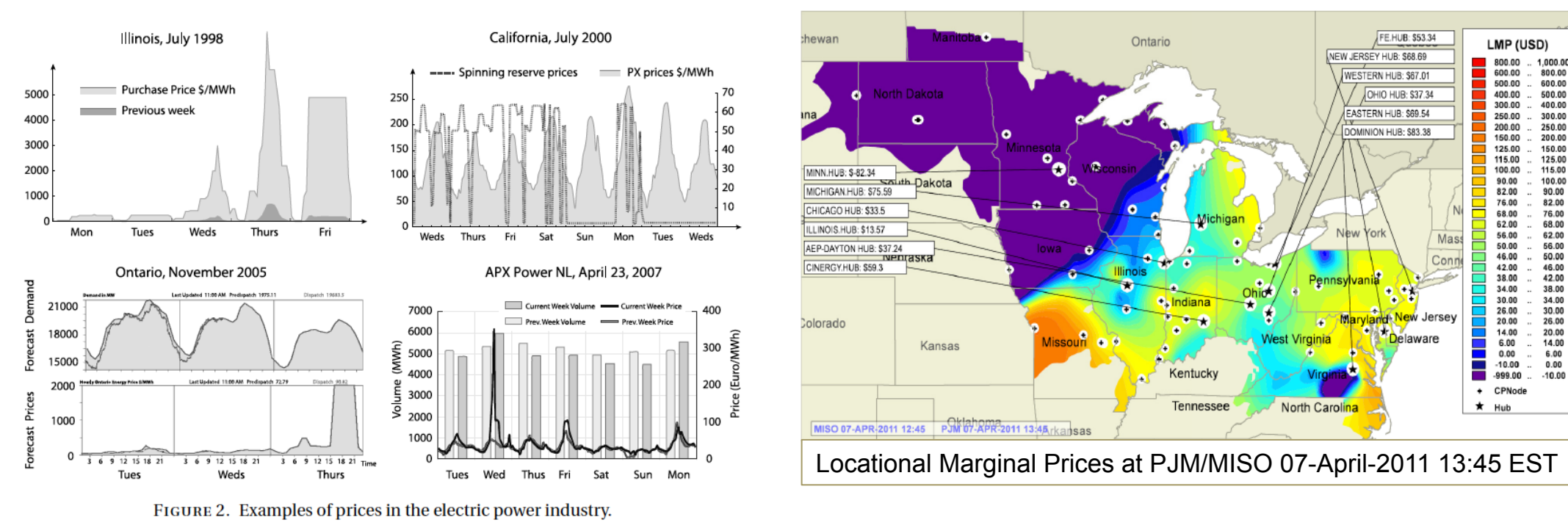
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Power Systems Are Large-Scale, Multi-Layer, Multi-Rate, Cyber-Physical Networks

- Complex intra-layer and cross-layer interactions pose challenges for analysis/design
- Introduction of new feedback loops can help mitigate some disturbances but can also lead to new fragilities
- Supply volatility will increase, leading to rapidly varying system configurations, undermining system reliability
- Price volatility may increase or lead to demand volatility, undermining system reliability



- This project addresses the impact of the integration of renewable intermittent generation and the integration of sophisticated sensing, communication, and actuation capabilities into the grid on the system's reliability, volatility, and economic efficiency, and seeks to develop system architectures, along with associated optimization and control algorithms to balance such trade-offs.

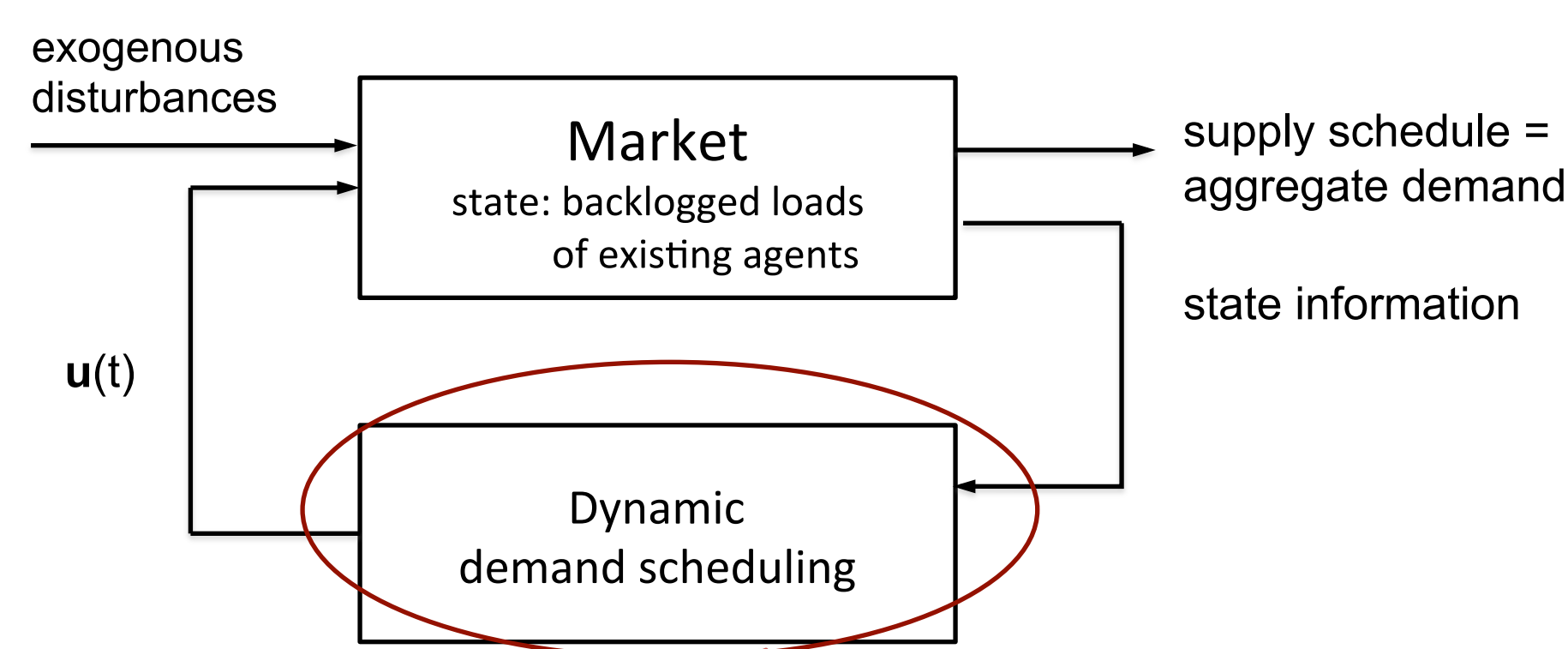
- Understand the trade-offs
- Achieve robustness and efficiency under normal operation
- Reconfigure to mitigate fragility/risk upon approaching a state of failure

