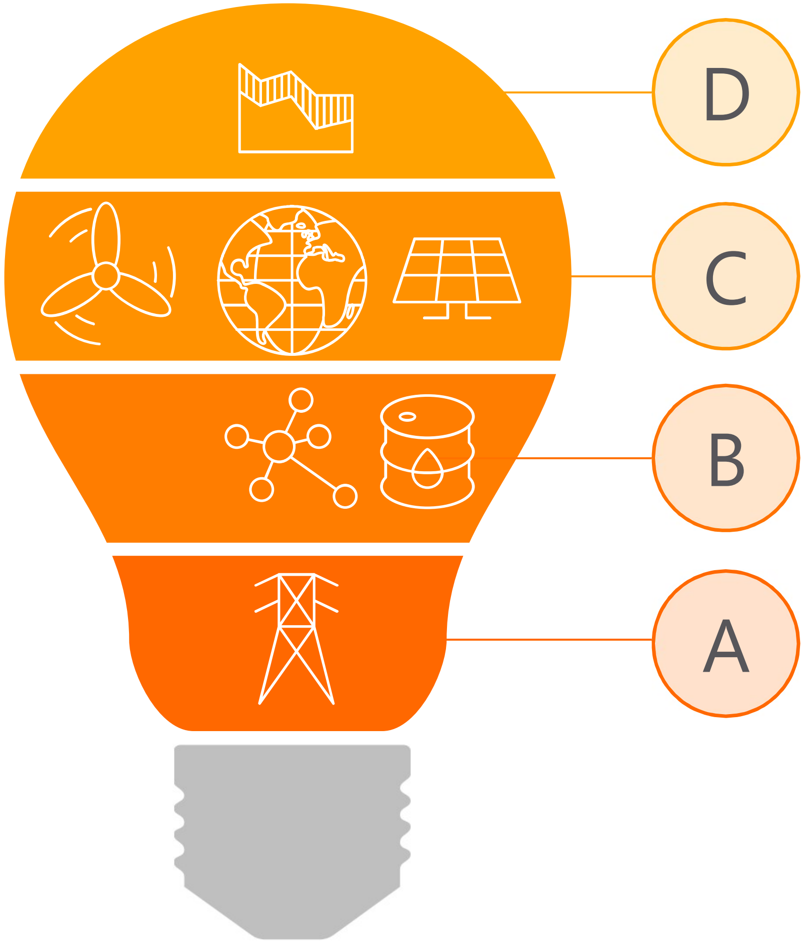
Maria Kaninia
2nd AIEE Energy Symposium
Rome, Nov. 2-4 2017

Spot trading profits of electricity storage systems in the region covered by EPEX SPOT

Electricity storage: Relevant for energy security

- Transition to intermittent (non-dispatchable) renewables (solar, wind): increases **variability**
- Storage can **mitigate risks** (buffer principle)
- Electricity grid = complex linked structure



Financial risk:
Buffering will decrease price volatility and increase consumer welfare

Geographical aspect: Decentralised grid
Distributed components are less vulnerable

Security of supply: Storage supports self-reliance indirectly (via support for variable renewables)

Buffer: Stabilizes the grid by buffering variable renewables (source of instability)

This paper: Are electricity storage plants **viable** only by participating in the spot market (**arbitrage**)?

~~subsidies~~

Literature - 1

Applied Energy 114 (2014) 512–519

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

ELSEVIER

Economic viability of energy storage systems based on price arbitrage potential in real-time U.S. electricity markets

Kyle Bradbury [a,*], Lincoln Pratson [a], Dalia Patiño-Echeverri [b]

[a] Division of Earth and Ocean Sciences, Nicholas School of the Environment, Duke University, Durham, NC 27708, United States
[b] Division of Environmental Science and Policy, Nicholas School of the Environment, Duke University, Durham, NC 27708, United States

- Complexity ⇧ (**locational** pricing in US wholesale market)
- Linear model with perfect foresight in multiplie wholesale market
- Computational requirements ⇧
- Technology comparison

Applied Energy 159 (2015) 422–432

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

ELSEVIER

Estimating the value of electricity storage in an energy-only wholesale market

Dylan McConnell [a,b,*], Tim Forcey [a], Mike Sandiford [a]

[a] Melbourne Energy Institute, University of Melbourne, Australia
[b] Australian German College of Climate and Energy Transitions, University of Melbourne, Australia

- Australian market (NEM): historically volatile, zonal pricing
- Structural differences, prices reach cap, profits generated

Literature - 2


Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

Estimating the value of electricity storage in PJM: Arbitrage and some welfare effects☆

Ramteen Sioshansi [a,*], Paul Denholm [b], Thomas Jenkin [b], Jurgen Weiss [c]

[a] Industrial, Welding, and Systems Engineering Department, The Ohio State University, United States
[b] National Renewable Energy Laboratory, United States
[c] Point Carbon North America, United States

- PJM: locational pricing, large volatility
- ESS profitable
- Storage: Potential to increase consumer welfare by reducing price volatility
- In turn, a «flattened» price curve limits ESS profit potential

?

Research question

What is the maximum profit that a «black-box» ESS can extract via arbitrage from the spot market?

- Assume «black-box» energy storage system (ESS)
- ESS is **price-taker** in wholesale electricity market
- Use linear programming (LP) model and rolling-horizon to find optimal dispatch that maximises profit
- Connect model to data (input: time series of prices)
  - Zones: CH, DE, FR
  - Years: 2013-2016
- Solve model
- Post-process
- Analyse results: Are profits from ESS operation (energy arbitrage only) sufficient to cover capital costs?

Model -1

- Assume an Energy Storage System (ESS). Technology-agnostic.
- Arbitrage is the only profit-generation mechanism.
  - **charge** when prices are low
  - **discharge** when prices are high
- We assume that the C-rate is the same for charging and discharging (this is not true of all types of electrochemical energy storage).
- The penalty corresponding to energy efficiency losses is attributed to the charging process only. This does not affect the results in any critical way.

Mathematical problem:

- Assume prediction horizon H and rolling period R. Within this horizon, the decision-making system has perfect foresight of the prices. Here: H=72h, R=1h

objective function:

$$\max R := \sum_{t=1}^{T} \pi_t \left(P_t^D - P_t^C\right) \delta t$$

battery dynamics: $Q_{t+1} = (1-\gamma)\,Q_t + (\eta\,P_t^C - P_t^D)\,\delta t \qquad \forall t$

non-linear constraint: $P_t^C\,P_t^D = 0 \qquad \forall t$

Model-2

ESS technological characteristics (**parameters**):

- Efficiency (round-trip energy efficiency)
- Self-discharge rate (ignored, $\gamma=0$)
- Maximum charging and discharging capacity in power units [MW].
- C-rate equivalent (energy to power ratio).
- Normalisation: Energy capacity is fixed

=1 MWh (norm.)

