

# *Optimization Methods for the Smart Grid*

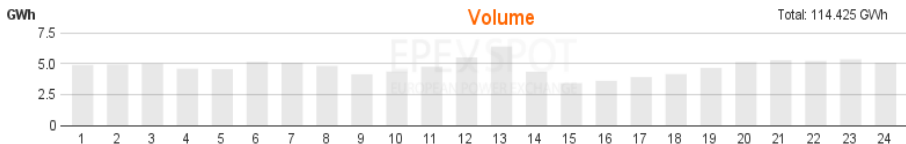
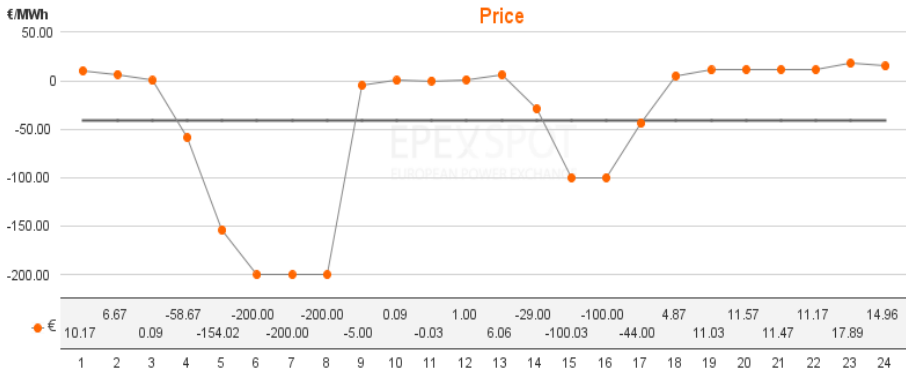
Report commissioned by the  
*Conseil Français de l'Énergie*

French Committee of the World Energy Council

Michel De Lara, Pierre Carpentier, Jean-Philippe Chancelier, Vincent Leclère  
*École des Ponts and ENSTA ParisTech, France*

June 24, 2014

# During the night of 16 June 2013, electricity prices were negative



# Outline of the presentation

- 1 Long Term Industry-Academy Cooperation
- 2 Power Systems Undergo a Deep Remolding
- 3 Energy Actors Express Renewed Demands towards Optimization
- 4 Uncertainty in Decision-Making Can Be Handled in Many Ways
- 5 Displaying Stochastic Optimization Resolution Methods
- 6 Relating Ongoing Works and Practices
- 7 Training and Research Need Be Fostered

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- 1 Long Term Industry-Academy Cooperation
  - École des Ponts ParisTech–Cermics–Optimization and Systems
  - Industry partners of the Optimization and Systems Group

# École des Ponts ParisTech is one of the world's oldest engineering institutes

- The **École nationale des ponts et chaussées** was founded in **1747** and is **one of the world's oldest engineering institutes**
- École des Ponts ParisTech is traditionally considered as belonging to the **5 leading engineering schools in France**
- Young graduates find positions in professional sectors like transport and urban planning, banking, finance, consulting, civil works, industry, environnement, energy. . .
- Faculty and staff
  - 217 employees (including 50 subsidiaries).
  - 165 module leaders, including 68 professors.
  - 1509 students.
- École des Ponts ParisTech is part of **University Paris-Est**

# École des Ponts ParisTech hosts a substantial research activity

- Figures on research
  - Research personnel: 220
  - About 40 École des Ponts PhDs students graduate each year
- 10 research centers
  - \* CEEA (atmospheric environment), joint École des Ponts-EDF R&D
  - \* CERREVE (water, urban and environment studies)
  - \* CERMICS (mathematics and scientific computing)
  - \* CERTIS (information technologies and systems)
  - \* CIRED (international environment and development)
  - \* LATTS (techniques, regional planning and society)
  - \* LVMT (city, mobility, transport)
  - \* UR Navier (mechanics, materials and structures of civil engineering, geotechnic)
  - \* Saint-Venant laboratory (fluid mechanics), joint École des Ponts-EDF R&D
  - \* Paris School of Economic PSE

# The CERMICS is the Centre d'enseignement et de recherche en mathématiques et calcul scientifique

- The scientific activity of CERMICS covers several domains in
  - scientific computing
  - modeling
  - optimization
- 15 senior researchers
  - 15 PhD
  - 12 habilitation à diriger des recherches
- Three missions
  - Teaching and PhD training
  - Scientific publications
  - Contracts
- 550 000 euros of contracts per year with
  - research and development centers of large industrial firms: CEA, CNES, EADS, EDF, Rio Tinto. . .
  - public research contracts

# The Optimization and Systems Group comprises 3 senior researchers, as well as PhD students and external associated researchers

- Three senior researchers
  - J.-P. CHANCELIER
  - M. DE LARA
  - F. MEUNIER
- Associated researcher
  - P. CARPENTIER (ENSTA ParisTech)
- PhD students

# Optimization and Systems Group research specialities

## • Methods

- Stochastic optimal control (discrete-time)
  - Large-scale systems
  - Discretization and numerical methods
  - Probability constraints
- Discrete mathematics; combinatorial optimization
- System control theory, viability and stochastic viability
- Numerical methods for fixed points computation
- Uncertainty and learning in economics

## • Applications

- Optimized management of power systems under uncertainty (production scheduling, power grid operations, risk management)
- Transport modelling and management
- Natural resources management (fisheries, mining, epidemiology)

## • Softwares

- Scicoslab, NSP
- Oadlibsim

# Industrial contracts mostly deal with energy issues, public ones touch on biodiversity management

- Industrial contracts

- Conseil français de l'énergie (CFE)
- SETEC Energy Solutions
- Électricité de France (EDF R&D)
- Thales
- Institut français de l'énergie (IFE)
- Gaz de France (GDF)
- PSA