Efficiency and Risk Trade-offs in Electricity Markets with Dynamic Demand Response

- Decision making in multi-agent systems:
- Well-known: strategic complementarity leads to efficiency loss
 - In an uncertain environment: efficiency ~ absorbing exogenous shocks
- Multi agent collaboration can reduce externality,
 - but also create endogenous risks
 - System can become more vulnerable to severe exogenous shocks

- In smart grid, real time electricity pricing and consumer side load shifting may help absorb supply / demand uncertainties.
- Consumer interaction may translate exogenous uncertainties to endogenous risk.

Model



Characteristics:
stringent deadlines, time-varying resource requirement, dynamics

System architectural properties
Cooperative / non-cooperative
Pricing method
Risk sensitivity
Information

Load-shifting Model Setup

Agent arrival:

- L types (deadline constraint)
- Uncertainty
 - Bernoulli arrival
 - Workload distribution $w_l(t), t \in \{1, \dots, L\}$

- Marginal cost pricing with quadratic cost $p(t) = \sum_i u_i(t)$

Decision process and dynamics:

Each agent participates in a finite window
Agent schedules demand to minimize his expected total payment

$$E[\sum_{\tau=t}^{t+1} u_i(\tau)p(\tau)]$$

Results

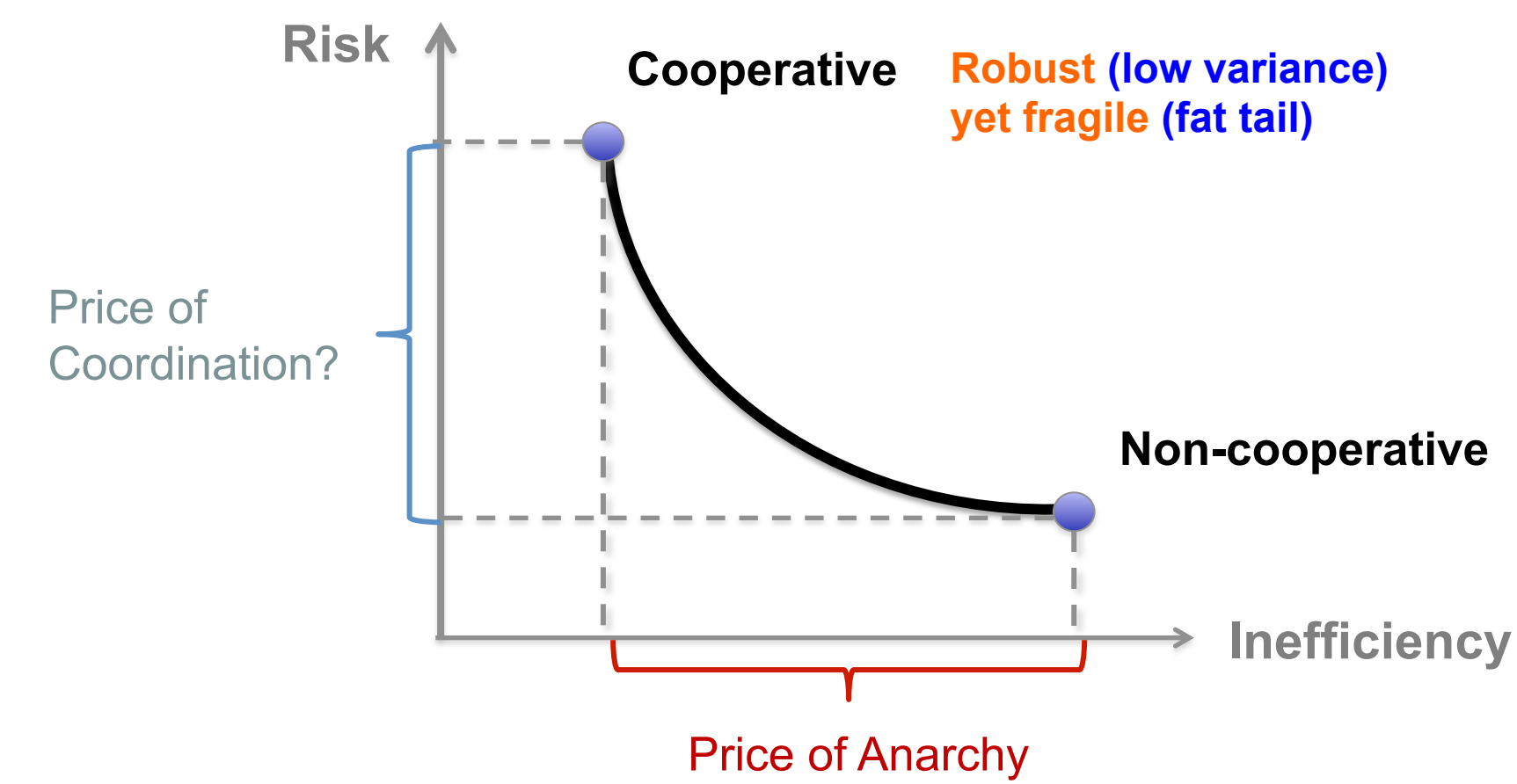
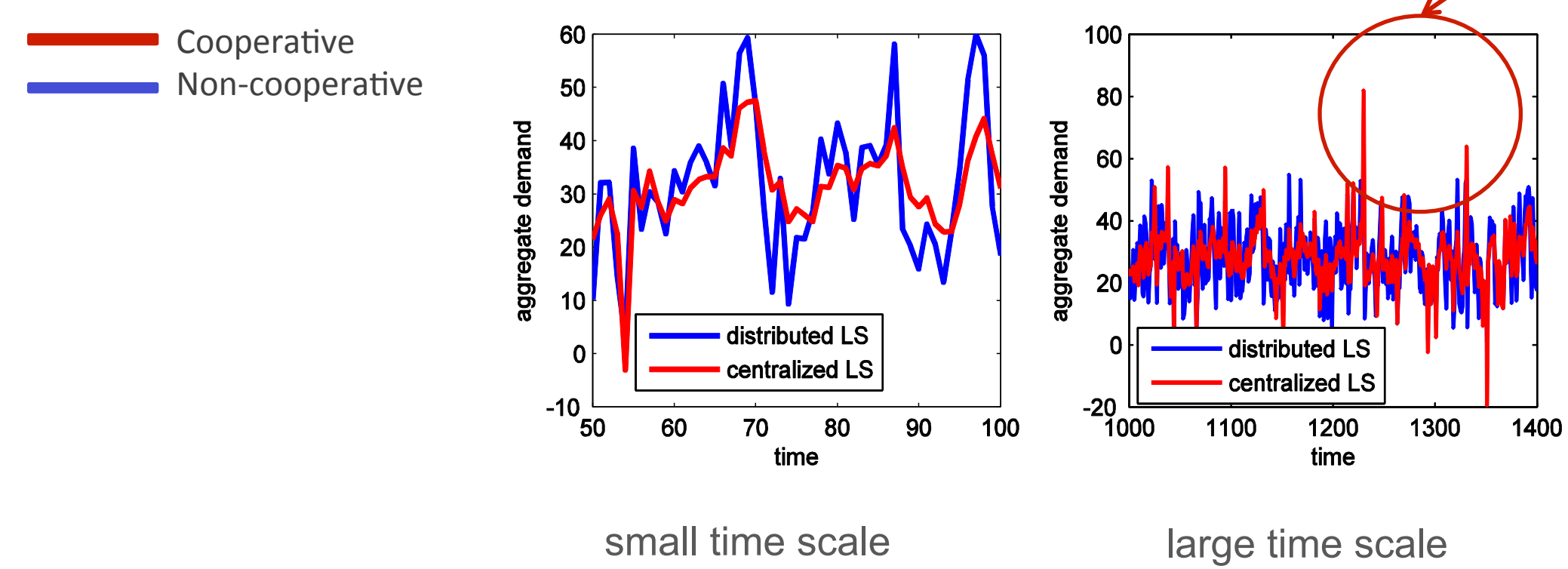
Non-cooperative

