Intrusive and non-intrusive control algorithms for the energy market

Jesus Lago Garcia

VITO/Energyville & TU Delft

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Outline

Who Am I?

Personal Information

- Originally Spanish but lived in Germany for the last 4 years.
- Started my PhD 1^{st} of September at VITO and TU Delft.
- Topic: intrusive and non-intrusive control of energy markets.

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Background

- M.Sc. Numerical Optimization, Optimal Control, and System Identification - University Freiburg.
- Master's thesis: *Optimal Control and Nonlinear Model Predictive Control of an Airborne Wind Energy system.*
- Happy to get involved in optimization and optimal control problems.

Outline

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Electicity as a commodity

Properties

- Unlike most goods, storage of electricity is, at the time and in many cases, not affordable.
- Electricity must be consumed as it is being produced.
- Energy price is settled in a continuous offer/demand trading.

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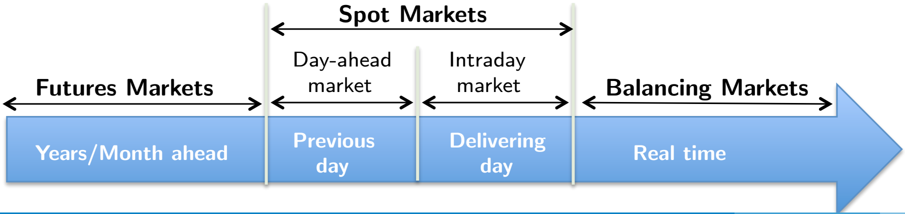
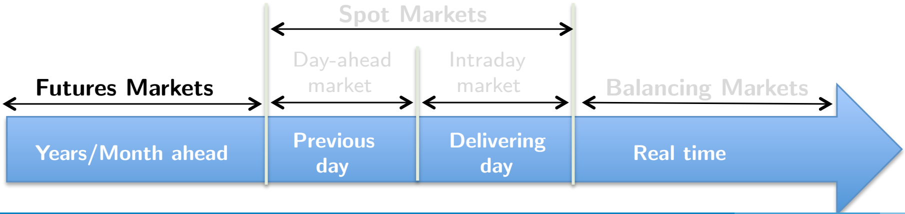


Energy Markets

Type of markets

- **Future markets**: electricity traded by long term contracts.
- **Spot markets**: electricity traded for immediately delivery.
  - **Day-ahead**: bids submitted a day ahead.
  - **Intraday**: bids submitted any time before the transactions.
- **Balancing market**: price due to real time imbalances.



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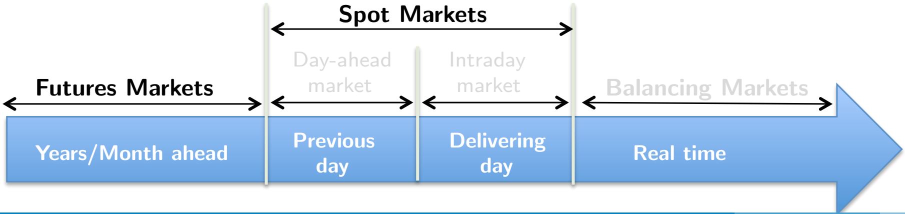

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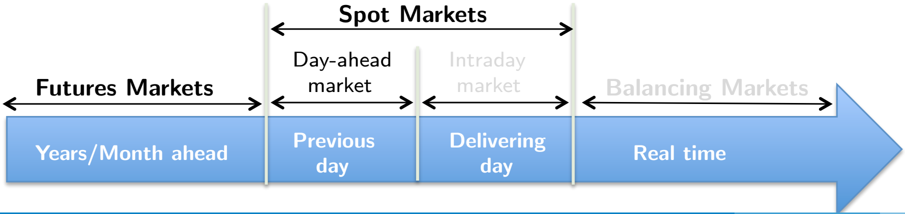

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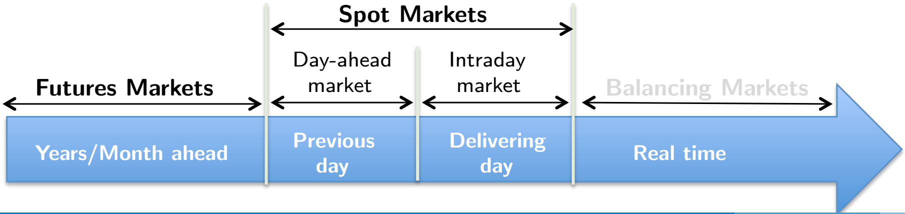