- Public contracts

- STIC-AmSud (CNRS-INRIA-Affaires étrangères)
- Centre d'étude des tunnels
- CNRS ACI Écologie quantitative
- RTP CNRS

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# We cooperate with industry partners, looking for longlasting research relations through training and capacity building

- As academics, we cooperate with industry partners, looking for longlasting close relations
- We are not consultants working for clients, but focus en capacity building
- Our job consists mainly in
  - training Master and PhD students, working within the company and interacting with us, on subjects designed jointly
  - developing methods, algorithms
  - contributing to computer codes developed within the company
  - training professional engineers in the company

# Électricité de France R & D / Département OSIRIS

- Électricité de France is the French electricity main producer

- 159 000 collaborateurs dans le monde
- 37 millions de clients dans le monde
- 65,2 milliards d'euros de chiffre d'affaire
- 630,4 TWh produits dans le monde

- Électricité de France Research & Development

- 486 millions d'euros de budget
- 2 000 personnes

- Département OSIRIS

Optimisation, simulation, risques et statistiques pour les marchés de l'énergie  
Optimization, simulation, risks and statistics for the energy markets

- 145 salariés (dont 10 doctorants)
- 25 millions d'euros de budget

# The Optimization and Systems Group has trained 9 PhD from 2004 to 2013 + 1 PhD student, the majority related with EDF and energy management

- \* Laetitia ANDRIEU, former PhD student at EDF, now researcher EDF
- \* Kengy BARTY, former PhD student at EDF, now researcher EDF
- \* Daniel CHEMLA, former PhD student
- \* Anes DALLAGI, former PhD student at EDF, now researcher EDF
- \* Laurent GILOTTE, former PhD student with IFE, researcher EDF
- \* Pierre GIRARDEAU, former PhD student at EDF, now with ARTELYS
- \* Eugénie LIORIS, former PhD student
- \* Babacar SECK, former PhD student at EDF
- \* Cyrille STRUGAREK, former PhD student at EDF, now with Munich-Ré
- \* Jean-Christophe ALAIS, former PhD student at EDF, now with ARTELYS
- \* Vincent LECLERE, PhD student (partly at EDF)

# PhD subjects reflect academic issues raised by industrial problems

- *Contributions to the Discretization of Measurability Constraints for Stochastic Optimization Problems,*
- *Optimization under Probability Constraint,*
- *Uncertainty, Inertia and Optimal Decision. Optimal Control Models Applied to Greenhouse Gas Abatement Policies Selection,*
- *Variational Approaches and other Contributions in Stochastic Optimization,*
- *Particular Methods in Stochastic Optimal Control,*
- *From Risk Constraints in Stochastic Optimization Problems to Utility Functions,*
- *Resolution of Large Size Problems in Dynamic Stochastic Optimization and Synthesis of Control Laws,*
- *Evaluation and Optimization of Collective Taxis Systems,*
- *Risk and Optimization for Energies Management,*
- *Risk, Optimization, Large Systems,*

## Recently, contacts have expanded with small companies

- **ARTELYS** is a company specializing in **optimization, decision-making and modeling**. Relying on their high level of **expertise in quantitative methods**, the consultants deliver efficient solutions to complex business problems. They provide services to diversified industries: **Energy & Environment**, Logistics & Transportation, Telecommunications, Finance and Defense.
- Créée en 2011, **SETEC Energy Solutions** est la filiale du groupe SETEC spécialisée dans les domaines de la **production** et de la **maîtrise de l'énergie** en France et à l'étranger. SETEC Energy Solutions apporte à ses clients la maîtrise des principaux process énergétiques pour la mise en œuvre de solutions innovantes depuis les phases initiales de définition d'un projet jusqu'à son exploitation.
- **SUN'R Smart Energy** is a Paris based company with a focus on building smarter solutions for **distributed energy resources** in the context of emerging deregulated energy markets and a solid political will towards the development of both renewables and energy storage. The company is part of a larger group founded in 2007 and is a growing, well-funded early stage business.

# French Energy Council, member of the World Energy Council, contracted the Optimization and Systems group to report on Optimization methods for smart grids

- Formed in 1923, the **World Energy Council** (WEC) is the UN-accredited global energy body, representing the entire energy spectrum, with more than 3000 member organisations located in over 90 countries and drawn from governments, private and state corporations, academia, NGOs and energy-related stakeholders
- WEC informs global, regional and national energy strategies by hosting high-level events, publishing authoritative studies, and working through its extensive member network to facilitate the world's energy policy dialogue
- In 2012, the **French Energy Council** contracted the Optimization and Systems group to produce a report on **Optimization methods for smart grids**

# Summary

The following slides on **Optimization methods for smart grids** express a viewpoint

- from an optimizer perspective
- working in an optimization research group
- in an applied mathematics research center
- in a French engineering institute
- having contributed to train students now working in energy
- having contacts and contracts with energy/environment firms

We now showcase the chapters of the report **Optimization methods for smart grids**

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- 2 Power Systems Undergo a Deep Remolding
  - Snapshots on New Issues for the Energy Generators, Retailers and Regulators
  - Three Key Drivers are Remolding Power Systems
  - Analysis of the Scientific Literature Combining Smart Grids and Optimization
  - What You Will and Will Not Find in the Report

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# Three key drivers are remolding power systems



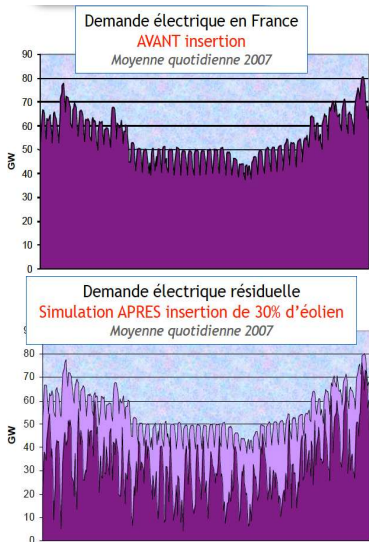
- Environment
- Markets
- Technology



● Multiple levels of integration – interoperability  
● Distributed Generation    ● Renewable Generation    ● Storage    ● Demand Response



