Stochastic MPC for optimal real-time power dispatch and bidding on the energy markets under uncertainty

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DYnamical **S**ystems, **C**ontrol and **O**ptimization

HYCON2
TAMING HETEROGENEITY AND COMPLEXITY

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Motivation

Present arrangements in power systems:

- have many inefficiencies
- are not suited to cope with future developments
- didn't have sufficient incentives for "proper" behavior

Neither reliable, nor economic, nor self-regulating*

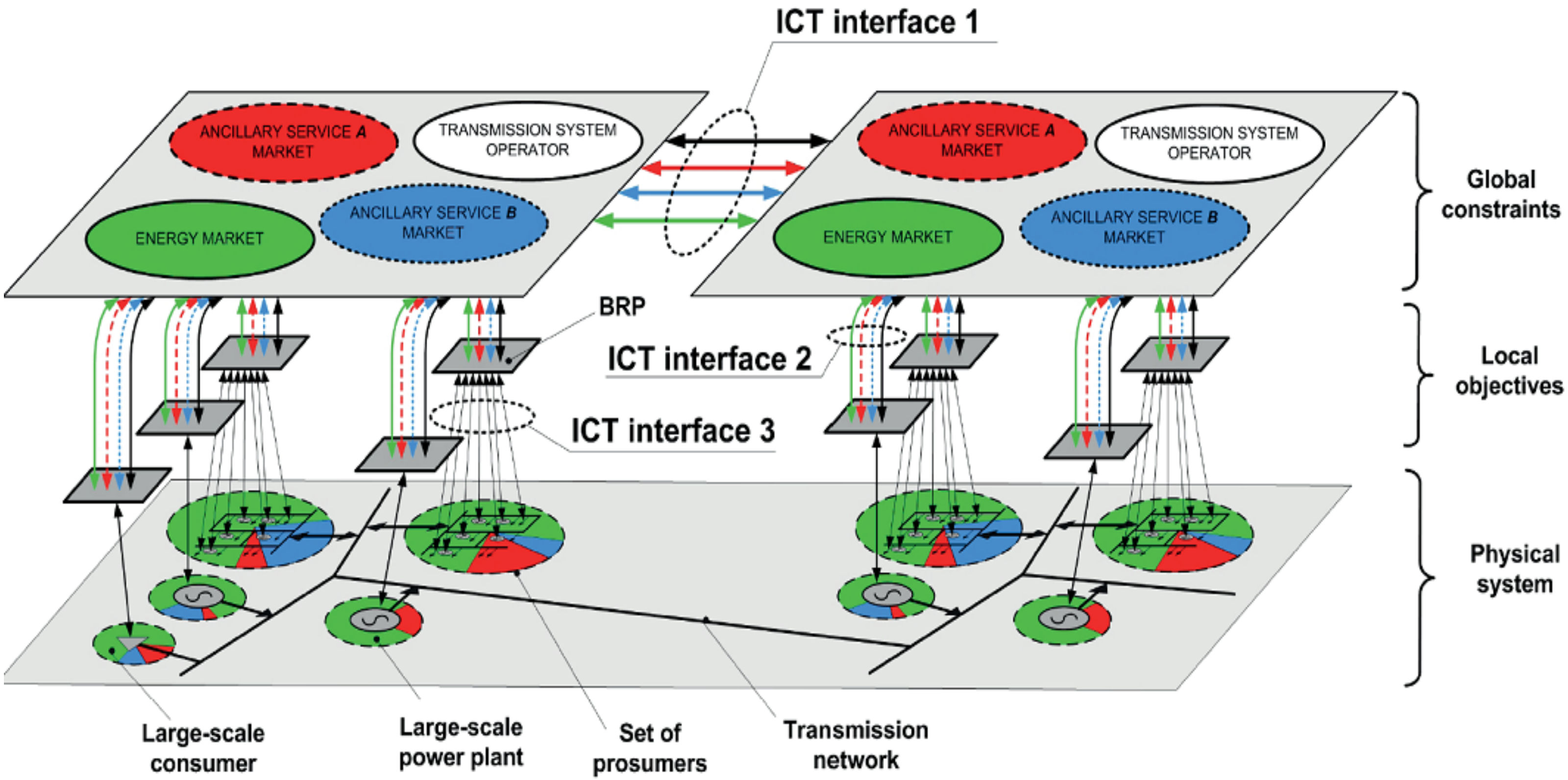
PRICE-BASED CONTROL OF ELECTRICAL POWER SYSTEMS

eprice

Self-regulating* approach for a reliable and economic power system that can cope with future challenges

* Self-regulating: if all parties try to achieve their own goals, the overall objectives are achieved and global constraints are satisfied (incentive-based control)

Outline



- **Stochastic MPC algorithms** for solving complex decision problems arising in management of Balance Responsible Partners (BRP).
  - **Real-time** power dispatch
  - **Bidding** on day-ahead (DA) and Ancillary Services (AS) markets

Real-time control of BRPs

- **Balance Responsible Parties (BRPs)** participate to the various energy markets and trade electricity to satisfy their loads and make profits

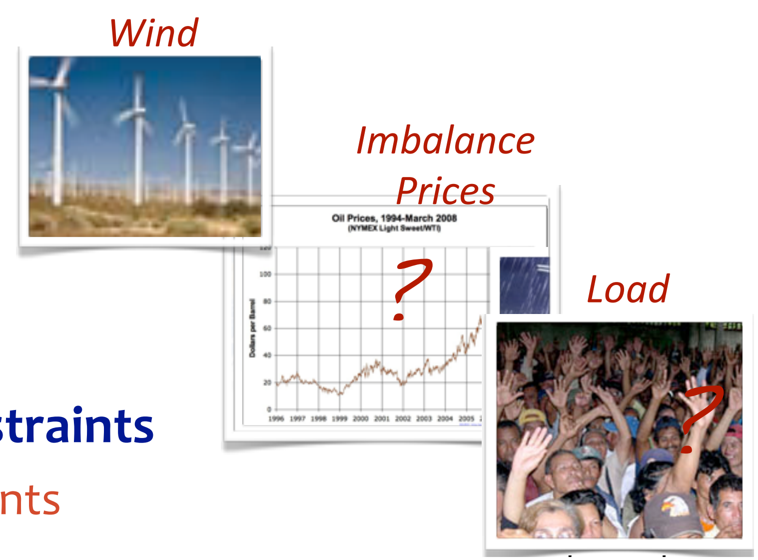
- Optimal control of BRPs is a challenging task, as in real-time a BRP must:

✓ **fulfill its E-Program,** plus perturbations induced by **uncertainties**
  - intermittent generation from renewable sources
  - time-varying internal loads

✓ **react to signals arriving from the TSO**
  - frequency deviations, Ancillary Services bids activated by the TSO

✓ **minimize generation and imbalance costs**
  - time-varying, stochastic imbalance prices

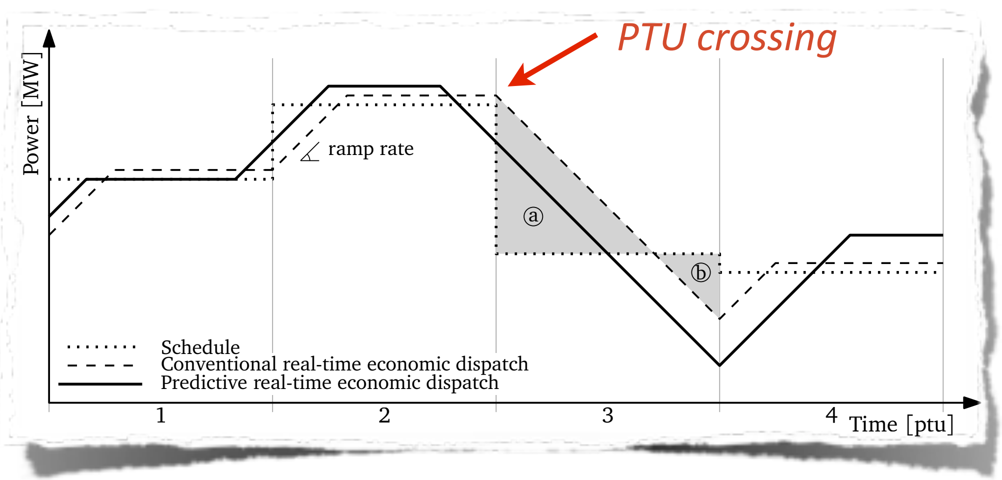
✓ **consider plants dynamics and respect constraints**
  - bounds on power output, ramp-rate constraints



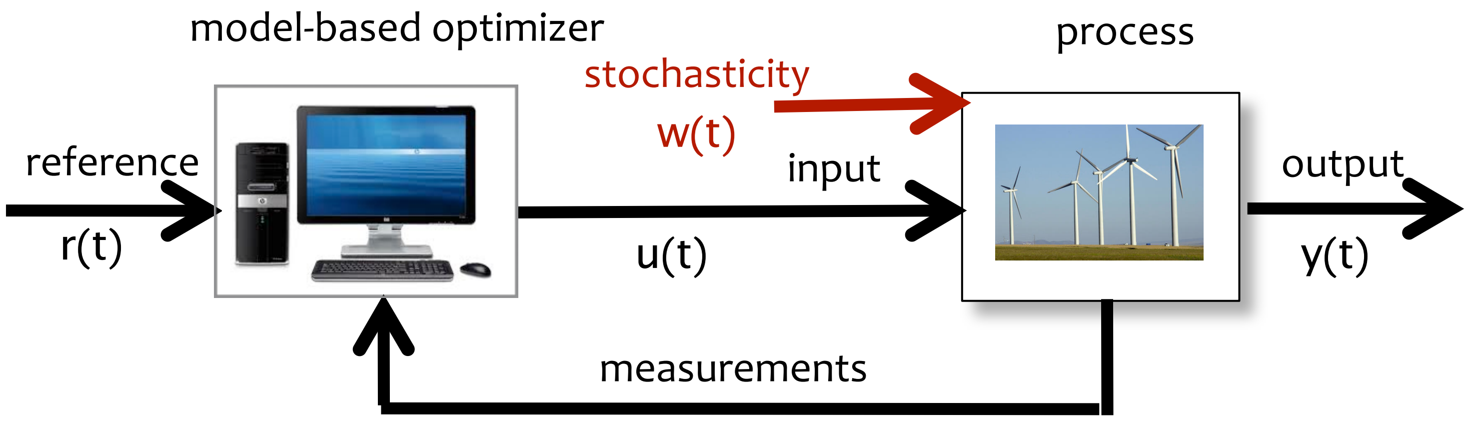
Real-time control of BRPs

- **Current practice:**
- ✓ **Day-Ahead:** generators schedule and power setpoints computation
  - Unit commitment: power setpoints are based on rough uncertainty estimates
- ✓ **In real-time:** track setpoints
  - response to momentary input values

- **Cons:**
  - difficulty in handling ramp-rate constraints
  - difficulty in handling PTU coupling (no integral action)
  - rough economic optimization