$$Q_t \leq Q_{\max}$$

$$P_t^C \leq P_{\max}^C$$
$$P_t^D \leq P_{\max}^D$$

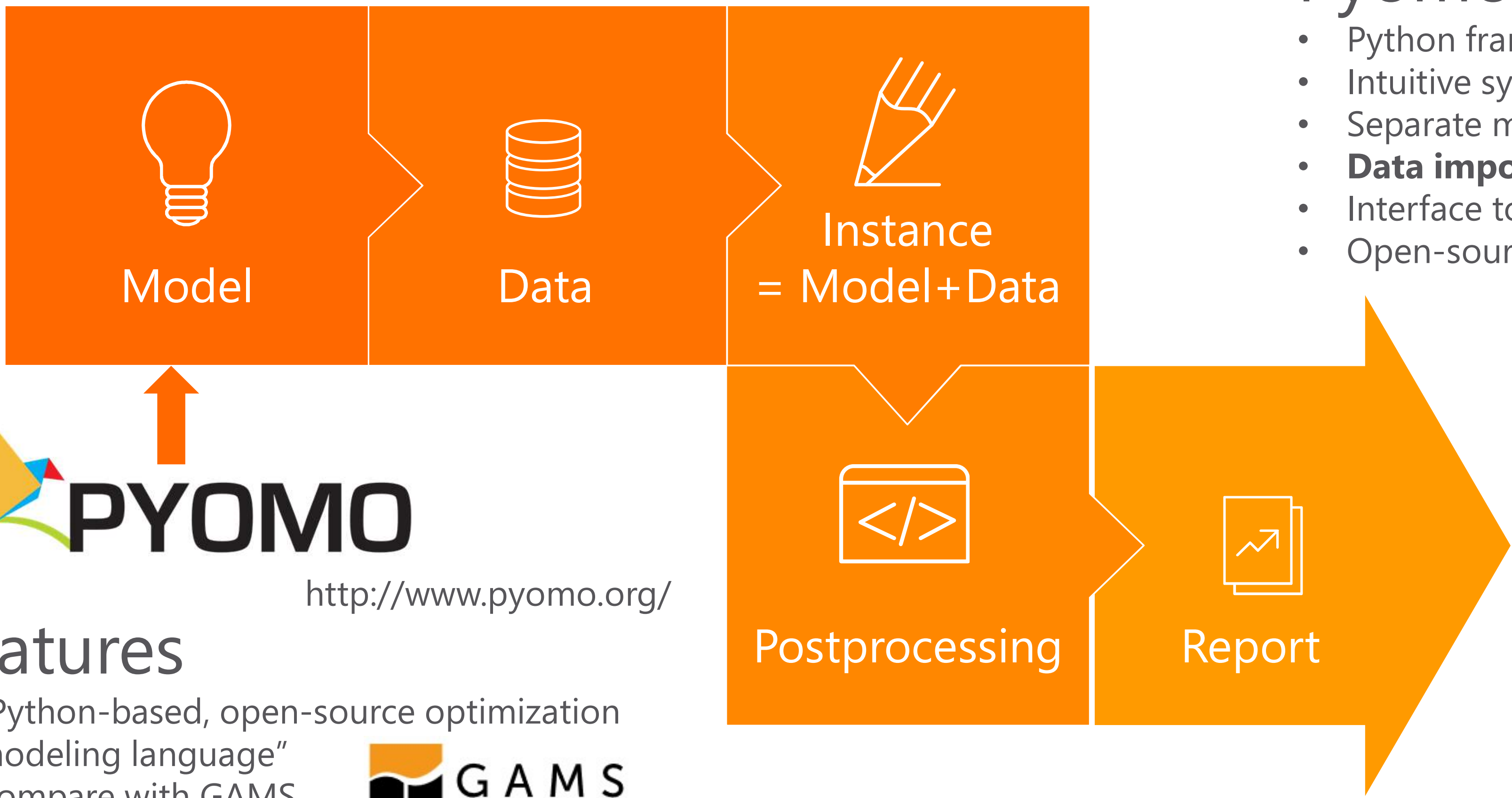
efficiency

$$Q_{t+1} = (1-\gamma)\, Q_t + (\eta\, P_t^C - P_t^D)\, \delta t \qquad \forall t$$

self-discharge rate

Pyomo: Abstract modeling in Python

Abstract model + data = Concrete model



Pyomo: Advantages

- Python framework
- Intuitive syntax
- Separate model from data
- **Data import/export simplified**
- Interface to solver simplified
- Open-source

PYOMO

http://www.pyomo.org/

Features

- "Python-based, open-source optimization modeling language"
- Compare with GAMS
- Interface to Python for pre/post-processing

GAMS

Pyomo: Abstract model

No «interference» from data at this stage

```
# Creation of an Abstract Model
model = AbstractModel()

## Define sets ##
model.t = Set(doc='time segments', ordered = True)

## Define parameters ##
model.P = Param(model.t, doc='price at time segment t')
model.NSEG = Param(doc='number of segments', within=PositiveIntegers)
model.QMAX = Param(doc='Storage capacity [MWh]', within=PositiveReals)
model.CHMAX = Param(doc='Charge capacity [MW]', within=PositiveReals)
model.DCHMAX = Param(doc='Discharge capacity absolute value [MW]', within=PositiveReals)
model.GAMMA = Param(doc='self-discharge coefficient', within=PositiveReals)
model.ETA = Param(doc='efficiency', within=PositiveReals)
```

PYOMO

Development environment: Windows 10, Python 3.6, IDE: PyCharm, Solver = GLPK, 120ms for each 72-hour step

Linear model: Black-box model does not require complex dynamics

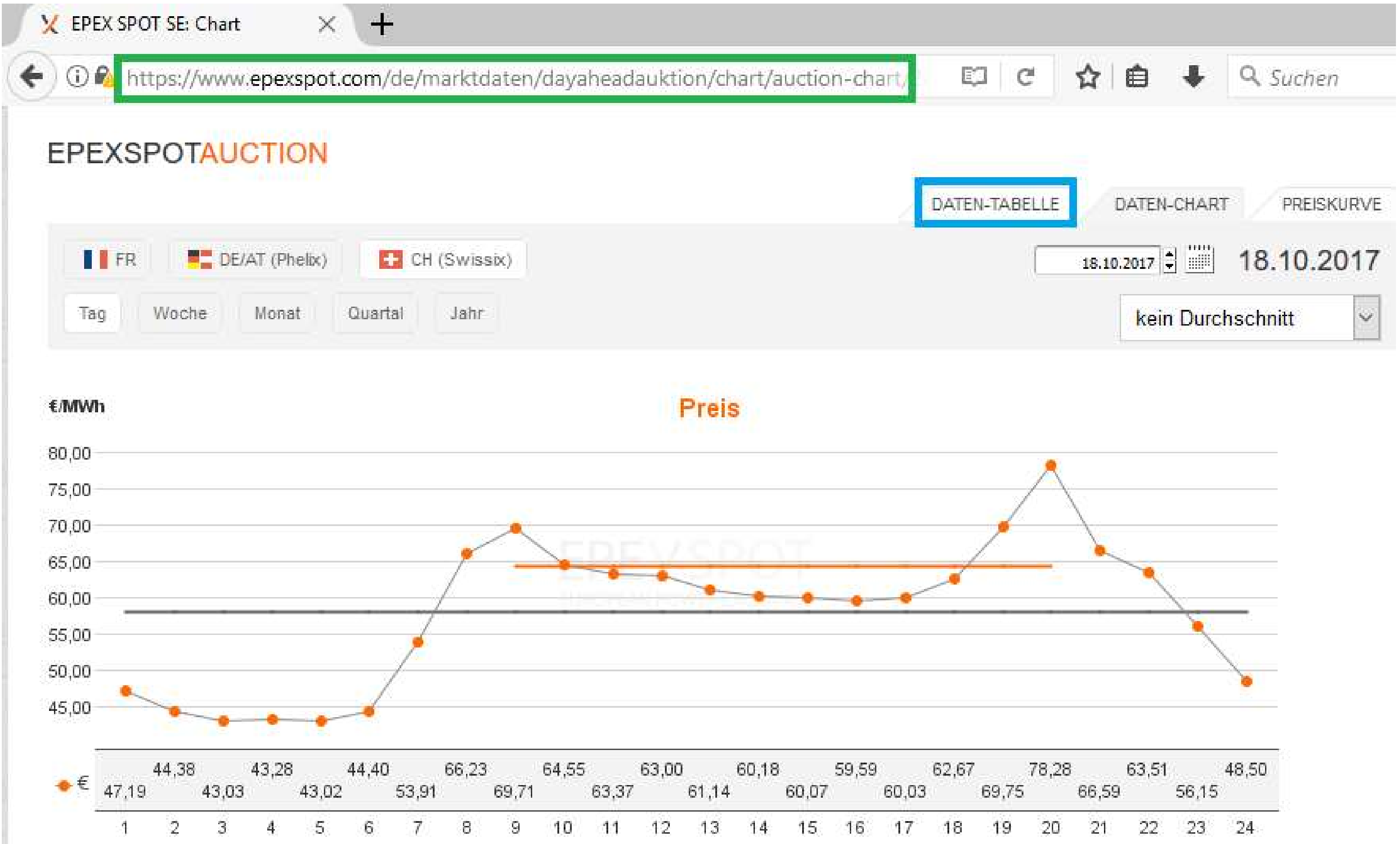
```
## Define variables ##

# IC > 0 : charging
# ID > 0 : discharging
model.IC = Var(model.t, within=NonNegativeReals, doc='charging [MWh]')
model.ID = Var(model.t, within=NonNegativeReals, doc='discharging [MWh]')
model.Q = Var(model.t, within=NonNegativeReals, doc='stored energy [MWh]')
```

```
constraint_eqbal = (model.Q[t+1] == model.GAMMA*model.Q[t] + model.ETA*model.IC[t] - model.ID[t])
```