# Key driver: environmental concern



The European Union climate and energy package materializes an environmental concern with three 20-20-20 objectives for 2020

- a 20% improvement in the EU's energy efficiency
- a 20% **reduction** in EU **greenhouse gas emissions** from 1990 levels
- raising the **share** of EU energy consumption produced from **renewable resources to 20%**



Successfully **integrating renewable energy sources** has become critical, and made especially difficult because they are **unpredictable and highly variable**, hence triggering the use of local storage

# Key driver: economic deregulation

- A **power system** (generation/transmission/distribution)
  - **less and less vertical** (deregulation of energy markets)
  - hence with **many players with their own goals**
- with some **new players**
  - industry (electric vehicle)
  - regional public authorities (autonomy, efficiency)
- with a **network in horizontal expansion**  
(the Pan European electricity transmission system counts 10,000 buses, 15,000 power lines, 2,500 transformers, 3,000 generators, 5,000 loads)
- with more and more exchanges (trade of commodities)



A **change of paradigm for management**  
from **centralized** to more and more **decentralized**

# Key driver: telecommunication technology



Linky

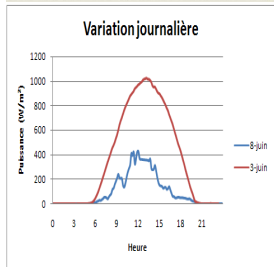
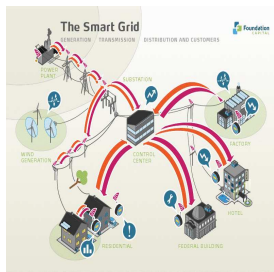
A power system with **more and more technology** due to evolutions in the fields of metering, computing and telecoms

- smart meters
- sensors
- controllers
- grid communication devices. . .



A **huge amount of data** which, one day, will be a new **potential for optimized management**

# The “smart grid”? An infrastructure project with promises to be fulfilled by a “smart power system”



- **Hardware** / infrastructures / smart technologies
  - Renewable energies technologies
  - Smart metering
  - Storage
- **Promises**
  - Quality, tariffs
  - More safety
  - More renewables (environmentally friendly)
- **Software** / smart management  
(energy supply being less flexible, make the demand more flexible)

smart management, smart operation, smart meter management, smart distributed generation, load management, advanced distribution management systems, active demand management, diffuse effacement, distribution management systems, storage management, smart home, demand side management...

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- **Analysis of the Scientific Literature Combining Smart Grids and Optimization**
- What You Will and Will Not Find in the Report



# Optimisation et Smart Grid

## Analyse de la littérature et de la recherche

### Master EDDEE internship report of Axel Ringeval (2012)

- 140 pages report by Axel Ringeval, Master student
- J. K. Kok, M. J. J. Scheepers, and I. G. Kamphuis.  
Intelligence in electricity networks for embedding renewables and distributed generation.  
*Intelligent Systems, Control and Automation: Science and Engineering, Intelligent Infrastructures*, 42:179–209, 2010.
- Roger N. Anderson, Albert Boulanger, Warren B. Powell, and Warren Scott.  
Adaptative stochastic control for the smart grid.  
In *Proceedings of the IEEE*, volume 99, issue 6, pages 1098–1115, June 2011.

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# You will not find “une liste à la Prévert”

- Convolution technique;
- Interval based technique (which includes Robust optimization);
- Moment estimation;
- Dynamic programming (which includes Partially observable Markov decision process, Approximate dynamic programming, Markov decision processes, Stochastic dynamic programming, etc.);
- Stochastic control (which includes Kalman-Bucy filtering, Model predictive control, etc.);
- Stochastic game;
- State estimation;
- Queueing theory;
- Stochastic inventory theory;
- Monte Carlo simulation.

## But we hope the reader will discover a structured exposition

- A motivation for stochastic optimization in the new context of energy, especially with testimonies by industrials
- How to frame stochastic optimization problems
- How to identify adapted resolution methods
- Examples of applications of stochastic optimization to energy problems, especially with testimonies by academics

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  - Challenges for Optimization
    - SETEC Energy Solutions
    - SUN'R Smart Energy
    - Artelys

# The following features of the new energy landscape challenge optimization

- Uncertainty
  - energy supply: wind, solar display intermittency and high variability
  - energy demand: more electricity usages
- Dynamics
  - storage to buffer intermittency (hydro, batteries)
- Spatial extension
  - networks
  - multiplicity of decision centers
  - decentralized information
  - large scale
- Multiplicity of actors and objectives
  - markets
  - game theory

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# SETEC Energy Solutions

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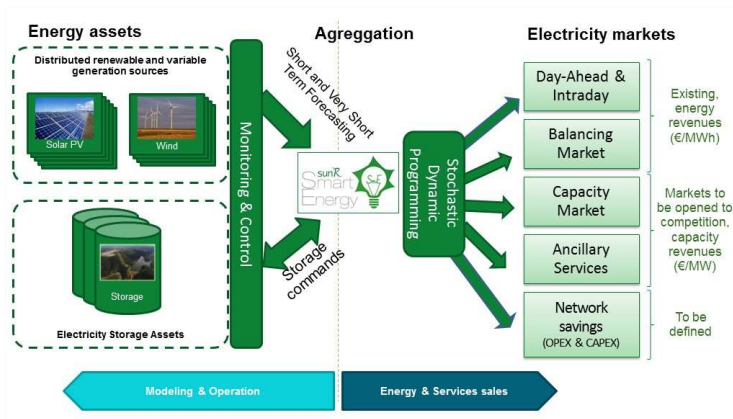
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# SUN'R Smart Energy