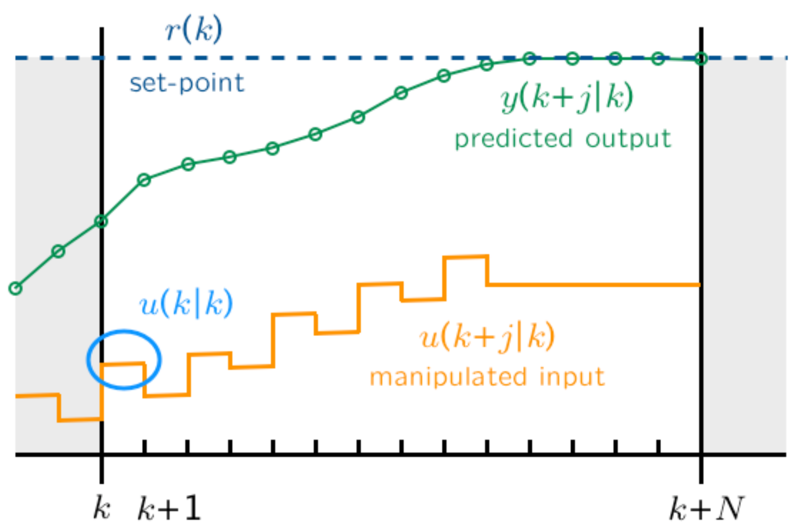


Stochastic Model Predictive Control

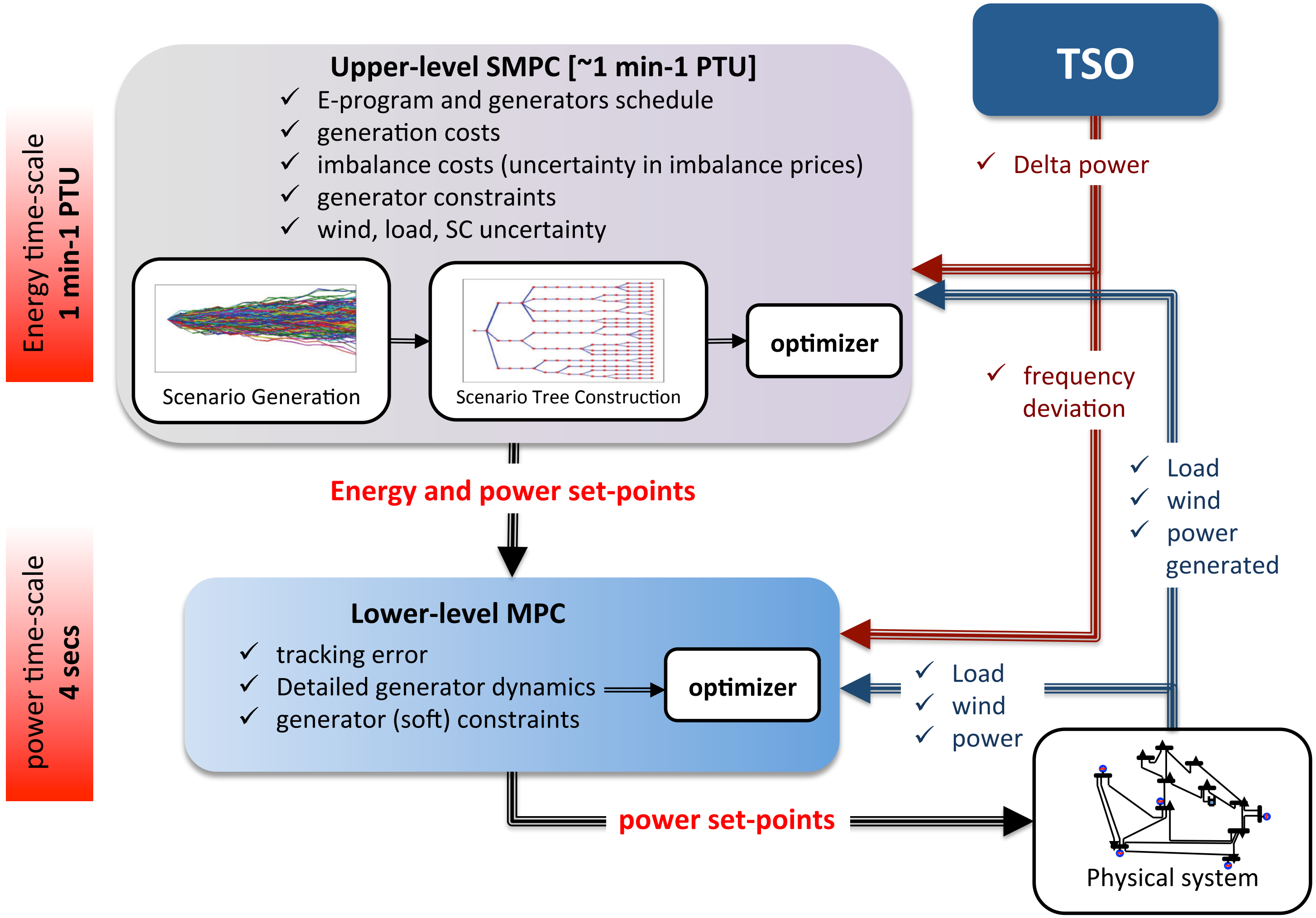


Use a ***stochastic*** *dynamical* ***model*** *of the process to* ***predict*** *its possible future evolutions and choose the "best"* ***control*** *action*

- **MPC strategy:**
  - At every time step k, solve a stochastic optimal control problem over a time horizon of N steps
  - Apply the **first control move** $u(k|k)$
  - At time k+1, get **new measurements** and repeat the optimization



HSMPC for BRP-RT Two-time-scale Hierarchical Stochastic MPC controller



- **increased profits** due to real-time calculation of economically optimal setpoints
- improved **E-Program tracking** due to real-time integral action
- effective **handling of ramp-rate constraints,** allowing smooth PTU transitions

BRP model on the energy time scale

- **Generation costs** for each of the n_p generators are modeled as convex quadratic functions of the power *p*

$$\ell_i^p(p^i) = a_i(p^i)^2 + b_i\bar{p}^i + c_i,\;\; a_i \geqslant 0,\;\; i \in \{1,\ldots,n_p\}$$