Dynamic stochastic game
Markov perfect equilibrium

Cooperative

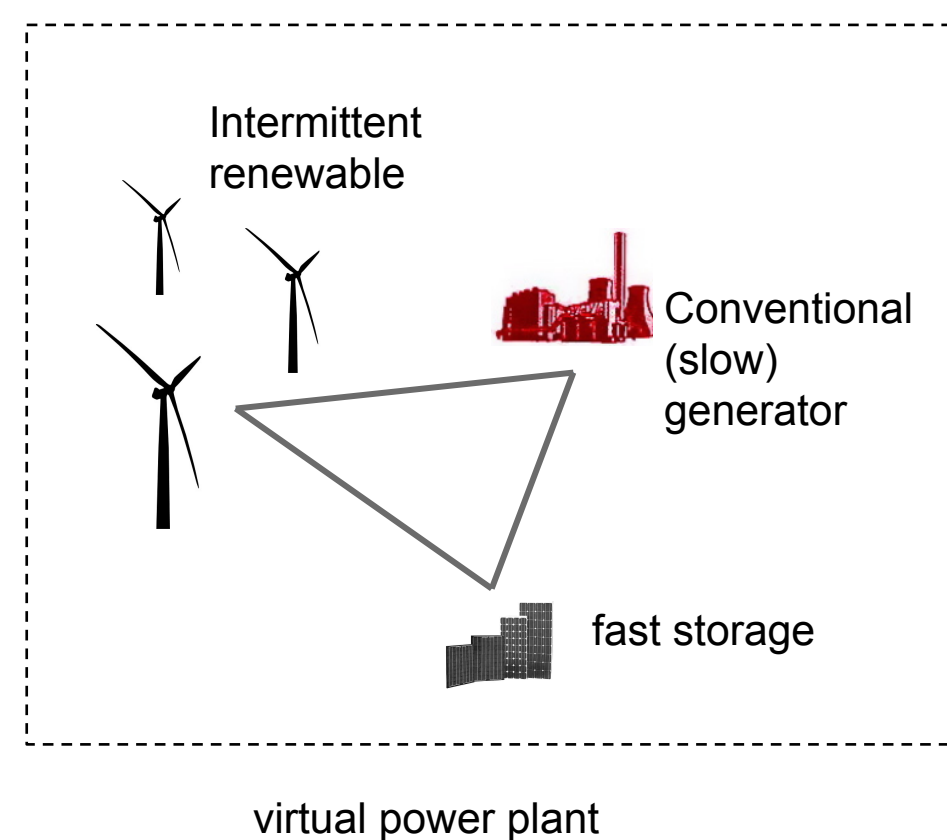
Infinite horizon
average cost MDP

Aggregate demand sample path



Robustness-Risk Trade-offs in Energy Markets with Cooperative Storage and Renewable Generation