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- The company is part of a larger group founded in 2007 and is a growing, well-funded early stage business

# The SunHydrO project aims at building a pumping station to buffer renewable energy intermittency and to optimize storage and release



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- 4 Uncertainty in Decision-Making Can Be Handled in Many Ways
  - Working Out Toy Examples in Energy Management
  - Laying Out Ingredients to Frame Optimization Problems under Uncertainty
  - Framing Stochastic Optimization Problems
  - Extensions to More General Risk Attitudes



# We work out toy examples in energy management

- Stochastic Economic Dispatch
- Stochastic Unit Commitment
- Aggregating a Random Source with Storage
- Managing Multiple Storage
- Managing a Smart Grid Network

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# We line up framing ingredients

- Basic variables
  - Basic variables: time/stage
  - Basic variables: spatial structure
  - Basic variables: uncertainty
  - Basic variables: control
  - Output variables
- Basic data: offline information on uncertainty
- Solution to an optimization problem: online information
  - Solutions as open-loop or plannings
  - Solutions as closed-loop or strategies
  - Solutions “on the fly”
- More on the non-anticipativity constraint
  - There are two ways to express the non-anticipativity constraint
  - What is a solution at time  $t$ ?
  - There are two classical ways to compress information
  - More on the state-based approach
  - More the scenario-based approach
- Constraints
- Criterion

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# Having lined up ingredients, we can now cook stochastic optimization problems

- Framing of a Static Stochastic Optimization Problem
- Multistage Stochastic Optimization Problem
  - Stochastic Programming (SP)
  - Stochastic Optimal Control (SOC)
  - Connection between SP and SOC
- Discussion of complexity

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# We lay out the many ways to capture risk attitudes

- How can we rank random variables?
  - Risk neutral
  - Robust, worst case, pessimistic, maximin, minimax
  - Optimistic, Hurwicz
  - Expected utility
  - Ambiguity, multi-prior
  - Convex risk measures
- Markowitz's mean-variance
- Probability or chance constraints

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# Outline of the presentation

- 5 Displaying Stochastic Optimization Resolution Methods
  - Resolution by Decomposition Methods in Multistage Stochastic Optimization
    - Progressive Hedging (PH)
    - Stochastic Dual Dynamic Programming (SDDP)
    - Approximate Dynamic Programming

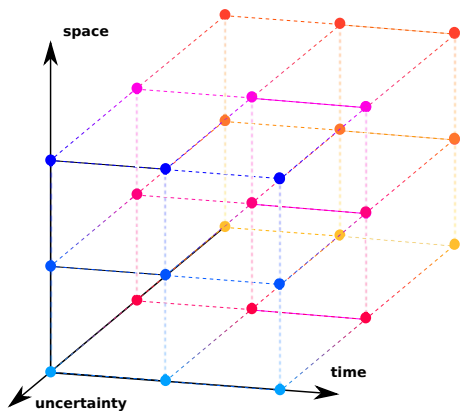
We lay out classical resolution methods depending on how they decompose the original paper: w.r.t.  
time, scenario, space

- Duality and Parallel Decomposition
- Spatial Decomposition
- Scenario Decomposition
  - Progressive Hedging (PH)
  - Stochastic Pontryaguin
- Time Decomposition
  - Dualizing the dynamics constraints
  - Dynamic Programming (DP)
  - Discussing DP and the notion of state
- Summary Table

# Decomposition-coordination: divide and conquer

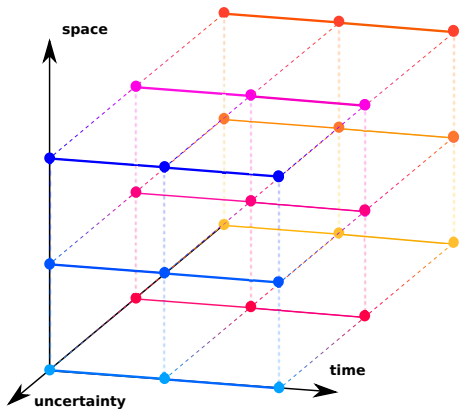
- **Spatial** decomposition
  - multiple players with their local information
  - local / regional / national /supranational
- **Temporal** decomposition
  - A **state** is an **information summary**
  - Time coordination realized through **Dynamic Programming**, by value functions
  - Hard nonanticipativity constraints
- **Scenario** decomposition
  - Along each scenario, **sub-problems** are **deterministic** (powerful algorithms)
  - Scenario coordination realized through **Progressive Hedging**, by updating nonanticipativity multipliers
  - Soft nonanticipativity constraints

# Coupling constraints: an overview



$$\min_{\mathbf{x}, \mathbf{u}} \sum_{s=1}^S \sum_{i=1}^N \sum_{t=0}^T \pi_s L_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_t)$$

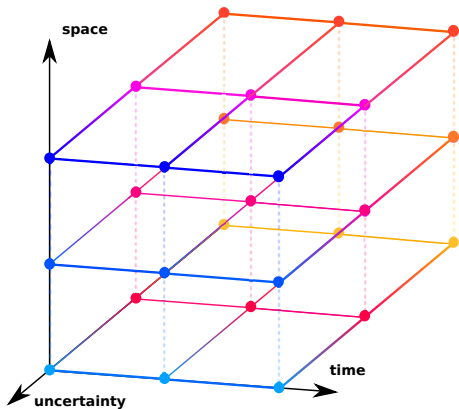
# Coupling constraints: time coupling



$$\min_{\mathbf{x}, \mathbf{u}} \sum_{s=1}^S \sum_{i=1}^N \sum_{t=0}^T \pi_s L_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_t)$$

$$\text{s.t. } \mathbf{x}_{i,t+1} = f_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_t)$$