- **Energy Imbalance** is defined as the difference between the energy produced by the BRP and the energy requested by the TSO at PTU n

$$\Delta e(n) = e(n) - e^{\text{final}}(n)$$

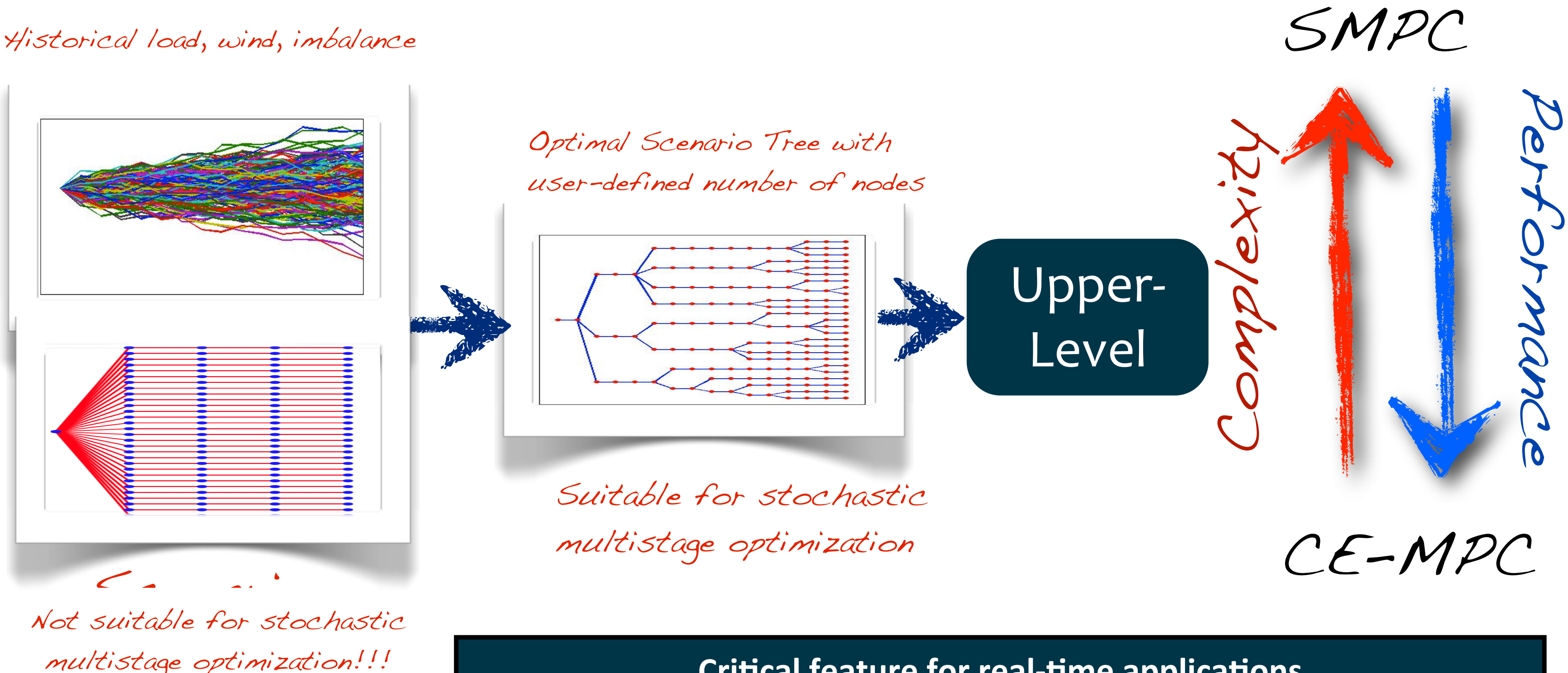
- If $\Delta(e(n)) > 0$ (*surplus*), TSO buys this energy from BRP at price λ_{IM}^{+}
- If $\Delta(e(n)) < 0$ (*shortfall*), BRP buys this energy from TSO at price λ_{IM}^{-}
- The imbalance prices can be negative, but usually $\lambda_{\text{IM}}^{-} \geq \lambda_{IM}^{+}$
- Hence, BRP **imbalance costs** are computed as

$$\ell_{\text{I}M}(\Delta e) = \tfrac{1}{2}(\lambda_{\text{I}M}^{-} - \lambda_{\text{I}M}^{+})|\Delta e| - \tfrac{1}{2}(\lambda_{\text{I}M}^{-} + \lambda_{\text{I}M}^{+})\Delta e$$

Modeling Uncertainty

☑ **On-line**, using historical data, build an optimal scenario tree with prespecified complexity.

☑ **Data-driven approach**. Learning from the past using historical data.



Critical feature for real-time applications

We can control the trade-off between complexity and performance!

BRP model on the power-time scale

- Detailed model of **generator dynamics** is considered in the lower level
- This model consists of two parts:
  - **fast model** for primary reserve action, (low and a high pass filter in series):

$$p^i_{\text{fast}}(s) = \frac{\tau^i_{\text{H}} s}{\tau^i_{\text{H}} s+1} \frac{K^i}{\tau^i_{\text{L}} s+1} p^i_{\text{prim}}(s)$$

  - **slow model** for the secondary reserve activation,

$$p^i_{\text{slow}}(s) = \frac{e^{-T^i_{\text{delay}} s}}{\tau^i s+1}(u^i(s) + p^i_{\text{prim}}(s))$$

  - the generator power output is given by their sum, $p^i(s) = p^i_{\text{fast}}(s) + p^i_{\text{slow}}(s)$

- This can be expressed as a discrete-time linear system with 4 states and 1 input for each generator i, $i \in \{1, \ldots, n_p\}$

$$\begin{aligned} x^i(t+1) &= A^i x^i(t) + B^i u^i(t) + E^i \delta f(t) \\ y^i(t) &= C^i x^i(t) \end{aligned}$$

- The **overall BRP model** is given by aggregating all n_p generator models

Simulation results

- Consider a BRP with **10 controllable plants** and **1 wind farm**

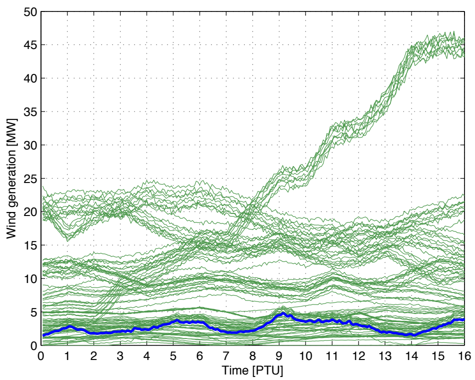
Plant ID	Fuel type	Max efficiency	Min power	Max power	Max ramp rate
#1	Gas	38%	25 MW	53 MW	3%/min
#2	Gas	42%	25 MW	64 MW	3%/min
#3	Gas	47%	133 MW	332 MW	3%/min
#4	Gas	47%	133 MW	332 MW	3%/min
#5	Gas	48%	140 MW	350 MW	3%/min
#6	Coal	39%	240 MW	602 MW	1.5%/min
#7	Gas	54%	670 MW	1675 MW	3%/min
#8	Gas	59%	280 MW	440 MW	5%/min
#9	Gas	59%	280 MW	440 MW	5%/min
#10	Coal/biomass	39%	400 MW	800 MW	1.5%/min