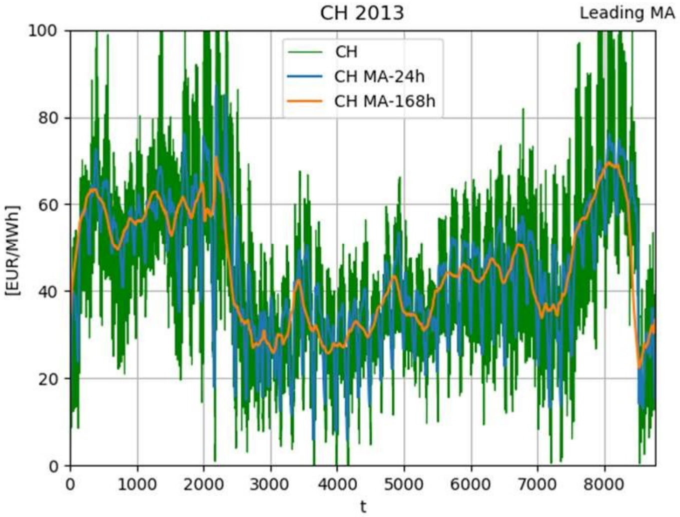
$$Q_{t+1} = (1-\gamma)\, Q_t + (\eta\, P_t^C - P_t^D)\, \delta t \qquad \forall t$$

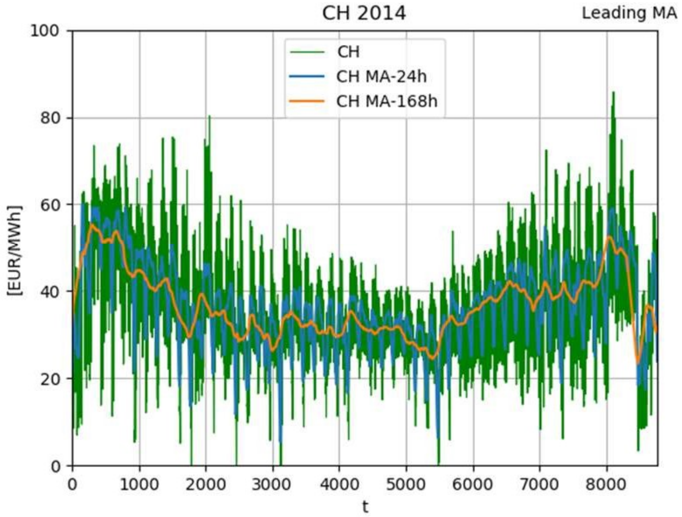
Input: Day-Ahead prices - 1

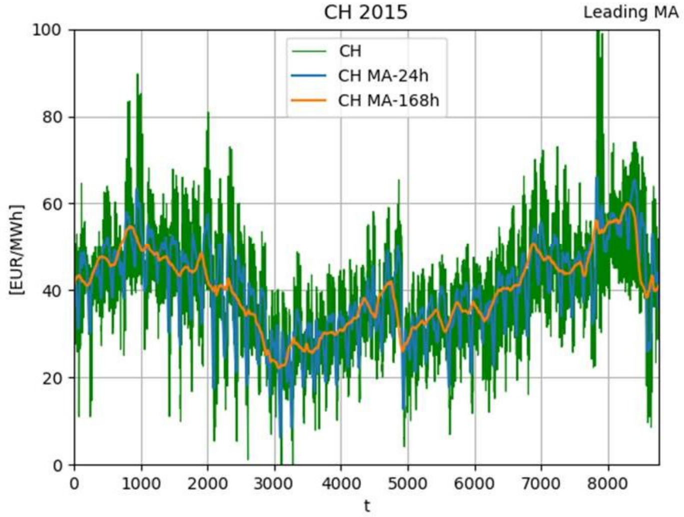


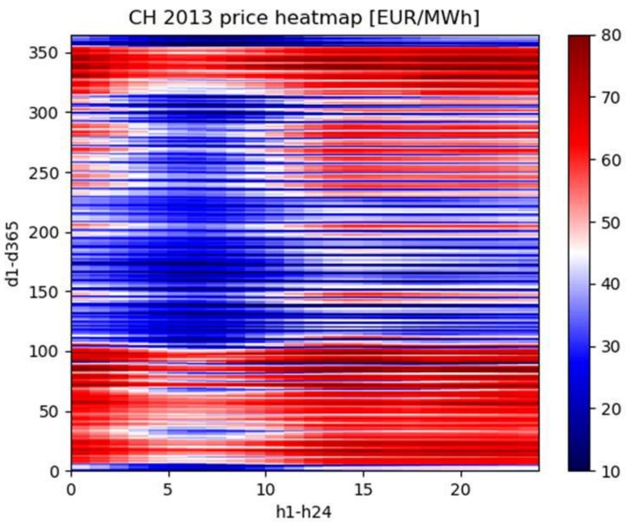
- Day-Ahead time series used as **PROXY** for spot prices
- **Data source**: EPEX-SPOT website
- Automated download (using Python packages, data scraping)
- Hourly interval

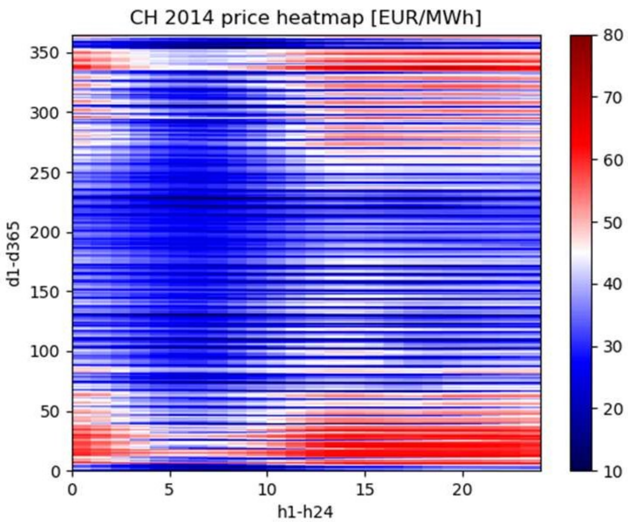
Input: Electricity prices: CH, 2013-2015