# Coupling constraints: scenario coupling

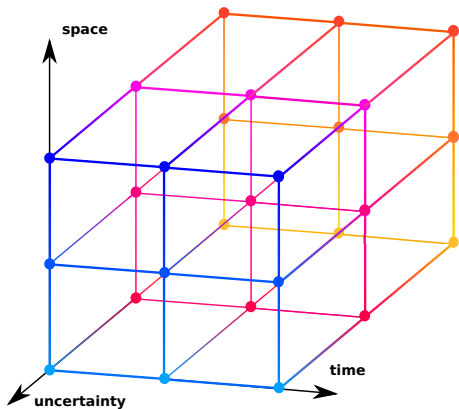


$$\min_{\mathbf{x}, \mathbf{u}} \sum_{s=1}^S \sum_{i=1}^N \sum_{t=0}^T \pi_s L_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_t)$$

$$\text{s.t. } \mathbf{x}_{i,t+1} = f_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_t)$$

$$\sigma(\mathbf{u}_{i,t}) \subset \sigma(\mathbf{w}_0, \dots, \mathbf{w}_t)$$

# Coupling constraints: space coupling



$$\min_{\mathbf{x}, \mathbf{u}} \sum_{s=1}^S \sum_{i=1}^N \sum_{t=0}^T \pi_s L_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_t)$$

$$\text{s.t. } \mathbf{x}_{i,t+1} = f_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_t)$$

$$\sigma(\mathbf{u}_{i,t}) \subset \sigma(\mathbf{w}_0, \dots, \mathbf{w}_t)$$

$$\sum_{i=1}^N \theta_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_t) = 0$$

# Decomposition/coordination methods: an overview

## Main idea

- 1 **decompose** a large scale problem into smaller subproblems we are able to solve by efficient algorithms
- 2 **coordinate** the subproblems for the concatenation of their solutions to form the initial problem solution

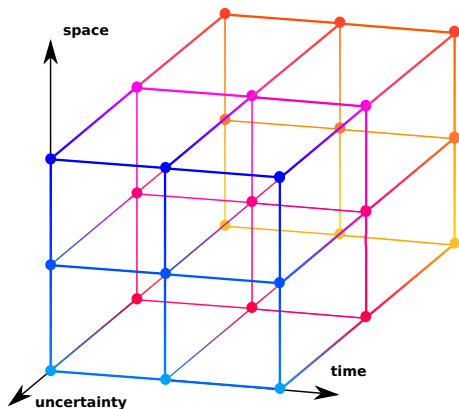
## How to decompose the problem by duality?

- 1 **identify** the coupling dimensions of the problem:  
time, uncertainty, space
- 2 **dualize** the coupling constraints by introducing **multipliers**
- 3 **split** the problem into the resulting subproblems and **coordinate** them by means of the multiplier

In the case of **time decomposition**, we can use the time arrow to **chain** static subproblems by the dynamics equation (without dualizing)



# Decomposition/coordination methods: an overview



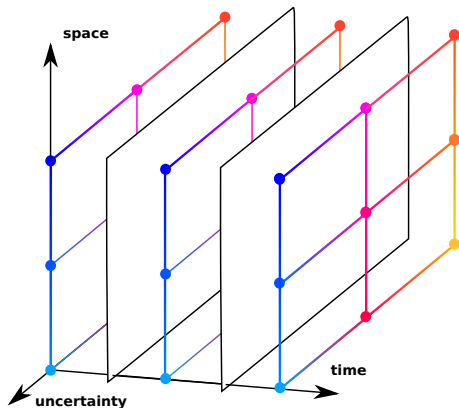
$$\min_{\mathbf{x}, \mathbf{u}} \mathbb{E} \left( \sum_{i=1}^N \sum_{t=0}^T L_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_t) \right)$$

$$\text{s.t. } \mathbf{x}_{i,t+1} = f_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_t)$$

$$\mathbf{u}_{i,t} = \mathbb{E}(\mathbf{u}_{i,t} \mid \mathbf{w}_0, \dots, \mathbf{w}_t)$$

$$\sum_{i=1}^N \theta_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_t) = 0$$

# Decomposition/coordination methods: time coupling



$$\min_{\mathbf{x}, \mathbf{u}} \mathbb{E} \left( \sum_{i=1}^N \sum_{t=0}^T L_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_t) \right)$$

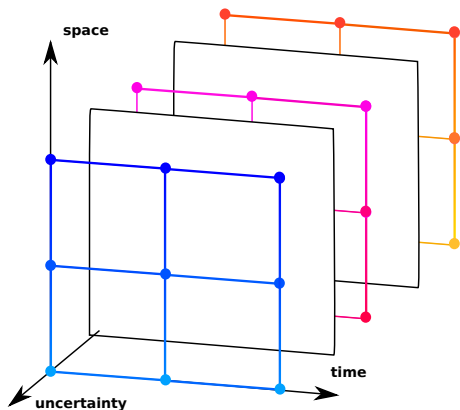
$$\text{s.t. } \mathbf{x}_{i,t+1} = f_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_t)$$

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[Stochastic Pontryagin]  
[Dynamic Programming]

# Decomposition/coordination methods: scenario coupling



$$\min_{\mathbf{x}, \mathbf{u}} \mathbb{E} \left( \sum_{i=1}^N \sum_{t=0}^T L_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_t) \right)$$

$$\text{s.t. } \mathbf{x}_{i,t+1} = f_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_t)$$

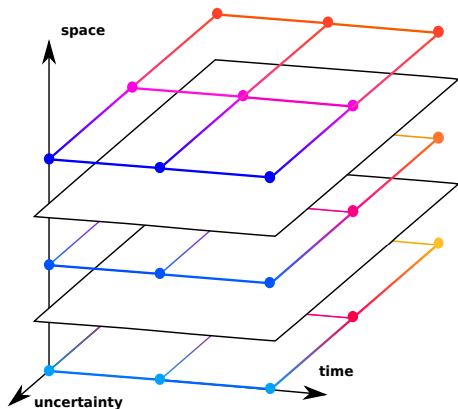
$$\mathbf{u}_{i,t} = \mathbb{E}(\mathbf{u}_{i,t} \mid \mathbf{w}_0, \dots, \mathbf{w}_t)$$

$$\sum_{i=1}^N \theta_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_t) = 0$$