- Comparison of HSMPC against
  - **SetPoint Tracking (SPT)** [current practice]: static computation of power setpoints for each plant of the BRP, done on the day-ahead to track the E-Program
  - **DMPC**: Deterministic MPC formulation where no stochastic models of the uncertainty are exploited
- **Simulation interval:** 16 PTUs (4 hours)

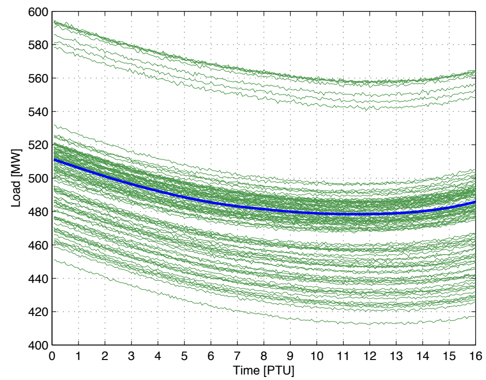
Simulation results

- **Historical data** have been used to carry out simulations (from TenneT and KEMA)

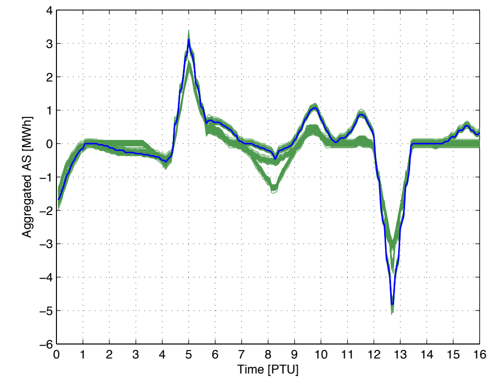
Wind generation



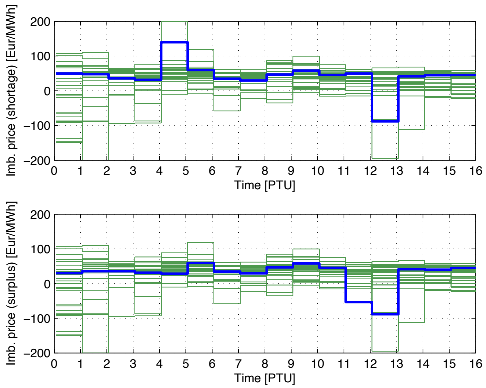
Internal loads



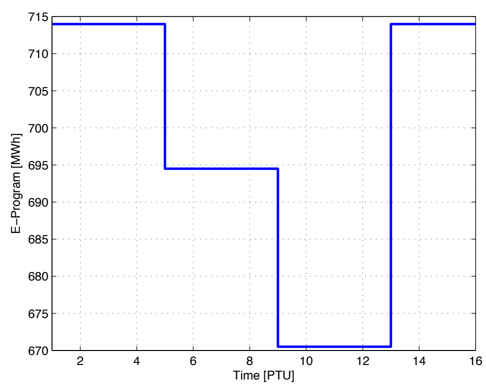
Activated AS bids



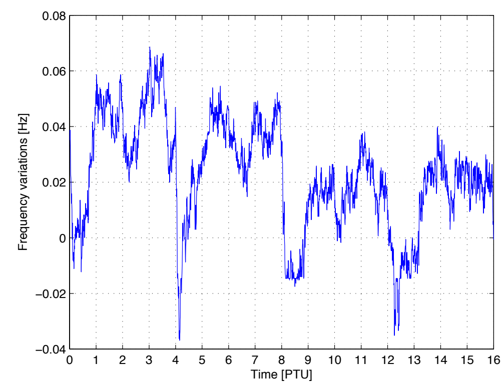
Imbalance prices



E-program



frequency variations

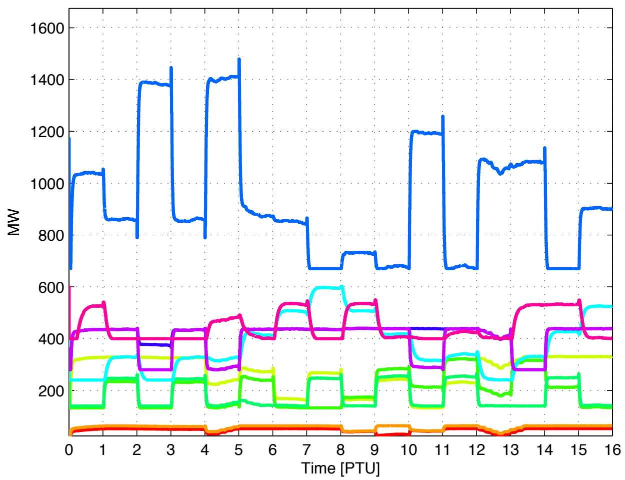


Simulation results

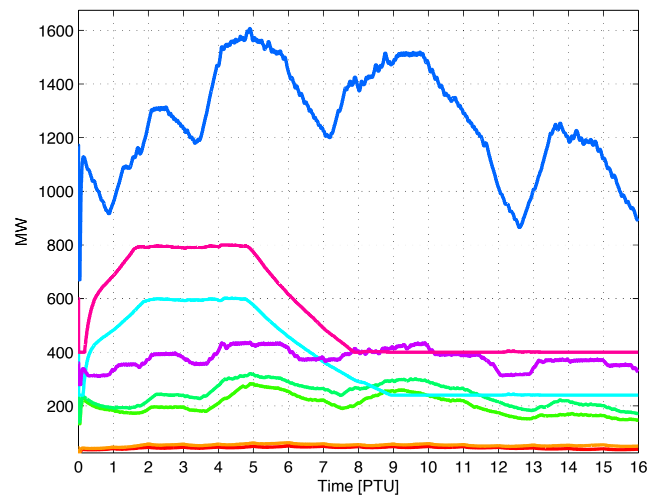
- **HSMPC outperforms SPT in terms of both constraints fulfillment and total cost**