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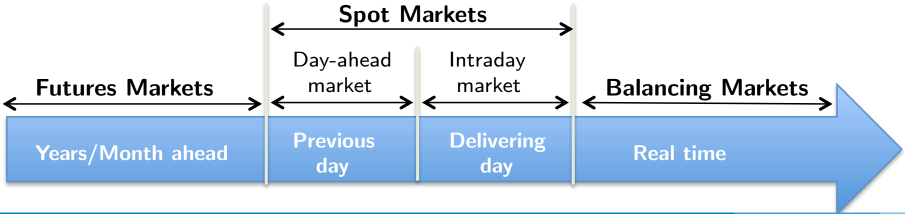

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Role of renewable energy sources

Markets for renewable energy sources (RES)

- Production of renewable energy depends on weather conditions
  $\Longrightarrow$ Energy production from RES is uncertain.

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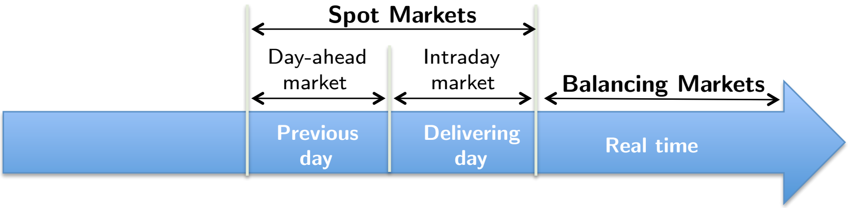
- Production of renewable energy depends on weather conditions $\Longrightarrow$ Energy production from RES is uncertain.
- Most of the produced renewable energy can only be traded on the spot and real time markets.



Role of renewable energy sources

Issues

1. Due to weather conditions, energy production from RES is uncertain.
2. Production uncertainty leads to volatile markets and imbalanced grids.
3. Volatility and imbalances make RES less attractive and profitable.
4. Market share of RES is limited.

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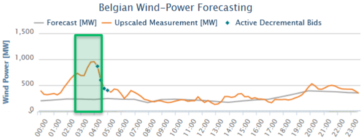

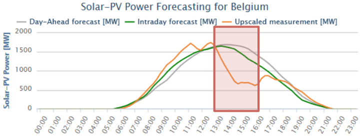

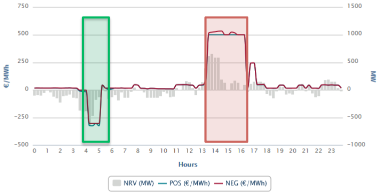

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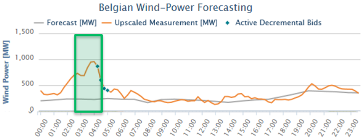

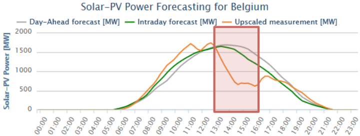

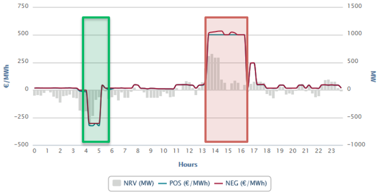

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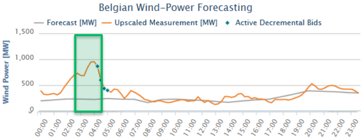

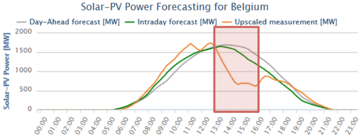

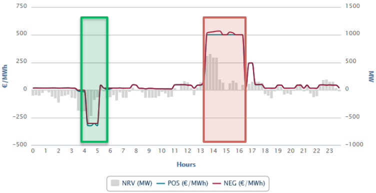

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Support the energy market so that more RES can be integrated.

- Ensure profits of RES by hedging against imbalance positions.
- Market becomes more stable $\Longrightarrow$ more RES can be integrated.

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Methodology

- Development of control algorithms that can influence the price of the energy market.
- Approaches:
  1. Non-intrusive control.
  2. Intrusive control.