- The goal of the coalition is to minimize the long-term expected cost of deviations from the promised output (imposed by the ISO/regulations).
- Also, an abstract model of the system as a whole

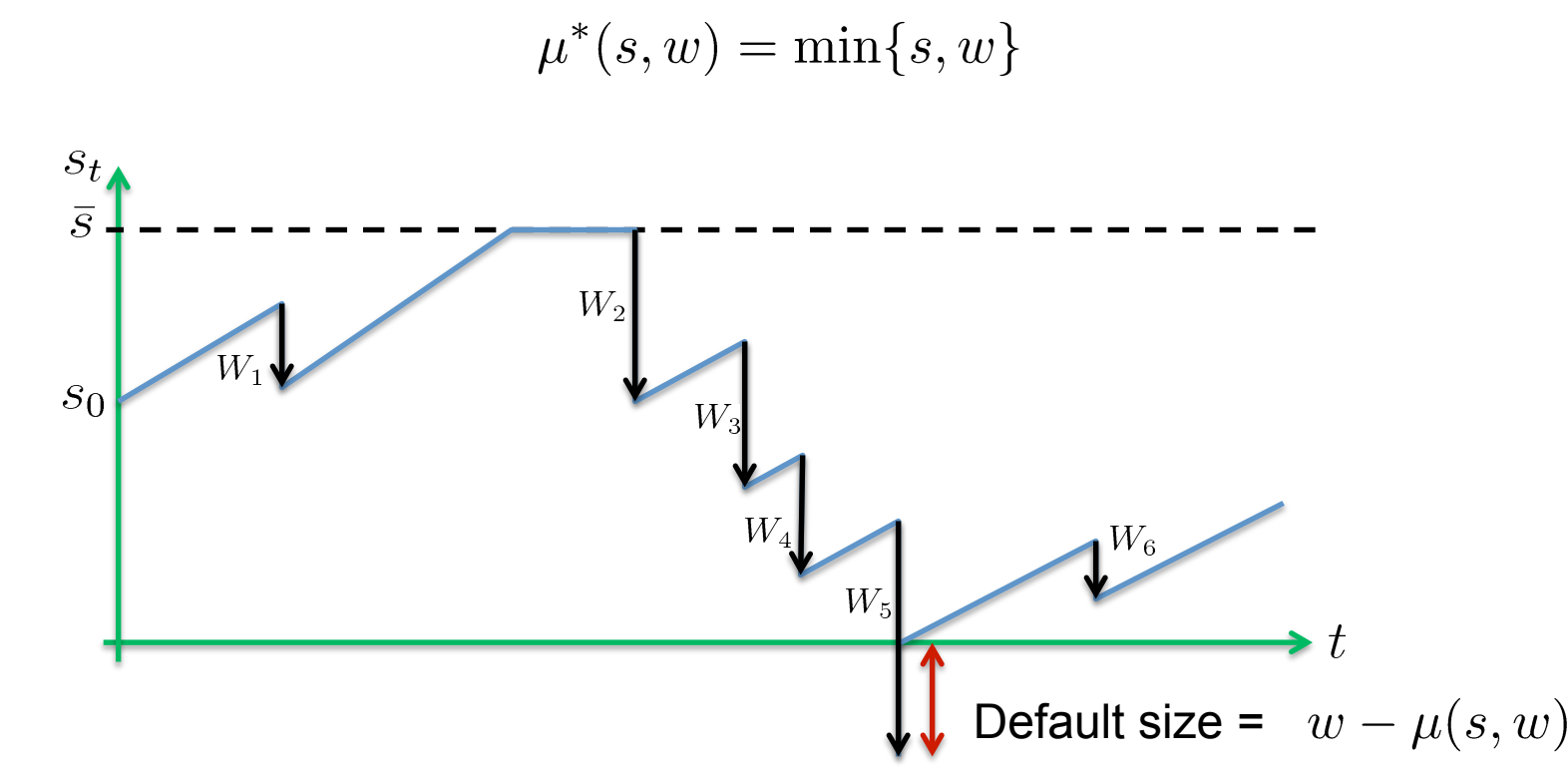


Assumptions:

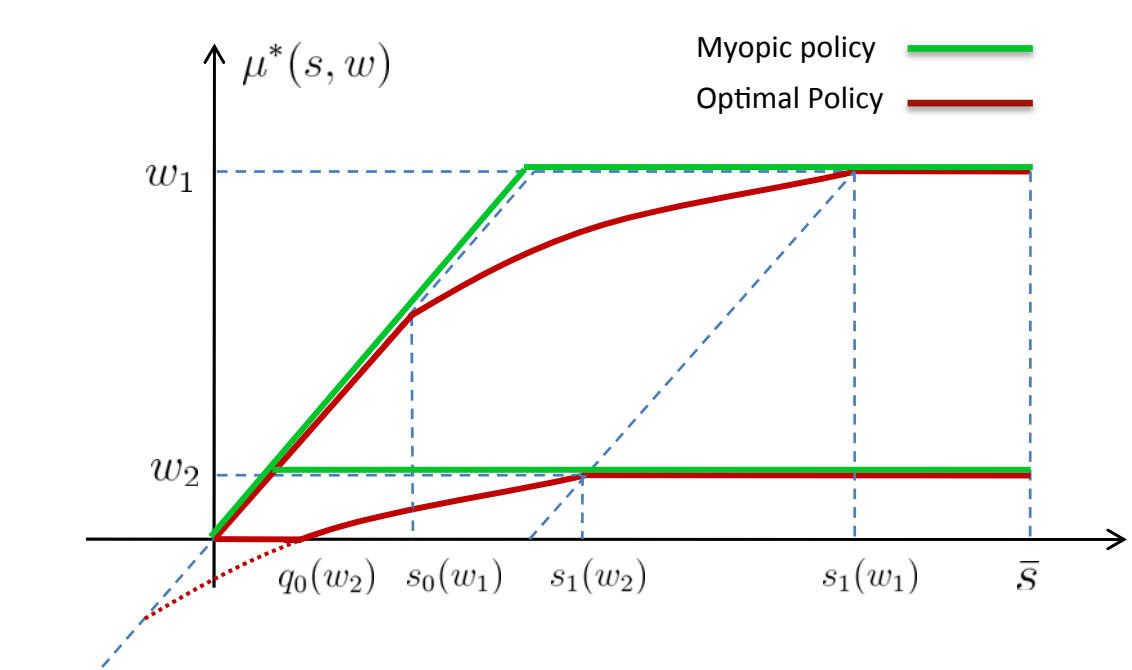
- Perfect prediction, except for supply shocks
- The conventional generator is slow
- Storage is very fast as a supply source but has upward ramp constraint
- The storage has finite capacity
- The deviation penalty imposed is a function of total lost energy

Emerging Risks in Energy Networks: The risk of cooperation

- The coalition's strategy for utilizing storage depends on the cost structure imposed by regulation
- Linear stage cost \rightarrow myopic policy: Cover every shock up to the available level of storage

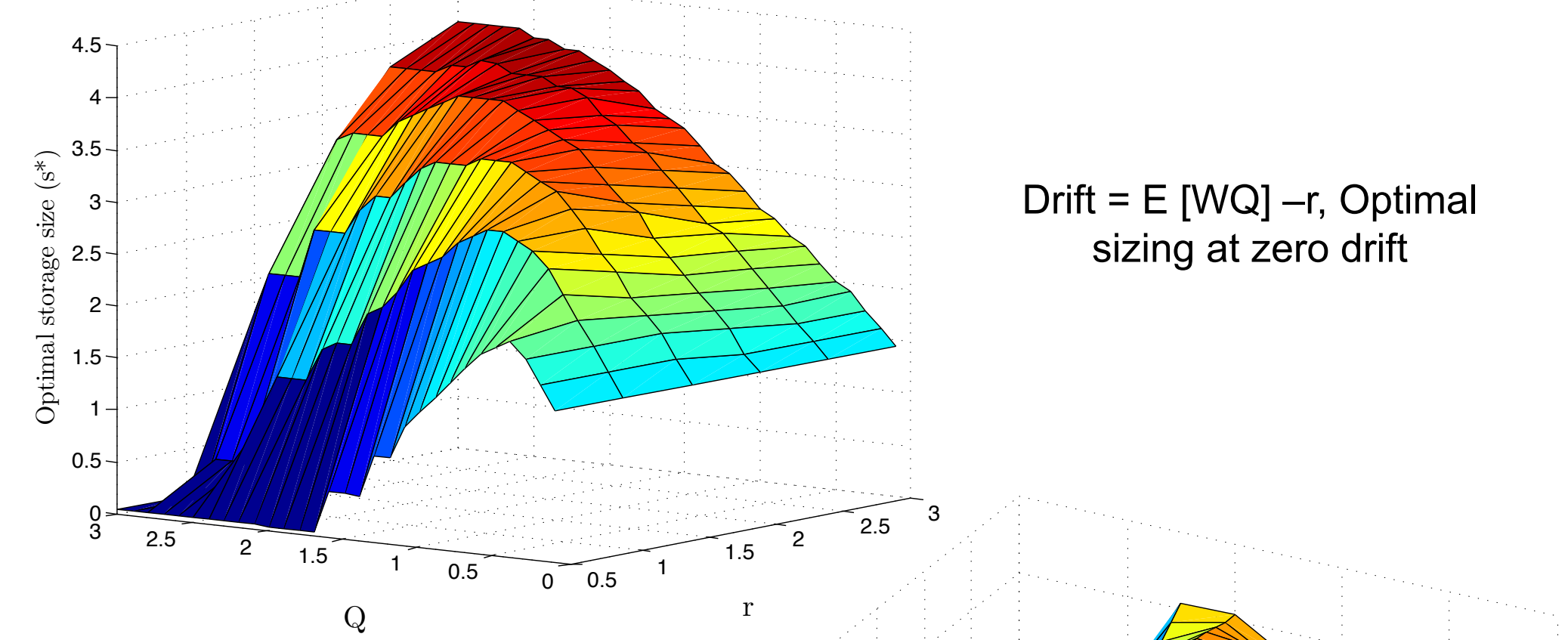
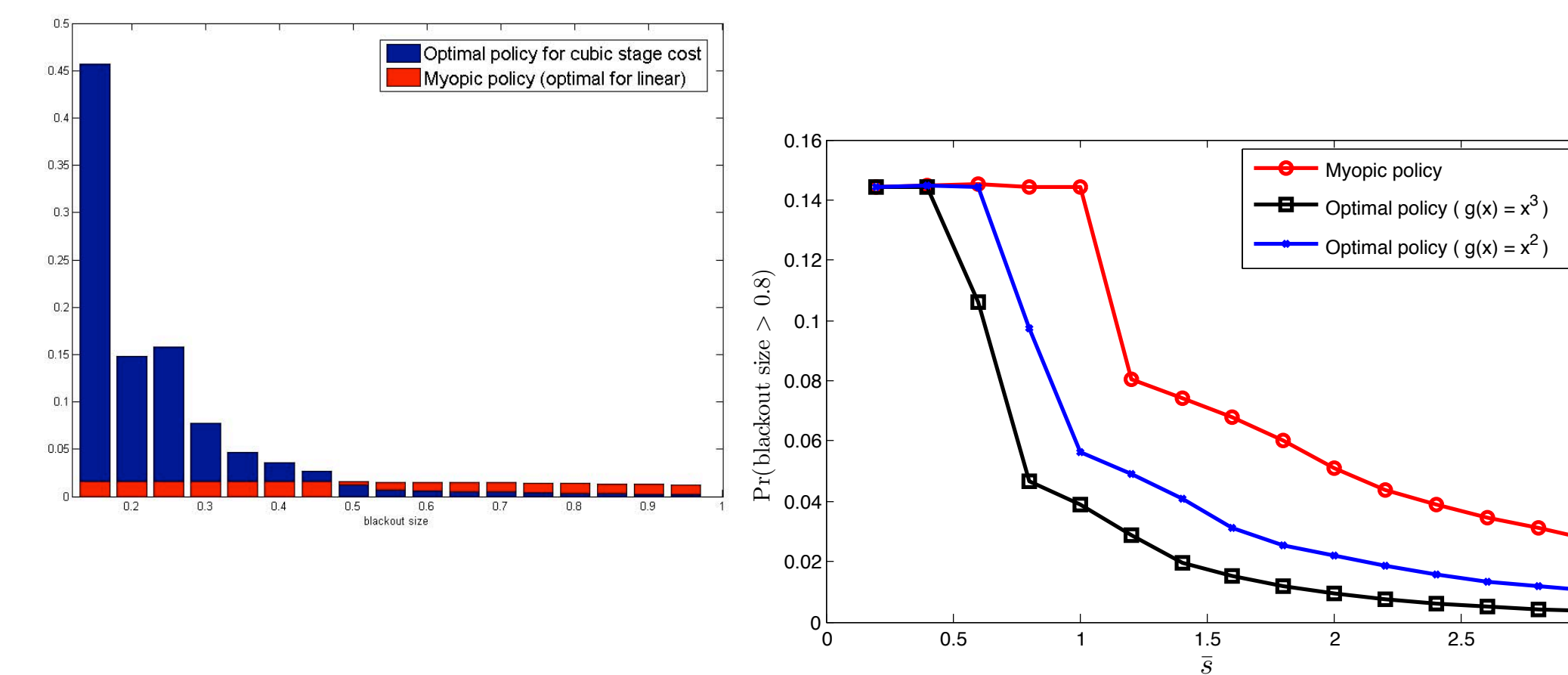