Controller	Generation (€)	Imbalance (€)	Total cost (€)	Savings (€/hour)
SPT	549,257	-3,285	545,973	
DMPC	578,674	-49,057	529,617	4,089
SHMPC	591,517	-73,139	518,378	6,899

power profiles with SPT



power profiles with HSMPC



x ramp-rate violations at PTU crossings

x can’t take advantage of imbalance prices

x higher total cost

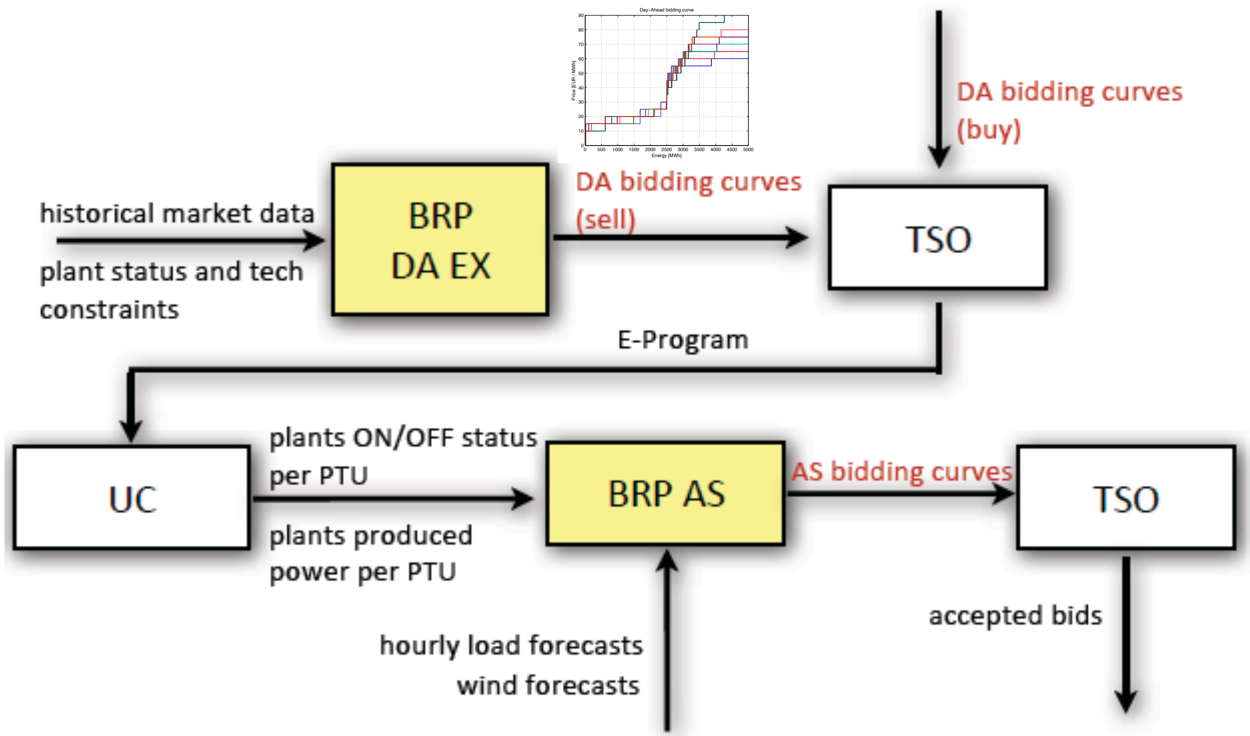
✓ safe handling of ramp-rate constraints

✓ exploits imbalance prices to make profits

✓ fast response to disturbances

Optimal bidding on energy markets

Determine price-volume pairs to bid on the DA and AS market



- ✓ **decoupled** bidding on Day-Ahead and Ancillary Services Markets, **BUT**
- ✓ **BRP DA EX** takes into account **AS bids** as stochastic disturbances
- ✓ **BRP DA AS** takes place after DA price is known. **Load and wind** are treated as stochastic disturbances

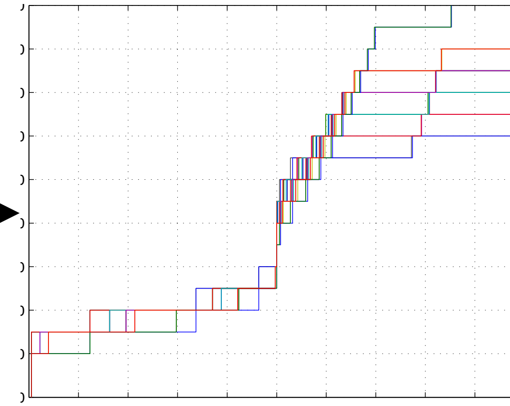
Bidding algorithm on the DA market

Plants specs

Expected wind and load

Market historical data

BRP DA EX



bid ladders
(MWh / eur)

Given:

1. a discrete set of **spot (EX) prices**
2. expected **load and wind profiles** for each hour of the following day
3. **generators specifications** (min and max power, efficiency, etc.)
4. scenarios for **AS upward/downward prices** (stochastic disturbance)

computes the optimal allocation of energy on the EX market for each hour and for each EX price, such that

- profits (income - generation costs) are maximized and
- imbalance risks are minimized,

providing 24 bidding curves, one for each hour of the following day

Bidding algorithm for DA market

Scenario generation: distribution of **Ancillary Services prices** is inferred from real **historical data** and used to construct a **two-stage scenario tree**