Outline

Non-intrusive control

Description

Algorithms that regulate the market without interfering in the consumption/production of the market agents:

- Placement of smart bids:
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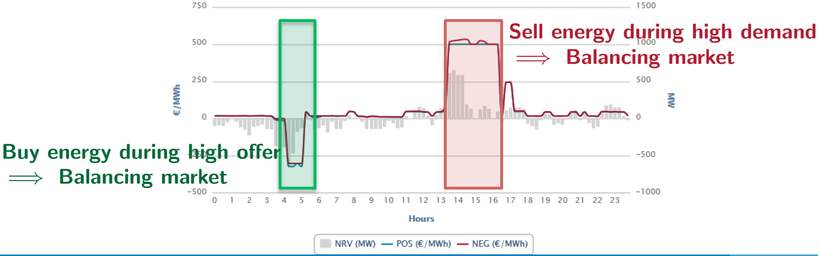

Non-intrusive control - Smart bids

Intermediate Goal

- Forecast individual prices of day ahead, intraday and imbalace markets $\Longrightarrow$ Optimal bid allocation within market.
- Forecast interrelations between the three markets $\Longrightarrow$ Optimal bid allocation across market.

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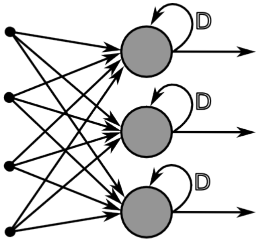
Final Goal

Model a multi-market controller that can forecast prices and identify spreads across the three markets and select optimal bids accordingly.

Non-intrusive control - Research in smart bids

Deep Learning

- Implementation of deep learning algorithms to forecast prices and find desired interrelations.
- Focus on Recursive Neural Nets: Long-short term memory (LSTM) cells with autoencoders for feature extraction.
- Performance comparison with classical forecasting techniques.



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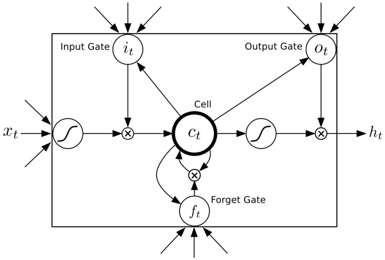

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Non-intrusive control - Research in smart bids

Multi-step forecast

- Improving classical forecasting methods by development of more accurate multi-step predictions.

https://www.otexts.org/fpp/

Outline

Intrusive control

Observation

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- Intrusive strategies are an alternative to provide extra flexibility and support to the grid.

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Algorithms that regulate the market by modifying the regular working regime of market agents:

- Increase the regular consumption when prices are low and reduce it when prices are high.
- Examples:
  1. Production plants with flexible production.
  2. Smart buildings and heating of sanitation water.
- Market is balanced by making profits.

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Energy price forecasting: State of the art

Review

- Traditional techniques applied to energy market forecasting include:
  1. Double and triple seasonal ARIMA.
  2. ARIMA with wavelet decomposition.
  3. TBATS (Exponential smoothing, ARMA errors, trend and seasonality).
- In the literature, people claimed 10% MAPE error.
- Error is subjective to specific dataset $\implies$ implementation of these methods in the Belgium market showed 15-20% MAPE error.

Energy price forecasting: State of the art

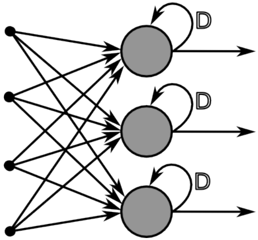
Drawbacks

- The model has to know in advance important features:
  1. Does the data have seasons? When do they occur?
  2. How much data into the past is relevant for the forecast?
- Integration of extra features, e.g. PV forecast or grid load, almost impossible.
- Stationary data is required.

Energy price forecasting: Deep learning

Possible solution: Recurrent neural networks:

- Relevant past data is learned and memorized in the network.
- Seasonal patters are learned by the network.
- Non-stationary data works fine.
- Easy integration of extra forecasting features.



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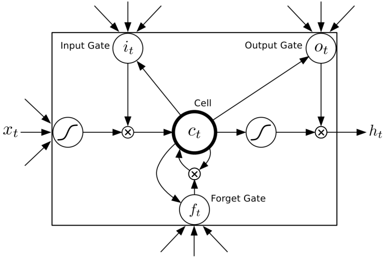

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Deep learning: First results

Results

- Traditional techniques 15-20% MAPE error.
- First implementation of recurrent neural network 14-17%.
- Room for further improvement.