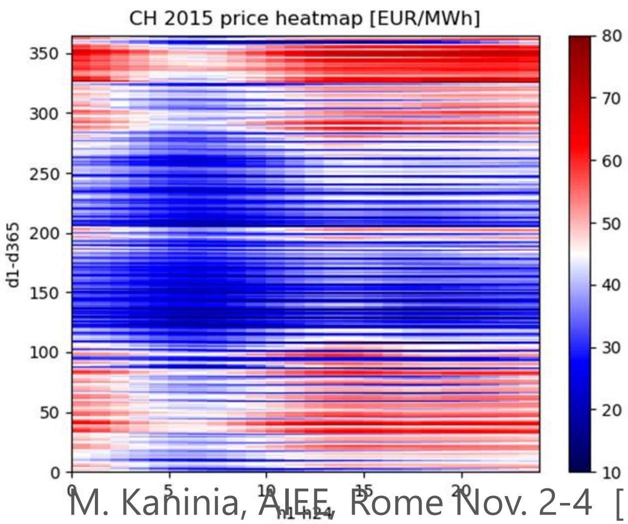




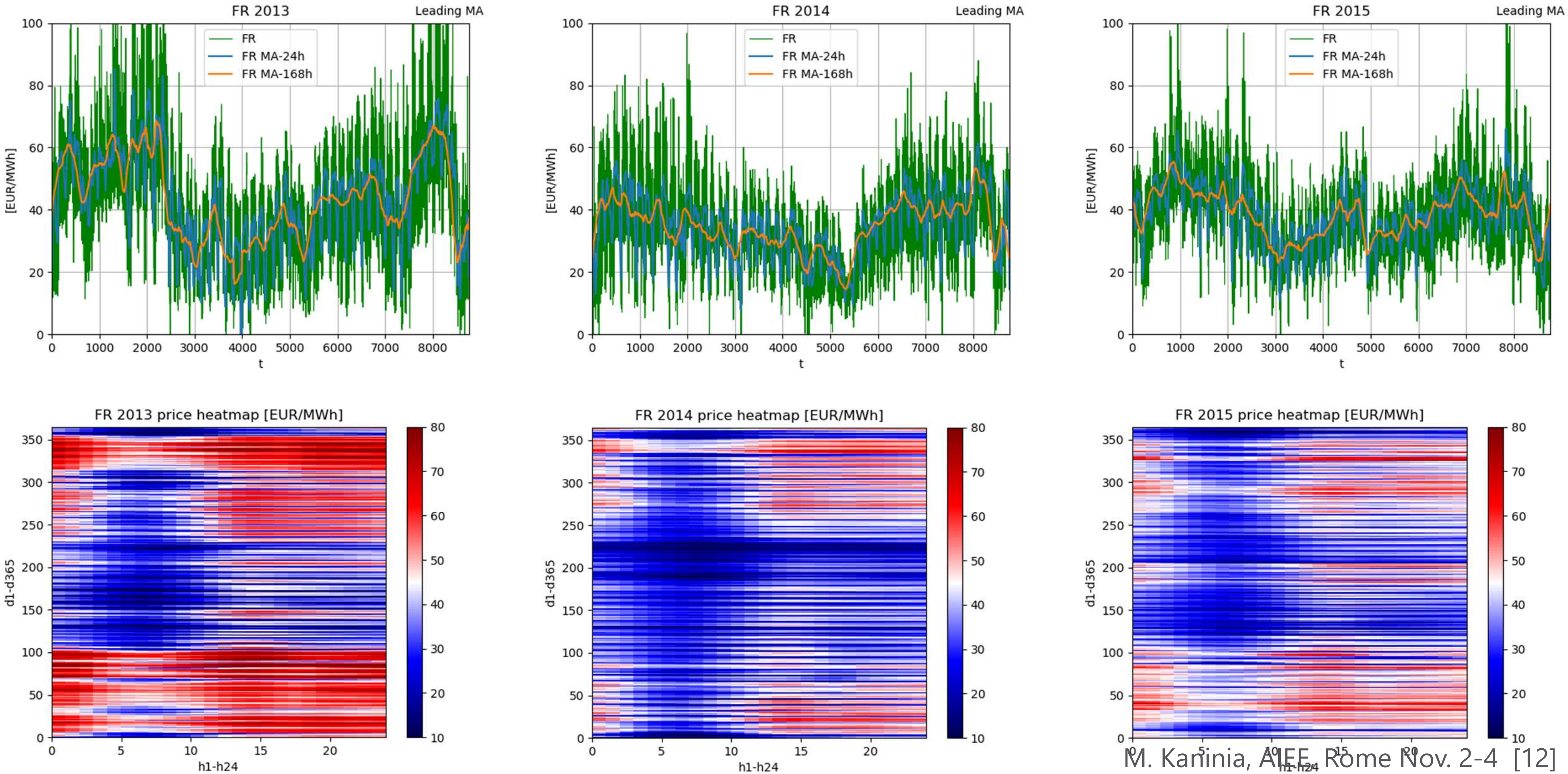




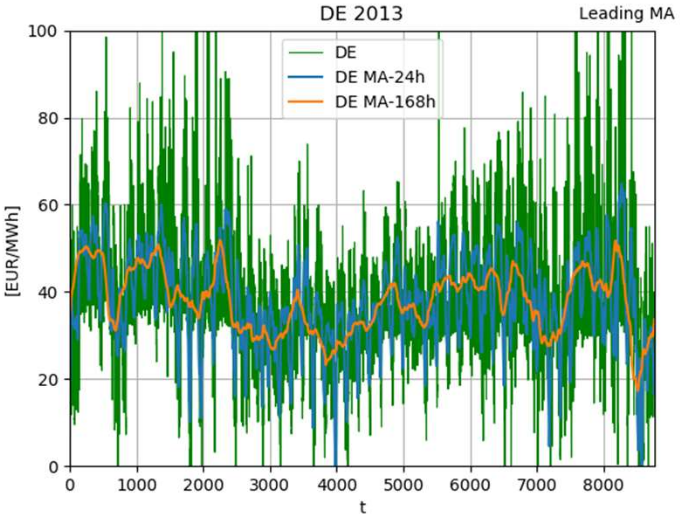


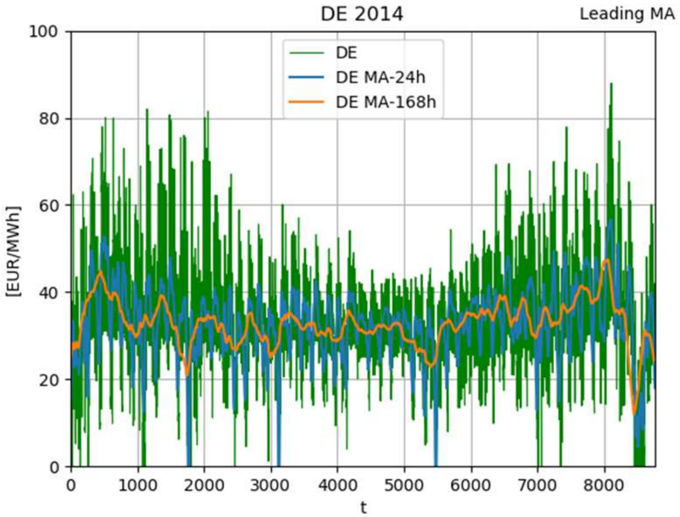


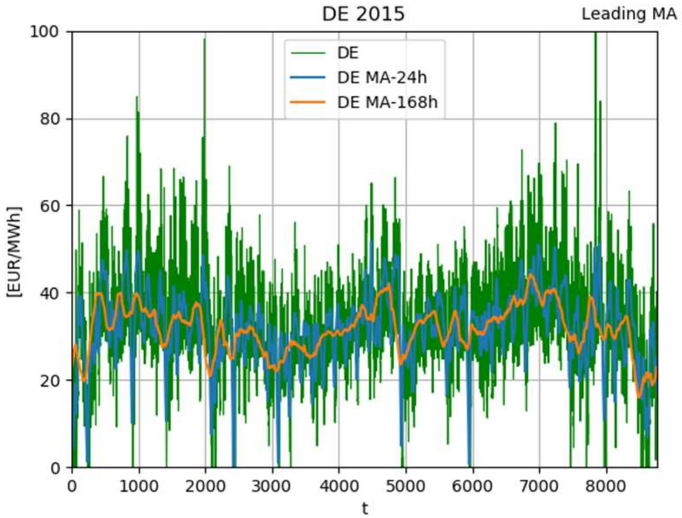
Input: Electricity prices: FR, 2013-2015