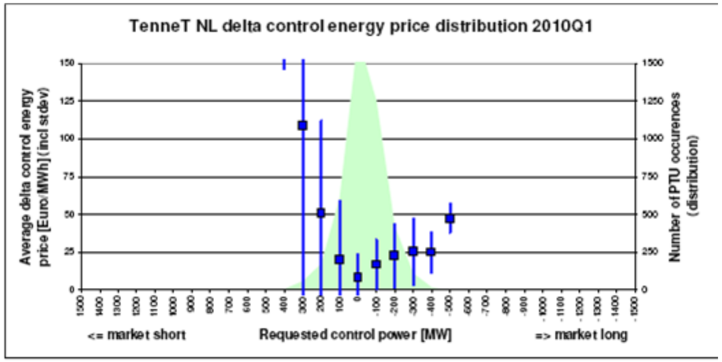
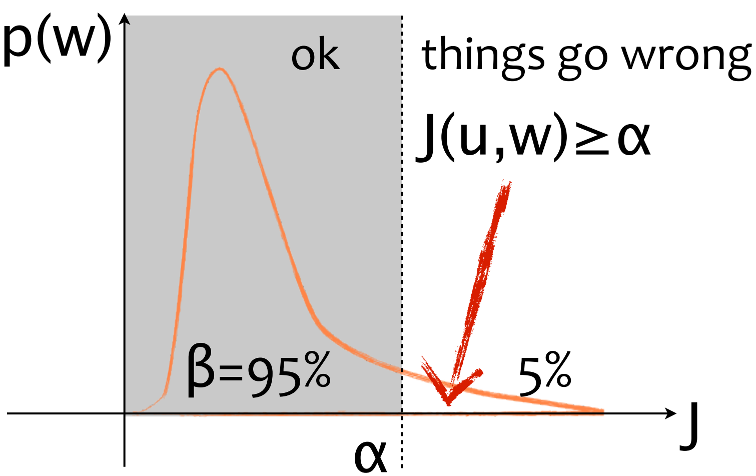


Figure 29 Control energy price distribution TenneT NL Q1



Control objective: minimize the **Conditional Value at Risk (CV@R)**, a risk measure of the profit that quantifies the average loss above a given threshold

- **Constraints:** min and max power setpoint of the generators, internal energy balance, non-decrease of the bid ladder are imposed as affine equality constraints
- **Problem formulation:** the two-stage optimization problem is formulated as a **Quadratic Program**, that can be solved efficiently

Ancillary Services market

Large BRPs are obliged to commit all their residual capacity on the AS market by submitting AS bids (price-volume pairs)

*BRPs **supply** reserve capacity power to the system* (**Current system**)

- S^+: BRP is willing to **be paid** for **injecting** energy (**upward**)
- S^-: BRP is willing to **be paid** for **absorbing** energy (**downward**)

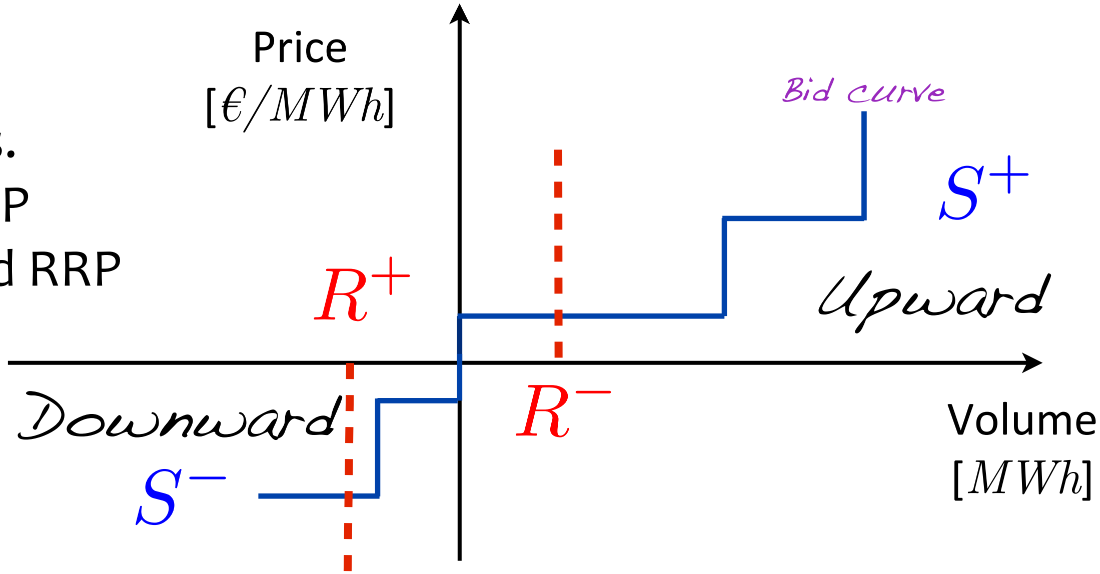
AS price λ^{AS} can be positive (**upward**) or negative (**downward**)

Price	Case	energy direction	cash flow direction
$\lambda^{\mathrm{AS}} \geq 0$	S^+	$\mathrm{BRP} \rightarrow \mathrm{TSO}$	$\mathrm{BRP} \leftarrow \mathrm{TSO}$
$\lambda^{\mathrm{AS}} < 0$	S^-	$\mathrm{BRP} \leftarrow \mathrm{TSO}$	$\mathrm{BRP} \leftarrow \mathrm{TSO}$

Bidding algorithm for AS markets

Current situation

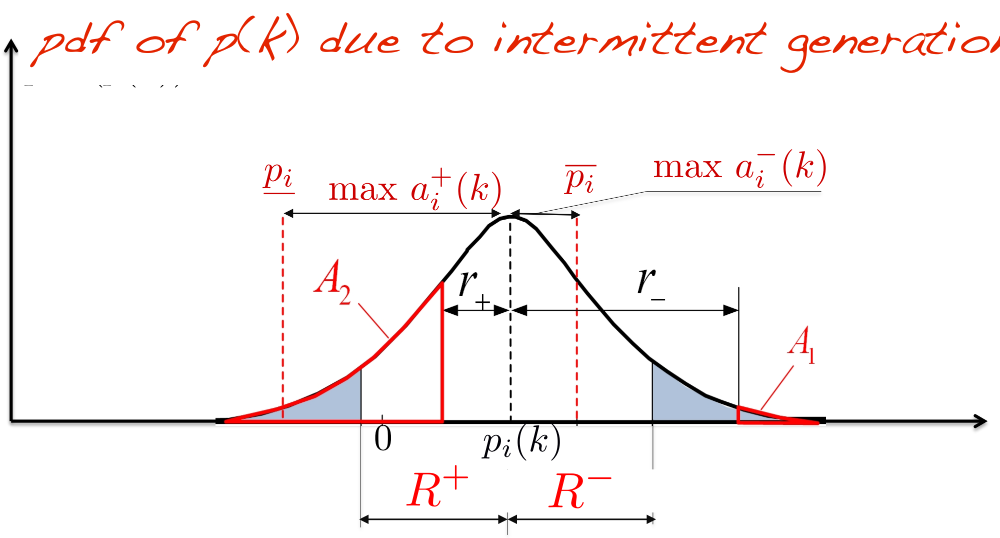
- The BRP submits ***supply*** curves.
  - *Positive price* for upward RRP
  - *Negative price* for downward RRP