[Progressive Hedging]

Rockafellar, R.T., Wets R. J-B.  
*Scenario and policy aggregation in optimization under uncertainty*,  
Mathematics of Operations Research,  
16, pp. 119-147, 1991

# Decomposition/coordination methods: space coupling



$$\min_{\mathbf{x}, \mathbf{u}} \mathbb{E} \left( \sum_{i=1}^N \sum_{t=0}^T L_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_t) \right)$$

$$\text{s.t. } \mathbf{x}_{i,t+1} = f_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_t)$$

$$\sigma(\mathbf{u}_{i,t}) \subset \sigma(\mathbf{w}_0, \dots, \mathbf{w}_t)$$

$$\sum_{i=1}^N \theta_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_t) = 0$$

[Dual Approximate Dynamic  
Programming (DADP)]

# Outline of the presentation

- 5 Displaying Stochastic Optimization Resolution Methods
  - Resolution by Decomposition Methods in Multistage Stochastic Optimization
  - Progressive Hedging (PH)
  - Stochastic Dual Dynamic Programming (SDDP)
  - Approximate Dynamic Programming

# Progressive Hedging (PH)

Progressive Hedging is a scenario decomposition that

- makes the best of deterministic solvers, by using them in parallel computations, scenario by scenario
- progressively blends the scenario by scenario solutions into a non-anticipative solution

# Outline of the presentation

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# Stochastic Dual Dynamic Programming (SDDP)

Stochastic Dual Dynamic Programming is grounded in

- time decomposition by Dynamic Programming
- mixed with analytical properties of the value functions



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# Outline of the presentation

- 1 Long Term Industry-Academy Cooperation
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- 4 Uncertainty in Decision-Making Can Be Handled in Many Ways
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- 6 Relating Ongoing Works and Practices**
- 7 Training and Research Need Be Fostered

# Outline of the presentation

- 6 Relating Ongoing Works and Practices
  - Stochastic Unit Commitment at ISO Scale – An ARP Ae Project
  - Clearing the Jungle of Stochastic Unit Commitment
  - Risk Averse Approach with the SDDP Algorithm and a Brazilian Case Study
  - Probability Constraints in Dynamical Settings
  - Dual Approximate Dynamic Programming (DADP)

# Roger Wets and David Woodruff, UC Davis

Stochastic Unit Commitment at ISO Scale – An ARP Ae Project

# Outline of the presentation

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- Probability Constraints in Dynamical Settings
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# Warren B. Powell, Princeton

## Clearing the Jungle of Stochastic Unit Commitment

# Outline of the presentation

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# Alexander Shapiro, Georgia Tech, USA

## Risk Averse Approach with the SDDP Algorithm and a Brazilian Case Study



# Outline of the presentation

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- **Probability Constraints in Dynamical Settings**
- Dual Approximate Dynamic Programming (DADP)

# Tourism issues impose constraints upon traditional economic management of a hydro-electric dam



- Maximizing the revenue from turbinated water
- under a tourism constraint of having enough water in July and August

# Outline of the presentation

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- Dual Approximate Dynamic Programming (DADP)

# Dual Approximate Dynamic Programming (DADP)

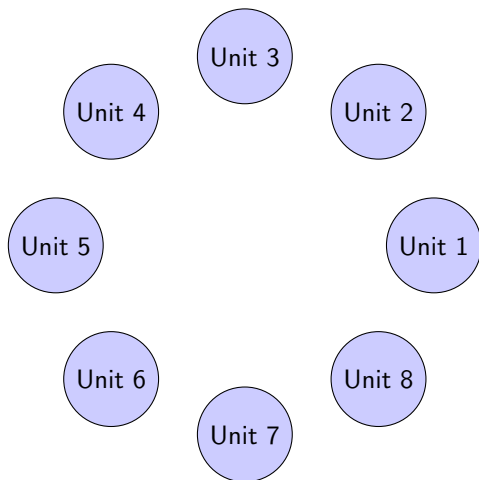
Dual Approximate Dynamic Programming is grounded in

- spatial decomposition
- mixed with time decomposition by Dynamic Programming

# We have a nice decomposed problem but...

Flower structure

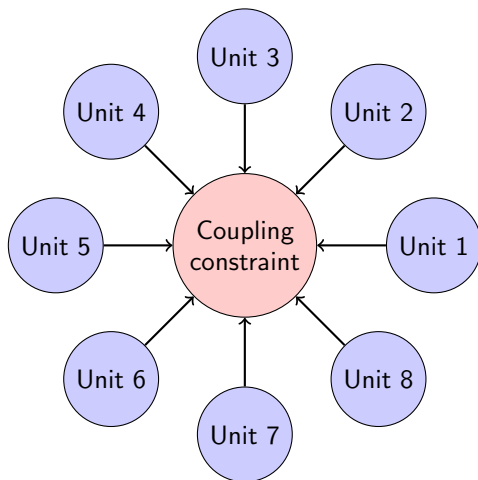
We are almost in the case where units could be **driven independently one from another**



# We have a nice decomposed problem but...

Flower structure

Unfortunately...