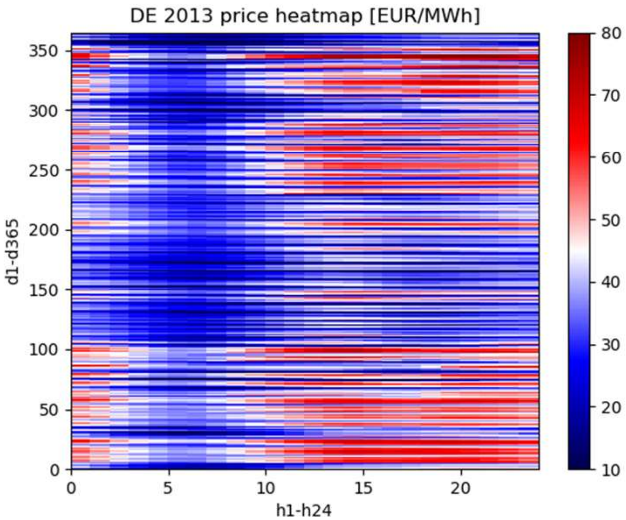


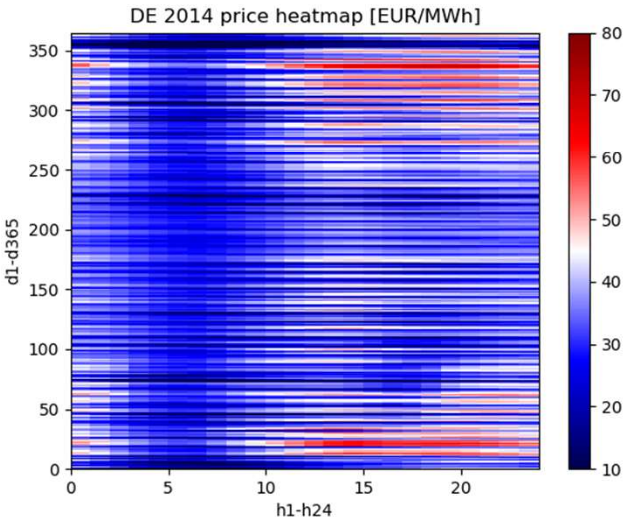
Input: Electricity prices: DE, 2013-2015

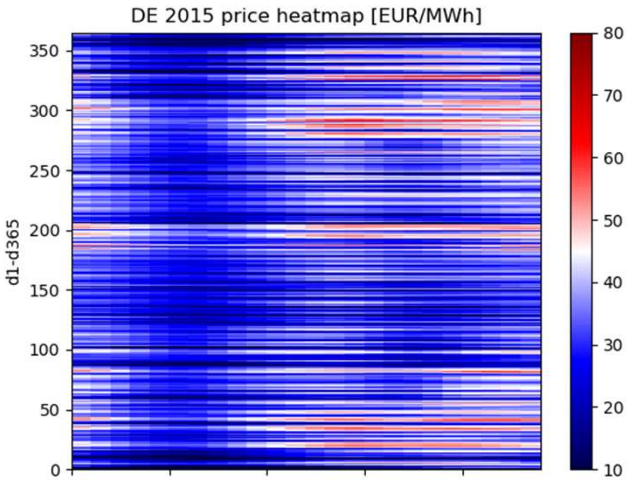












Input: Electricity prices: price-duration-curves

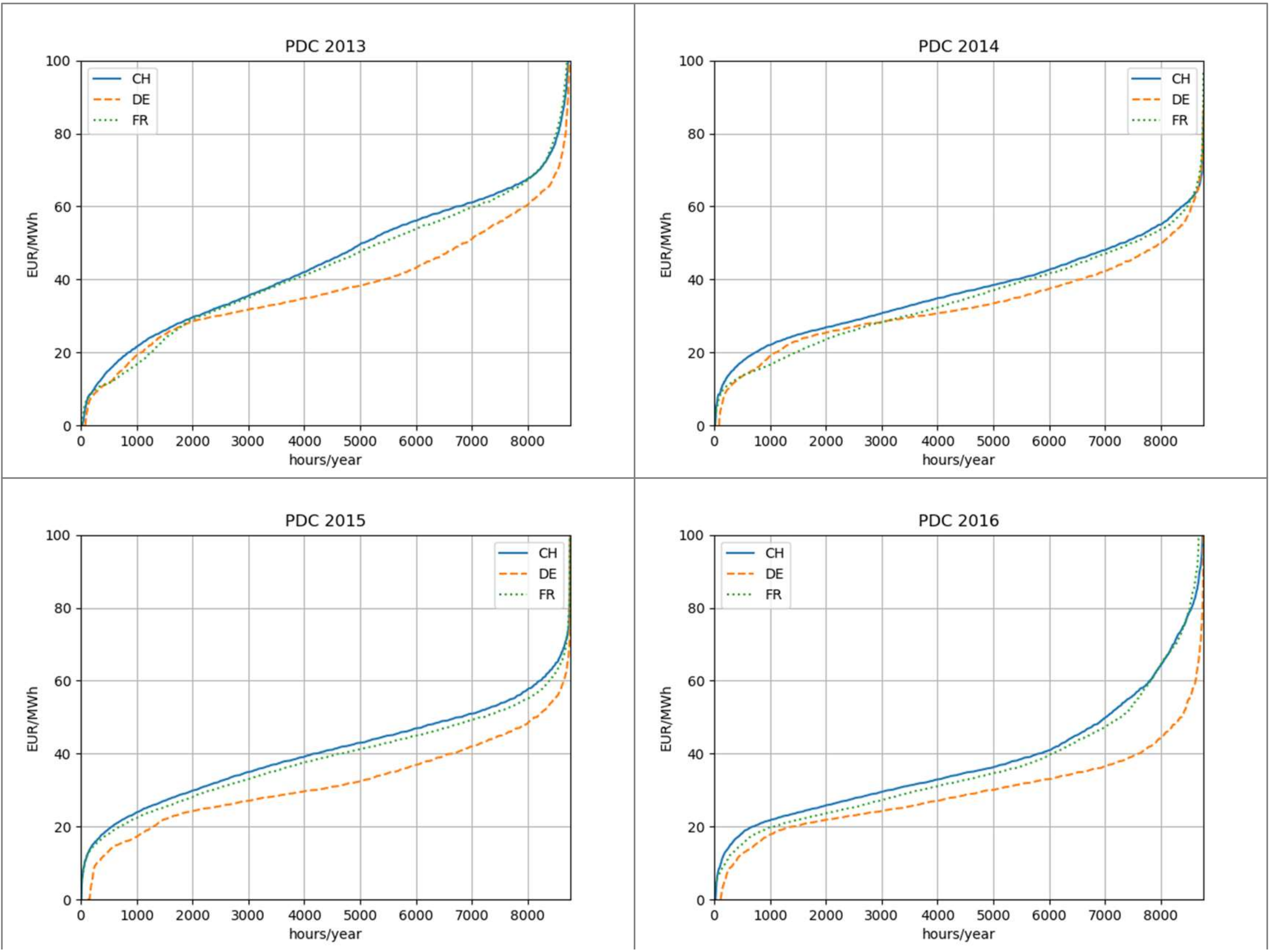


TABLE I
PRICE STATISTICS FR

year	mean	median	std	min	max
2013	43.2	43.5	20.3	-200.0	180.0
2014	34.6	34.1	13.9	-2.1	96.7
2015	38.5	39.0	12.9	0.0	123.5
2016	36.7	32.4	24.5	-10.7	874.0