E-PRICE-Double-sided AS market

Request for reserve capacity

- BRP is willing to **pay** for **absorbing** or **injecting** energy
- give an estimate of the possible deviations from the scheduled E-program, so that the market is prepared and can react
- reduces risk of imbalance



Bidding algorithms for AS markets

- **Scenario based optimization problem is solved** where a **loss function** is minimized.
- Done for a discrete set of λ^{AS} and then the curve is interpolated.
- **Scenarios** define ***prosumption*** = contribution of uncertain wind and load.

$$\text{Profit } i^{\text{th}} \text{ scenario} = \quad \lambda^{AS} x^{AS} - f_c(u_i) - \lambda^{imb} \epsilon_i$$

- **Decision variables:**
  - x^{AS} energy bid on AS market
  - u_i power set-point
  - ε_i imbalance
- **Inputs:**
  - λ^{AS} AS price
  - λ^{imb} imbalance price
  - $f_c(.)$ generation costs

- Subject to:
  - production boundaries
  - internal balancing
  - non decreasing conditions

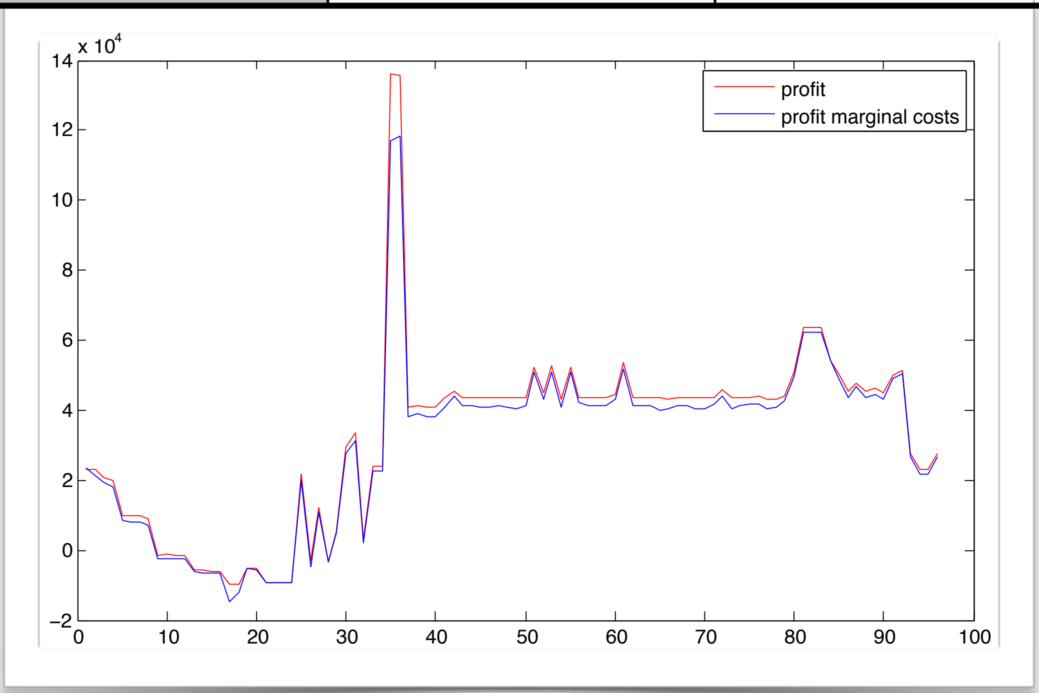
Simulation results

Open loop simulation results

- Comparison with perfect information cost and marginal cost bidding strategy.

Model	mean profit (€)	mean imb (MWh)
Perfect info	59259	0
Marginal cost	30598	-300
BRP AS 95%	32639	-181

Profit



PTU

Conclusions

- **new hierarchical stochastic model predictive control algorithm for real-time management of BRPs**
  - provides a reliable and robust solution for **integrating renewables**
  - reduces **generation and imbalance costs**
  - **responds promptly** to signals sent by TSO
  - handles **ramp-rate limits** safely eliminating discrepancies at PTU crossings
- **new scenario-based stochastic optimization algorithms for DA and AS bidding**
  - optimal trade-off between **expected profit** and **risk** [CV@R]
  - integration of **intermittent** energy sources
  - decoupling between EX and AS markets

References

E-PRICE deliverables (http://www.e-price-project.eu)

D3.1 - Stochastic model predictive control approaches to energy management

D3.2 - Performance assessment of stochastic control methodologies

D3.3 - Multi-objective model predictive control

Publications

Patrinos, P., Bernardini, P., Maffei, A., Jokic, A., Bemporad A., **Two-time-scale MPC for economically optimal real-time operation of balance responsible parties**, in *IFAC 8th Power Plant and Power Systems Control Symposium*, Toulouse, France, 2012.

Patrinos, P., Trimboli, S., Bemporad A., **Stochastic MPC for real-time market-based optimal power dispatch**, in Proc. 50th IEEE Conf. on Decision and Control and European Control Conf., Orlando, FL, 2011.

L. Puglia, D. Bernardini and A. Bemporad, **A multi-stage stochastic optimization approach to optimal bidding on energy markets**, in Proc. 50th IEEE Conf. on Decision and Control and European Control Conference, Orlando, FL, 2011, pp. 1509-1514.