Outline

Multi-step ahead forecasting: A Review

Formulation

- System at time k.
- Past data $[y_k, \ldots, y_{k-n}]$ available.
- Required estimation of m values into the future: $[y_{k+1}, \ldots, y_{k+m}]$.

Multi-step ahead forecasting: A Review

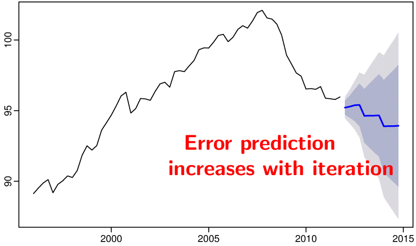
First approach: iterative method

A model is trained using a one-step ahead function:

$$\hat{y}_{k+1} = f(y_k, \ldots, y_{k-n})$$

Prediction done using previous estimations:

$$\hat{y}_{k+3} = f(\hat{y}_{k+2}, \hat{y}_{k+1}, y_k, \ldots, y_{k-n+2})$$



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Multi-step ahead forecasting: A Review

Second approach: direct method

A different model trained for each step ahead:

$$\begin{aligned}\hat{y}_{k+1} &= f_1(y_k, \ldots, y_{k-n}) \\ &\vdots \\ \hat{y}_{k+m} &= f_m(y_k, \ldots, y_{k-n})\end{aligned}$$

Problem

1. Time dependency between different predictors is lost.
2. Information is thrown away.

Third approach: dirrect method

Models are trained sequentially. Trained prediction of previous models used as inputs.

$$\begin{aligned}
\text{First estimate :} \quad & \hat{y}_{k+1} = f_1(y_k, \dots, y_{k-n}) \\
\text{Second estimate :} \quad & \hat{y}_{k+2} = f_2(\hat{y}_{k+1}, y_k, \dots, y_{k-n+1}) \\
\vdots \quad & \quad \vdots \\
\text{Finally estimate :} \quad & \hat{y}_{k+m} = f_m(\hat{y}_{k+m-1}, \dots, \hat{y}_{k+1}, y_k, \dots, y_{k-n+m-1})
\end{aligned}$$

Problem

Information is still lost:

1. Models are allowed to be different.
2. However, they represent the same system behavior.

Multi-step ahead forecasting: Possible approach

Idea

- Each step ahead i is again modeled by a function f_i.

$$\hat{y}_i = f_i(\hat{y}_{i-1}, \ldots, y_{k-n+i-1}, p_i)$$

- f_i is defined by a parameter set p_i.
- Models are optimized enforcing similar solutions: $p_1 \approx p_i \approx p_m$.

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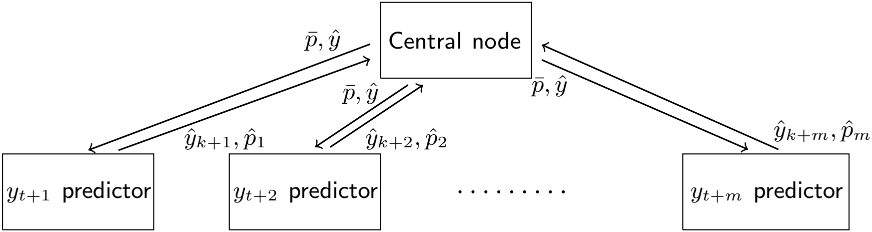

Multi-step ahead forecasting: Possible approach

Idea

1. Given similarity parameter $\bar{p}$, node i estimates $\hat{p}_i$ by:

$$\hat{p}_i = \arg\min_{p_i} \quad \|y_{k+i} - f_i(\hat{y}_{i-1}, \ldots, y_{k-n+i-1}, p_i)\|_2^2 + \lambda_i \|p_i - \bar{p}\|_2^2$$

2. At each iteration, node i broadcasts $[\hat{y}_{k+i}, p_i]$.
3. Central node assembles $\hat{y} = [\hat{y_1}, \ldots, \hat{y_m}]$, computes $\bar{p} \in \mathcal{R}$ based on $[\hat{p}_1, \ldots, \hat{p}_m]$, λ_i based on $(\hat{p}_i - \bar{p})$, and broadcast them back.
4. Process stop when consensus is reached.