TABLE II
PRICE STATISTICS DE

year	mean	median	std	min	max
2013	37.8	36.1	16.5	-100.0	130.3
2014	32.8	31.6	12.8	-65.0	88.0
2015	31.6	30.5	12.7	-79.9	99.8
2016	29.0	28.2	12.5	-130.1	105.0

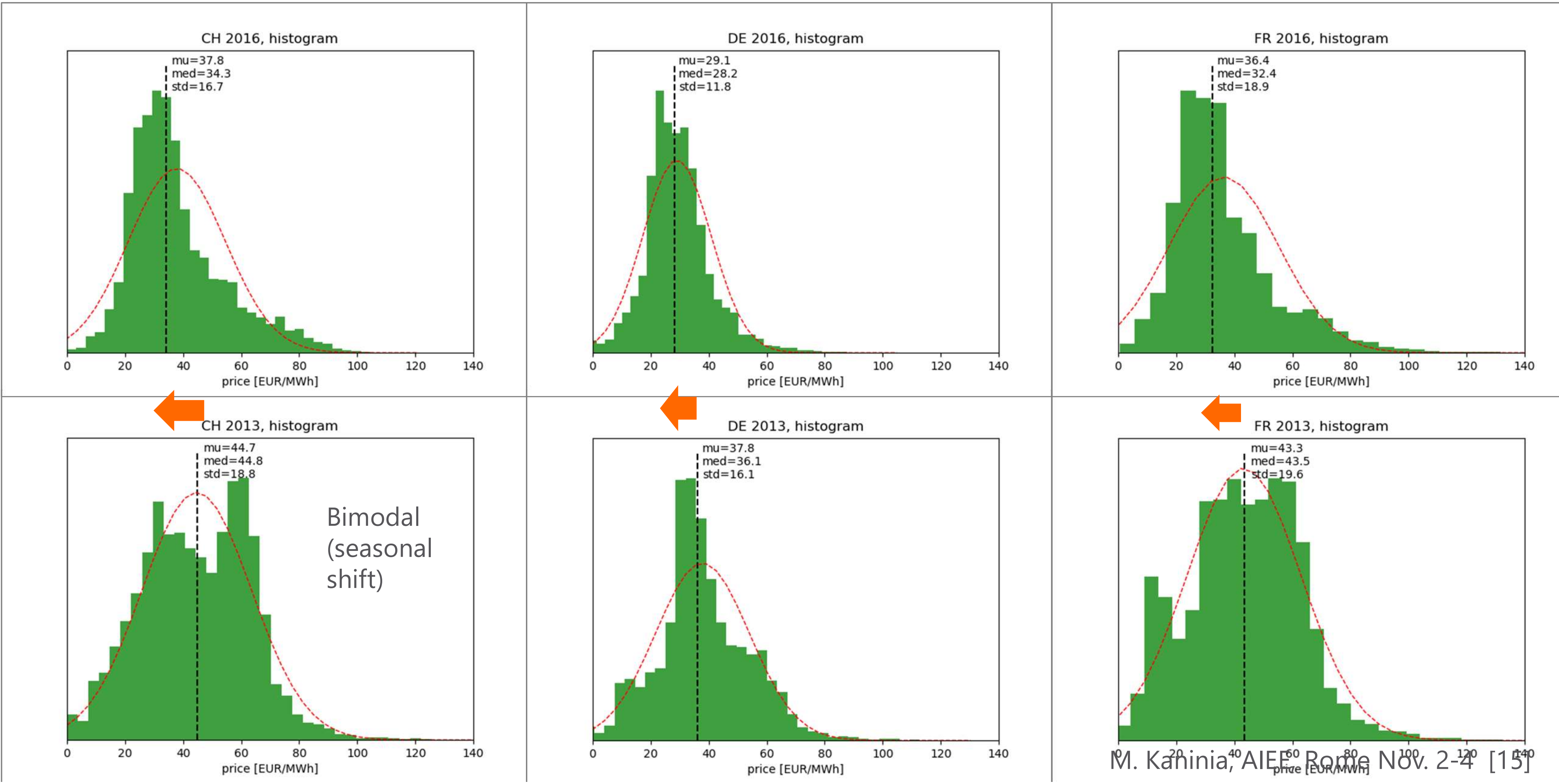
TABLE III
PRICE STATISTICS CH

year	mean	median	std	min	max
2013	44.7	44.8	18.8	0.0	147.7
2014	36.8	36.2	12.8	-13.7	85.8
2015	40.2	40.8	13.2	-11.7	123.5
2016	37.8	34.3	16.8	-45.7	120.9

TABLE IV
HOURS PER YEAR WITH NEGATIVE PRICES

year	CH	FR	DE
2013	0	15	64
2014	15	8	64
2015	9	0	126
2016	24	2	97

Input: Electricity prices: Histograms, 2013, 2016



Methodology: Rolling Horizon

Solving a dynamic optimisation problem as a series of **static** optimisation problems.

For every step i:

- 1. Get initial conditions. The only initial condition is the amount of energy stored Q[i].
- 2. Build model for period [i, i+T), where T is the prediction horizon. Assume perfect foresight for period [i, i+T)
- 3. Obtain optimal solution for period [i, i+T)
- 4. Apply setpoint for time se gment i only, "discard" other setpoints
- 5. Move to next time segment. Update i = i + 1
- 6. Repeat

The optimisation time horizon for each step of the algorithm was empirically fixed at 72 hours.
Any further extension of the look-ahead prediction horizon did not affect the results.
Assuming perfect foresight for 72 hours ahead is optimistic. Stochastic component.

Results – 1: Comparison tables, profits

- Low profitability in energy-market only
- Ideal efficiency (98%), C-values = 0.3, 0.5, 0.6
- Negative IRR
- Assume 10 years lifetime (no degradation), multiply yearly profit by lifetime:
  - Result: maximum estimated profit over entire lifetime < capital costs → **negative IRR**
  - No electrochemical storage technology viable

PROFITS, C=0.30, EFF=0.98

year	CH	FR	DE
2013	12.6	15.3	14.1
2014	9.4	11.3	11.0
2015	8.9	10.8	11.0
2016	7.7	11.5	9.0

PROFITS, C=0.60, EFF=0.98

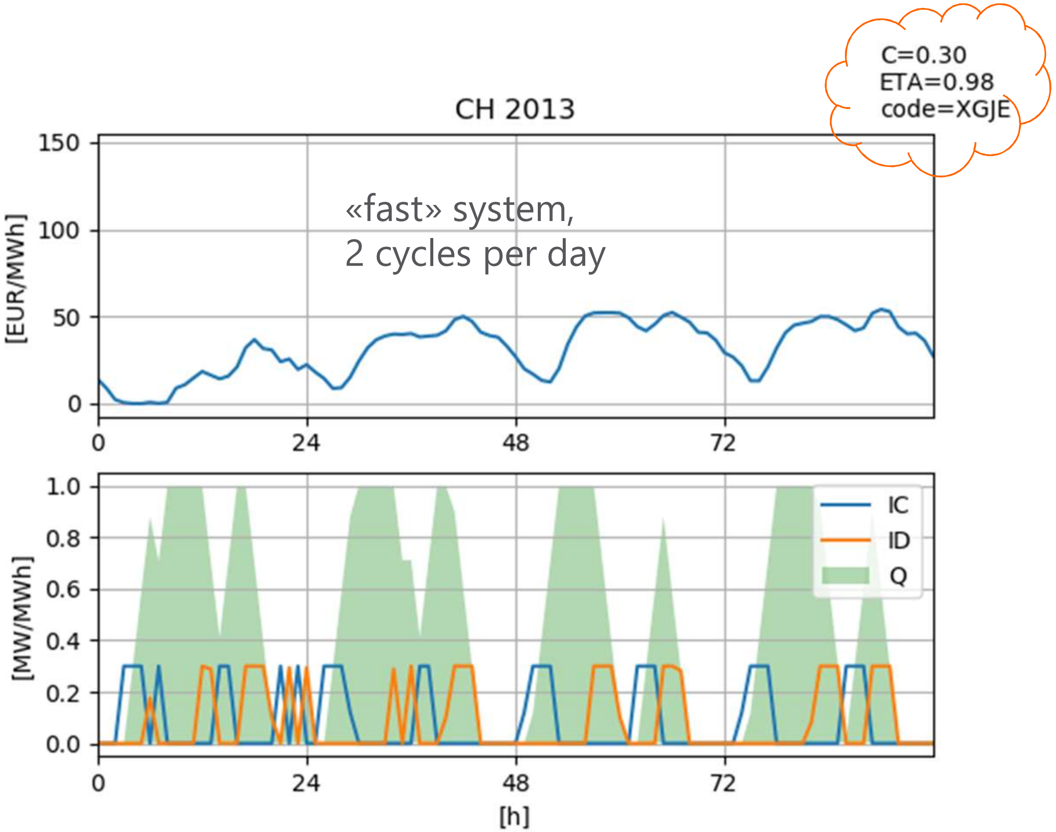
year	CH	FR	DE
2013	14.8	19.1	16.8
2014	10.9	13.9	13.0
2015	10.3	13.2	13.0
2016	9.4	14.3	10.5