The associated optimization problem can be written as

$$\underbrace{\min_{(u_1, \dots, u_N)} \sum_{i=1}^N J_i(u_i)}_{\text{costs minimization}} \quad \text{under} \quad \underbrace{\sum_{i=1}^N \Theta_i(u_i) = D}_{\text{supply} = \text{demand}}$$

where

- $u_i$  is the **decision** of each unit  $i$
- $J_i(u_i)$  is the **cost** of making decision  $u_i$  for unit  $i$
- $\Theta_i(u_i)$  is the **production** induced by making decision  $u_i$  for unit  $i$

Under appropriate duality assumptions,  
the associated optimization problem  
can be written without constraints

- For a proper Lagrange multiplier  $\lambda$

$$\min_{(u_1, \dots, u_N)} \sum_{i=1}^N J_i(u_i) + \lambda \underbrace{\left( \sum_{i=1}^N \Theta_i(u_i) - D \right)}_{\text{constraint}}$$

- We distribute the coupling constraint to each unit  $i$

$$\min_{(u_1, \dots, u_N)} \left( \sum_{i=1}^N J_i(u_i) + \lambda \Theta_i(u_i) \right) - \lambda D$$

- The problems splits into  $N$  optimization problems

$$\min_{u_i} (J_i(u_i) + \lambda \Theta_i(u_i)), \quad \forall i = 1, \dots, N$$



# Proper prices allow decentralization of the optimum

$$\min_{(u_1, \dots, u_N)} \sum_{i=1}^N J_i(u_i) \quad \text{under} \quad \sum_{i=1}^N \Theta_i(u_i) = D$$

The simplest **decomposition/coordination scheme** consists in

- buying the production of each unit at a **price**  $\lambda^{(k)}$  at iteration  $k$
- and letting each unit minimize its modified costs

$$\min_{u_i} J_i(u_i) + \underbrace{\lambda^{(k)}}_{\text{price}} \Theta_i(u_i)$$

- then, updating the price depending on the coupling constraint

$$\lambda^{(k+1)} = \lambda^{(k)} + \rho \left( \sum_{i=1}^N \Theta_i(u_i) - D \right)$$

(like in the “tâtonnement de Walras” in Economics)

# What are the stakes if we extend spatial coupling constraint decomposition to the dynamical and stochastic setting?

- Allowing for time and uncertainties, we classically consider the criterion

$$\min_{\{\mathbf{u}_{i,t}\}_{i \in \{1,N\}}^{t \in \{0,T-1\}}} \mathbb{E} \left( \sum_{i=1}^N \left( \sum_{t=0}^{T-1} L_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_{i,t}) + K_i(\mathbf{x}_{i,T}) \right) \right)$$

- under the constraints

$$\sum_{i=1}^N \Theta_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_{i,t}) - \mathbf{d}_t = 0, \quad t \in \llbracket 0, T-1 \rrbracket$$

$$\mathbf{x}_{i,t+1} = f_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_{i,t}), \quad i \in \llbracket 1, N \rrbracket, t \in \llbracket 0, T-1 \rrbracket$$

# Looking after decentralizing prices models

- Going on with the previous scheme, each unit  $i$  solves

$$\min_{\mathbf{u}_{i,0}, \dots, \mathbf{u}_{i,T-1}} \mathbb{E} \left( \sum_{t=0}^{T-1} \left( L_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_{i,t}) + \underbrace{\lambda_{i,t}^{(k)}}_{\text{price}} \Theta_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_{i,t}) \right) + K_i(\mathbf{x}_{i,T}) \right)$$

$$\mathbf{x}_{i,t+1} = f_{i,t}(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}, \mathbf{w}_{i,t}), \quad t \in \llbracket 0, T-1 \rrbracket$$

- The optimal controls  $\mathbf{u}_{i,t}^*$  of this problem depend
  - upon the local state  $\mathbf{x}_{i,t}$
  - and ... upon **all past prices**  $(\lambda_{i,0}^{(k)}, \dots, \lambda_{i,t}^{(k)})$  !
- **Research axis:** find an approximate **dynamical model for the price process**, driven by proper information; for instance, replace  $\lambda_{i,t}^{(k)}$  by  $\mathbb{E} \left( \lambda_{i,t}^{(k)} \mid \mathbf{y}_t \right)$ , where the information variable  $\mathbf{y}_t$  is a Markov process (short time memory) → “demand response”, “adaptive tariffs”,

# Dual Approximate Dynamic Programming

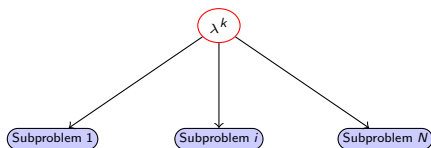
Samples/scenarios of  
dual variable  
at iteration  $k$

$$\lambda^k$$

# Dual Approximate Dynamic Programming

Samples/scenarios of  
dual variable  
at iteration  $k$

We solve subproblems  
using  $\mathbb{E}(\lambda^k | y)$   
by Dynamic Programming

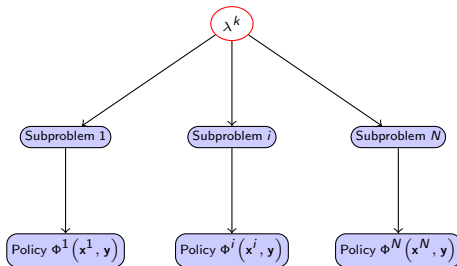


# Dual Approximate Dynamic Programming

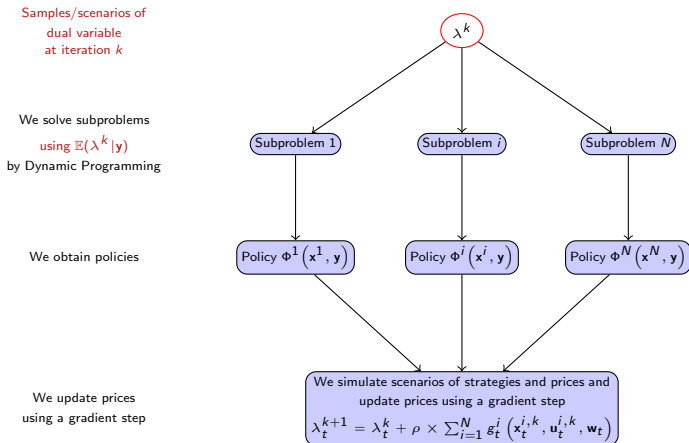
Samples/scenarios of  
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We solve subproblems  
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We obtain policies