Central node

y_{t+1} predictor | y_{t+2} predictor | .... | y_{t+m} predictor

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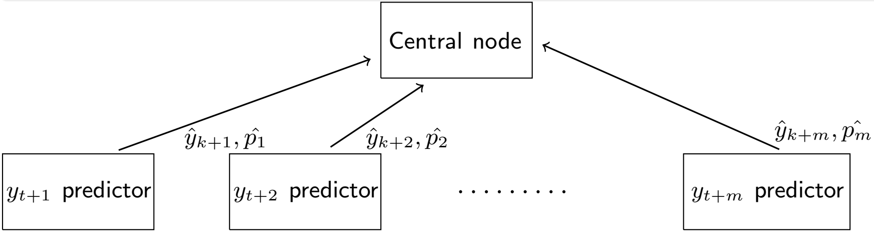

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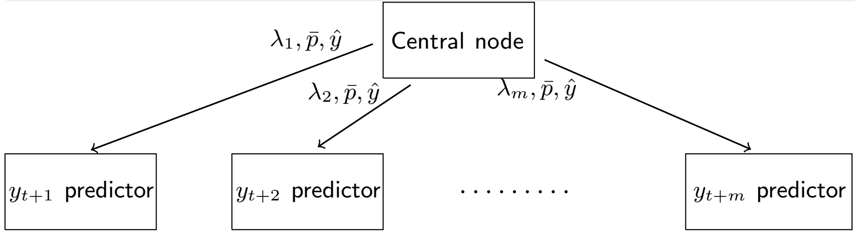

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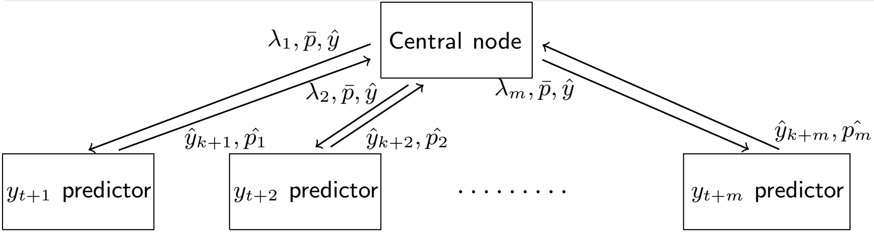

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Intrusive control - System identification

First Observation

- Some systems, which could be potentially used for energy demand response, have complex and unknown controllers that can not be modified (they implement security measures or critical control tasks).
- The systems become unsuitable to provide demand response as its regular controller can not be altered.
- Examples:
  1. A building management system (BMS) controlling that a building stays in the comfort zone.
  2. A manufacturing plant that is controlled by some agent that decides when to steer and keeps security measures.

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Intrusive control - System identification

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- The same systems react and modify its behavior according to external observations.
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Possible research

- Identify system response against external inputs.
- Use model and introduce virtual inputs to steer the system.
  1. BMS: modification of heating rate to provide demand response while keeping security measures.
  2. The plant scenario is discussed in next slides in more detail.

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- They provide to their clients price forecast for next day, obtain consumption request from the clients, aggregate all the demands, and locate a bid in the day-ahead market.
- If using single price forecast for every client, aggregation of demands can produce several issues:
  1. Line congestion due to high demand in the same low price regions.
  2. Big losses in wrong forecasting as all the demand curves were build using the same forecast.

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  2. Big losses in wrong forecasting as all the demand curves were build using the same forecast.

Intrusive control - Aggregators

Observation

- Aggregators (market agent that controls the portfolio of several smaller players) target maximization of profit my using optimal bids.
- They provide to their clients price forecast for next day, obtain consumption request from the clients, aggregate all the demands, and locate a bid in the day-ahead market.
- If using single price forecast for every client, aggregation of demands can produce several issues:
  1. Line congestion due to high demand in the same low price regions.
  2. Big losses in wrong forecasting as all the demand curves were build using the same forecast.

Intrusive control - Optimal experimental design

Possible research

- Identification of plant controller, i.e. model the consumption scheduling given a certain price profile.
- Explore optimization problems where the price profile given to each plant is a variable and the portfolio risk is minimized (or benefit maximize).
- As the identification task is very computationally heavy (each plant can only provide a small number of demand responses per day), optimal experimental design can be investigated as a way to reduce the number of required profiles to accurately estimate the controller.

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