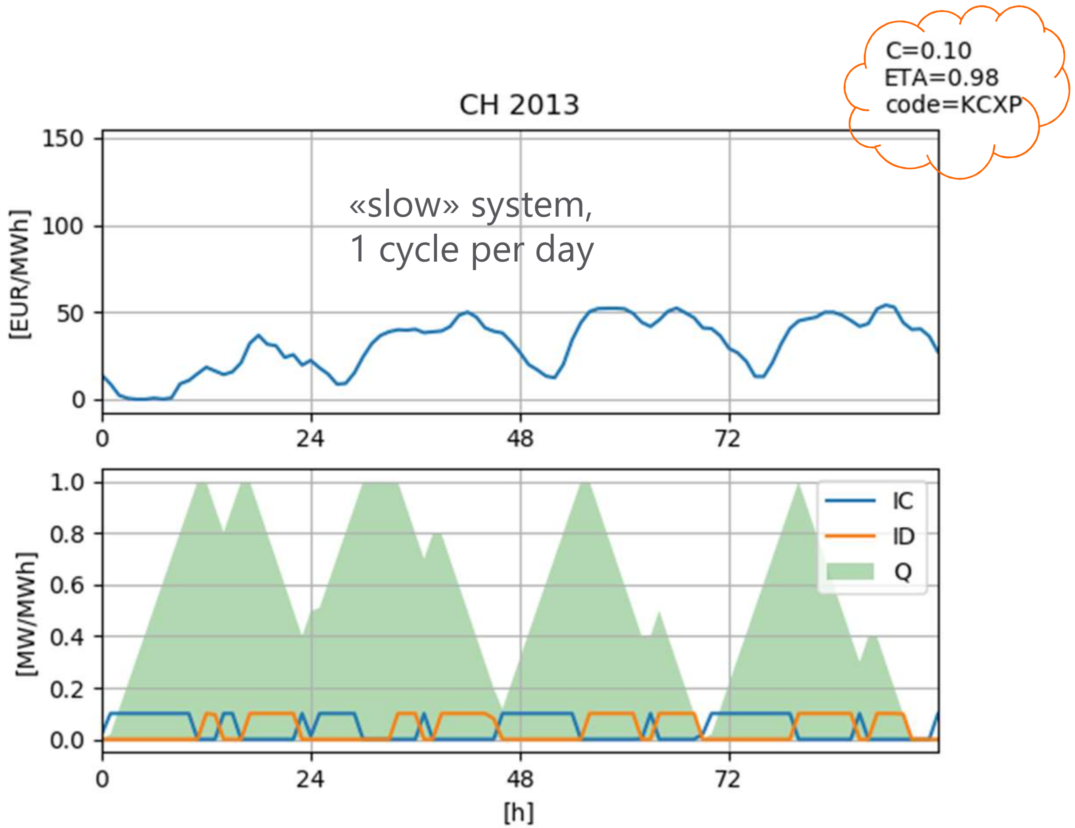
PROFITS, C=0.50, EFF=0.98

year	CH	FR	DE
2013	14.5	18.5	16.4
2014	10.7	13.5	12.7
2015	10.1	12.8	12.7
2016	9.3	13.8	10.3

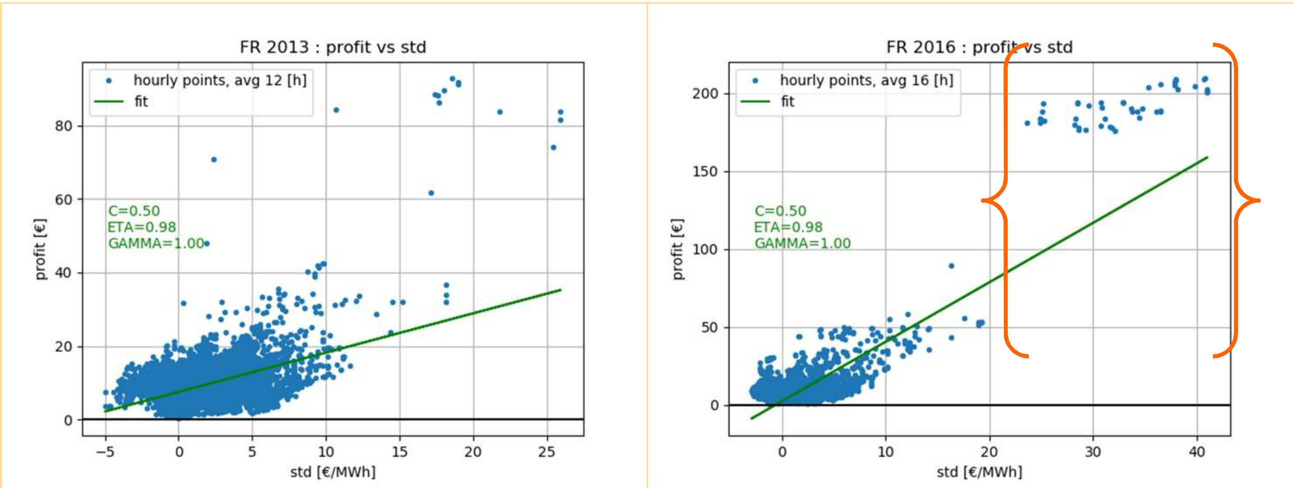
Results – 2: Comparison table, profits

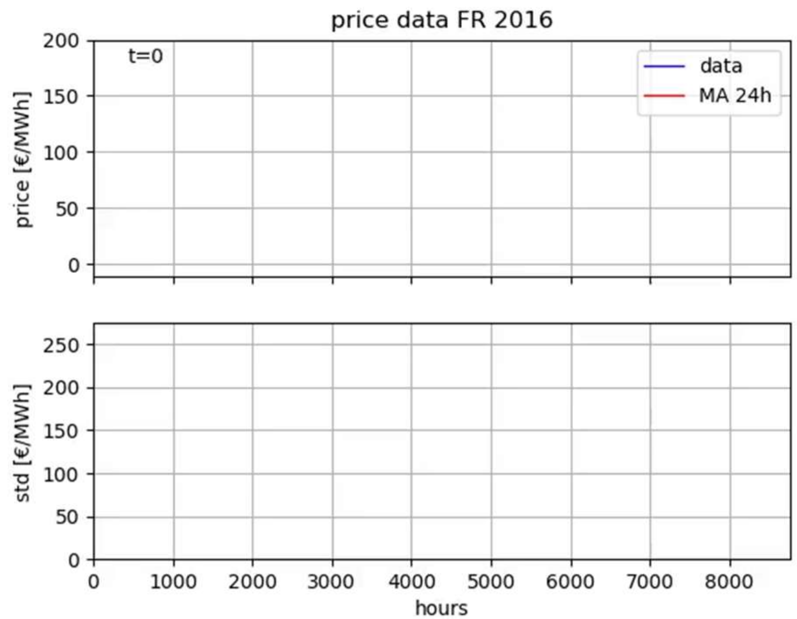
- C-rate: Indicates how fast the storage system can «absorb» fluctuations