- When the stage cost is strictly convex, the myopic policy is not optimal

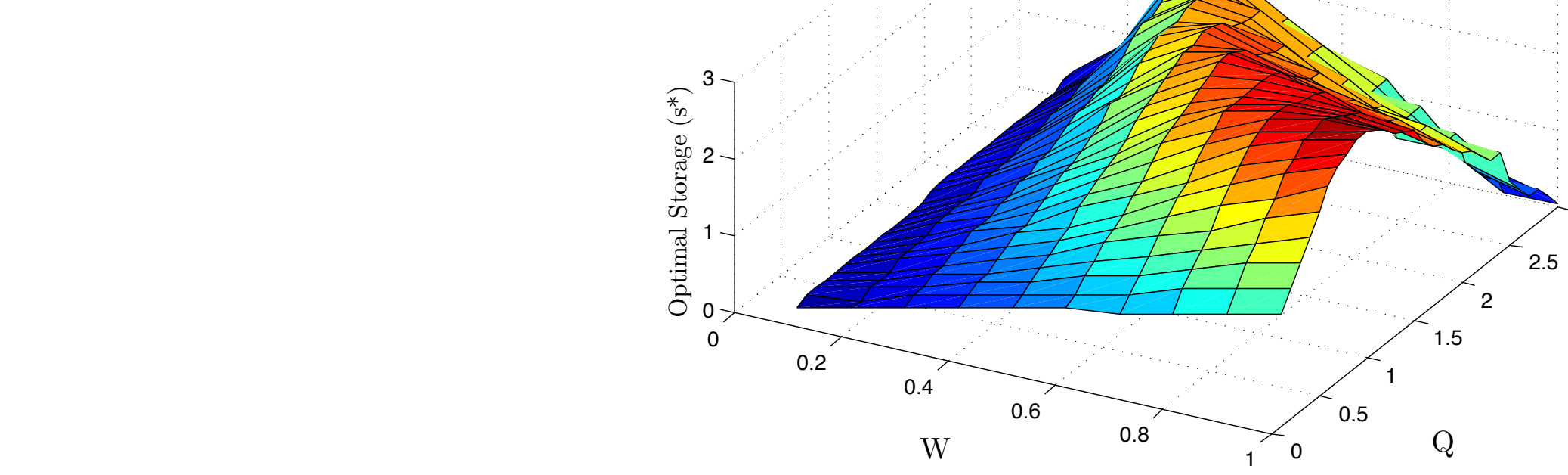


- it is better to incur a small deviation penalty now to avoid a large default in the future

Deviation statistics:



Drift = E[WQ] - r, Optimal sizing at zero drift



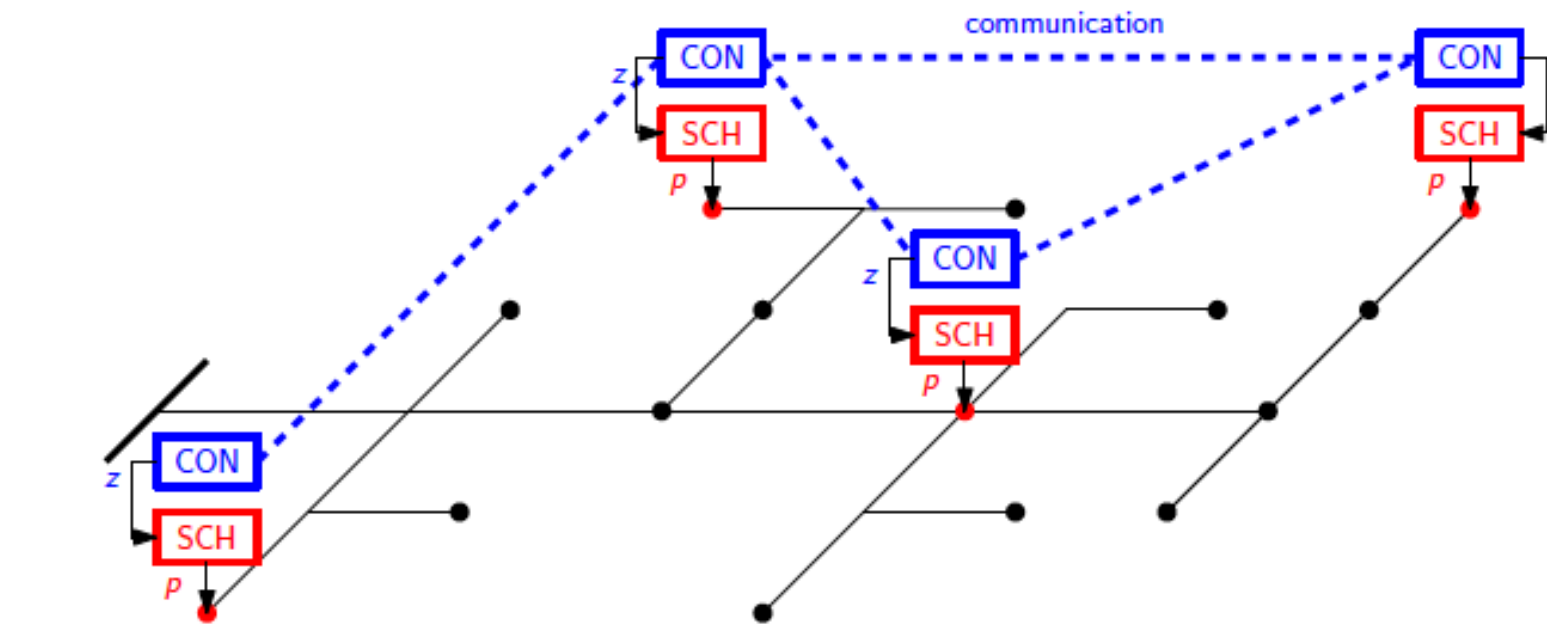
- Attempting to mitigate small defaults increases the probability of incurring large defaults.

- It may be optimal to curtail some of the demand, and allow a small default in the interest of maintaining a higher level of reserve, which may help avoiding a large default in the future.

- Market mechanism determines the outcome

- Optimal sizing depends on the target level of volatility

Architectures for Congestion Control and Scheduling



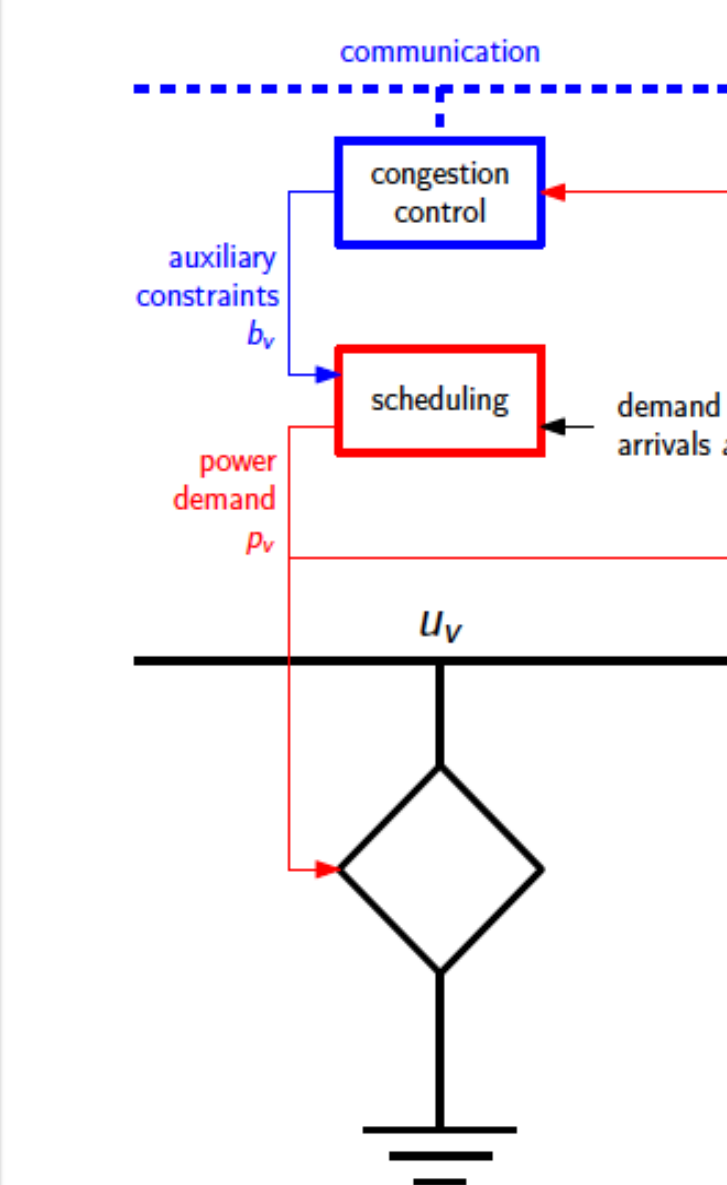
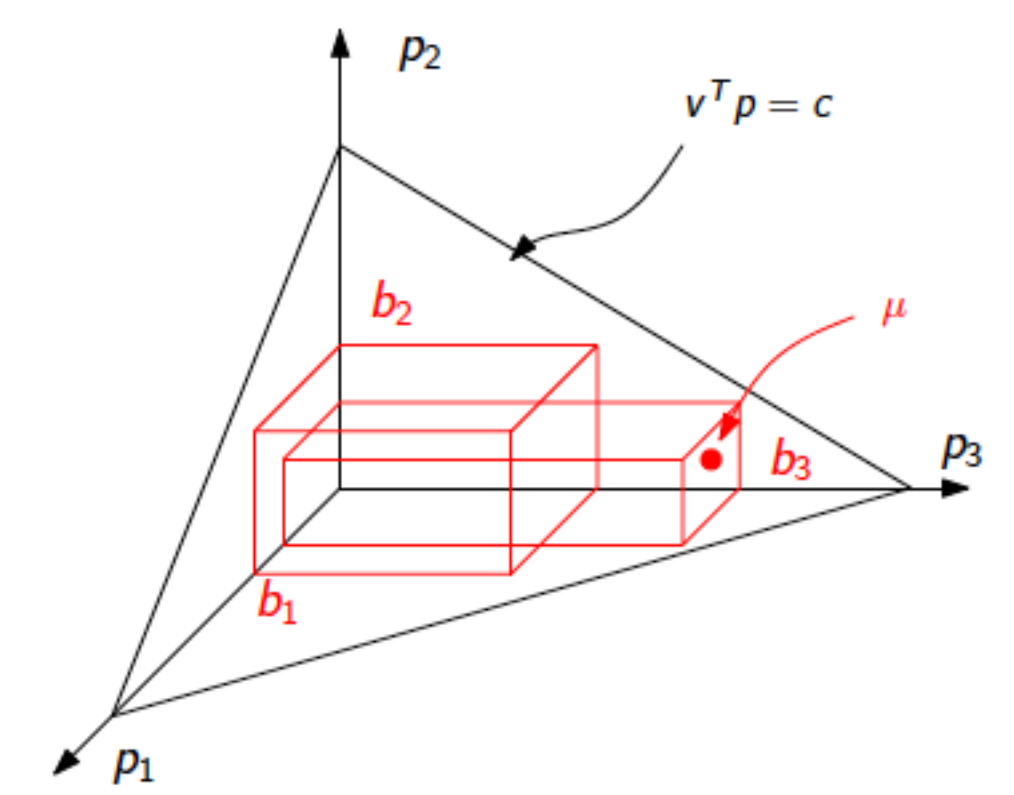
We consider a functional decomposition into two layers:

- a congestion control layer
- a scheduling layer

The congestion layer computes a set of bounds $b_i, i = 1, \dots, N$, so that

$$p \in [0, b_1] \times [0, b_2] \times \dots \times [0, b_N] \Rightarrow v^T p \leq c.$$

i.e., one among the possible box sets that are contained in the feasible set $\{p : v^T p \leq c\}$.



In order to recover the original capacity region, the auxiliary constraints need to be dynamically adapted.

Key feature for scalability/privacy: Congestion control policy is driven by the decision p_i of the scheduling modules.

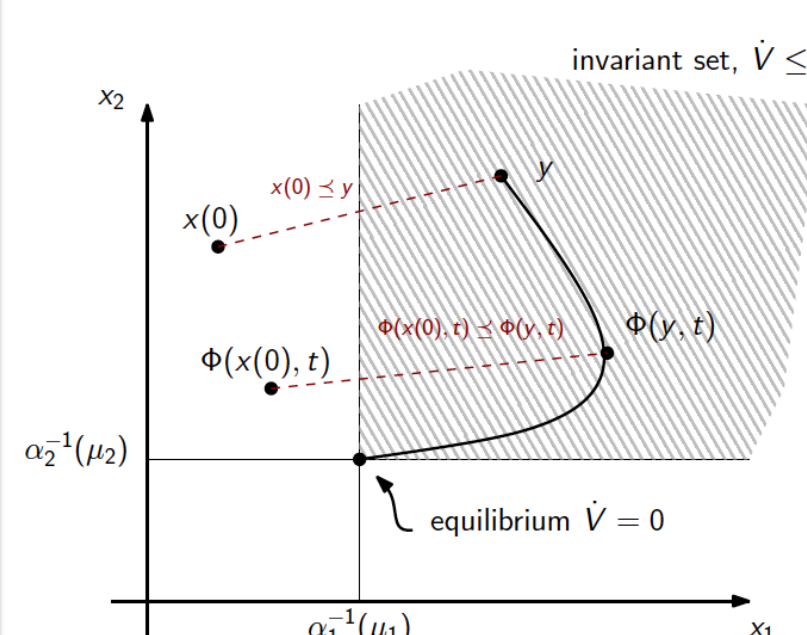
The backloged demands x_i^j , the arrivals a_i^j , and the scheduling policies, are private information.

Under this fluid limit, the total backloged demand $x_i = \sum_{j=1}^{N_i} x_i^j$ at bus i evolves as

$$\dot{x}_i = \mu_i - p_i$$

and the outcome of the scheduling at bus i becomes

$$p_i = \mathcal{K}_i(x_i, b_i) := \min\{\alpha_i(x_i), b_i\}$$



Congestion control law:
 $b = \mathcal{C}(b, p) = \mathcal{C}(b, \mathcal{K}(x, b))$

In the proposed layered architecture

- privacy of the scheduling problem of individual users is preserved
- users deal locally with the complexity of their scalable problem
- grid constraints are disentangled, so that no coordination among the different schedulers is needed
- modular design: scheduling policies and congestion control policies can be designed independently, as long as they satisfy some specifications