# Dual Approximate Dynamic Programming



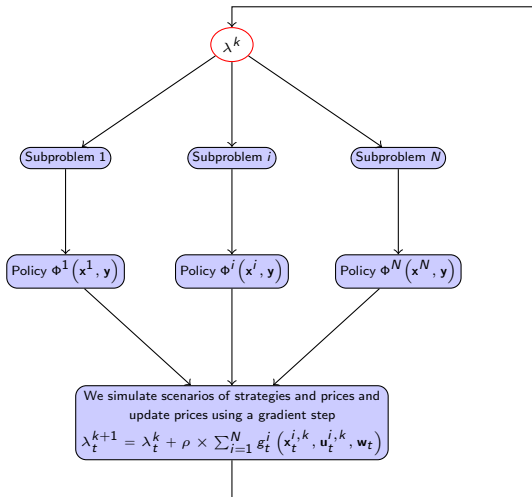
# Dual Approximate Dynamic Programming

At iteration  $k + 1$

We solve subproblems  
using  $\mathbb{E}(\lambda^k | y)$   
by Dynamic Programming

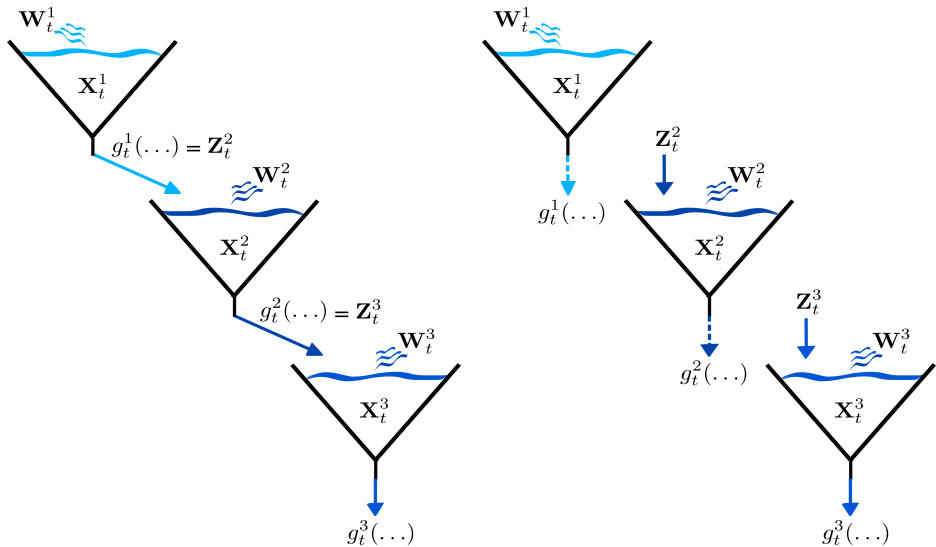
We obtain policies

We update prices  
using a gradient step





# Extension to interconnected dams



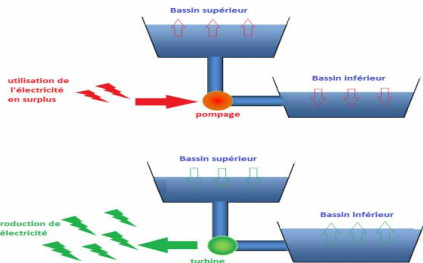
# Contribution to dynamic tariffs

- Spatial decomposition of a dynamic stochastic optimization problem
- Lagrange multipliers attached to spatial coupling constraints are stochastic processes (prices)
- By projecting these prices, one expects to identify approximate dynamic models
- Such prices dynamic models are interpreted as dynamic tariffs

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# Trends are favorable to statistics and optimization



- More telecom technology  
 ⇨ more data
- More data, more unpredictability  
 ⇨ more statistics
- More unpredictability  
 ⇨ more storage  
 ⇨ more dynamic optimization
- More unpredictability  
 ⇨ more stochastic dynamic optimization

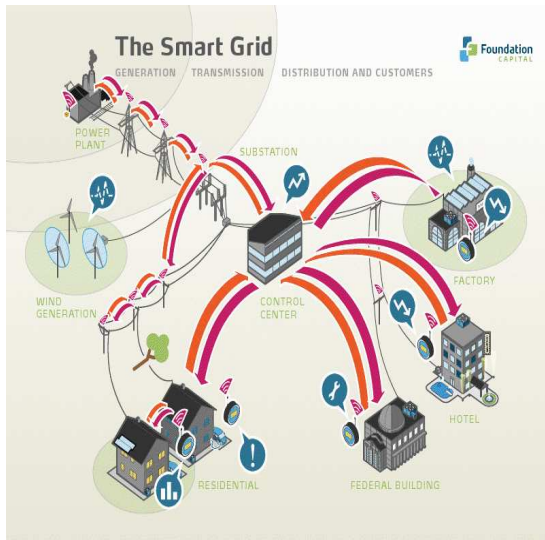
# A context of increasing complexity



● Multiple levels of integration – interoperability  
● Distributed Generation    ● Renewable Generation    ● Storage    ● Demand Response

- Multiple energy resources: photovoltaic, solar heating, heatpumps, wind, hydraulic power, combined heat and power
- Spatially distributed energy resources (onshore and offshore windpower, solarfarms), producers, consumers
- Strongly variable production: wind, solar
- Intermittent demand: electrical vehicles
- Two-ways flows in the electrical network
- Environmental and risk constraints (CO<sub>2</sub>, nuclear risk, land use)

# Challenges ahead for stochastic optimization



- large scale stochastic optimization
- various risk constraints
- decentralized and private information
- game theory, stochastic equilibrium, market design...