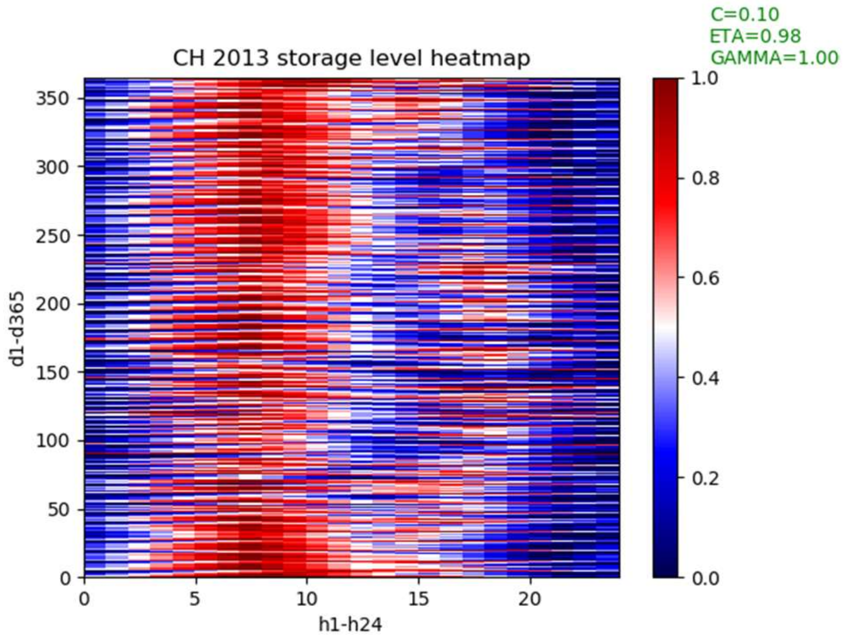
Results - 3: Effect of volatility

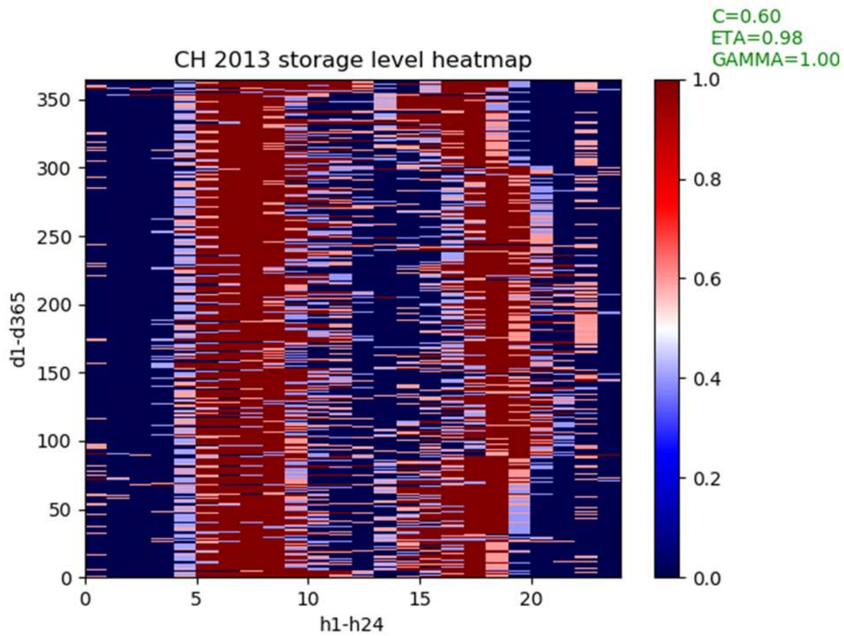




- Extreme-prices events generate large profits
- Large contribution as a percentage
- Not reliable for extrapolating
- An investment decision should be made based on “structural” fluctuation, not on extreme spikes

Results - 4: Optimal dispatch schedule (depicted as heatmap)

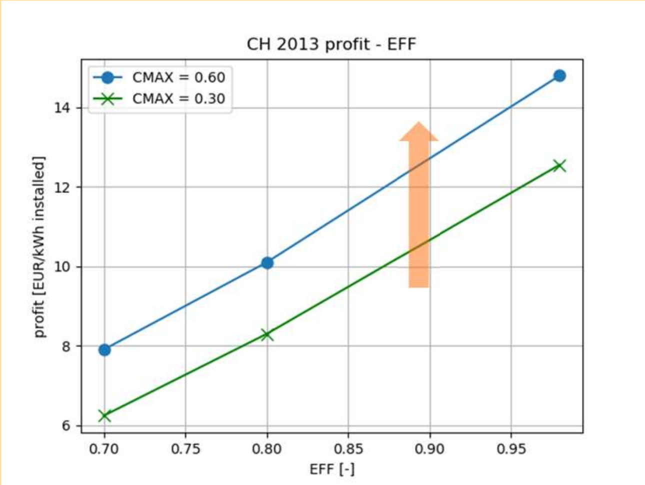


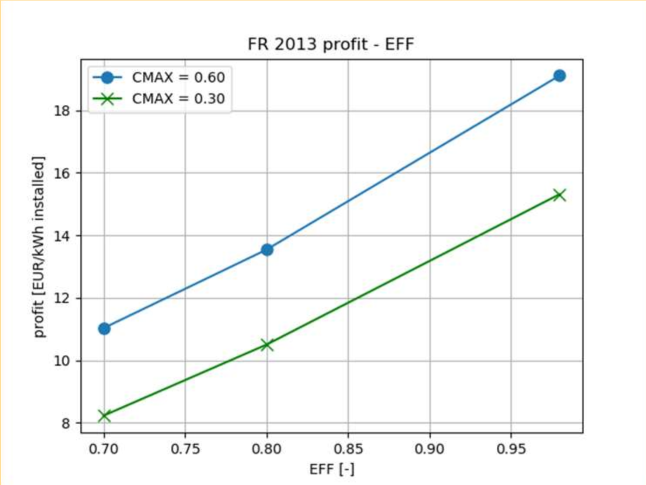


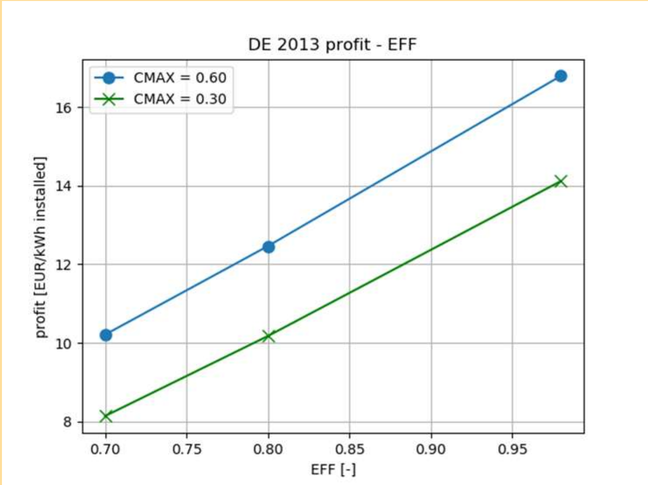
- C-rate determines maximum achievable number of daily cycles

Results - 5: Sensitivity analysis, profit versus **efficiency**

- Roundtrip efficiency on an energy basis



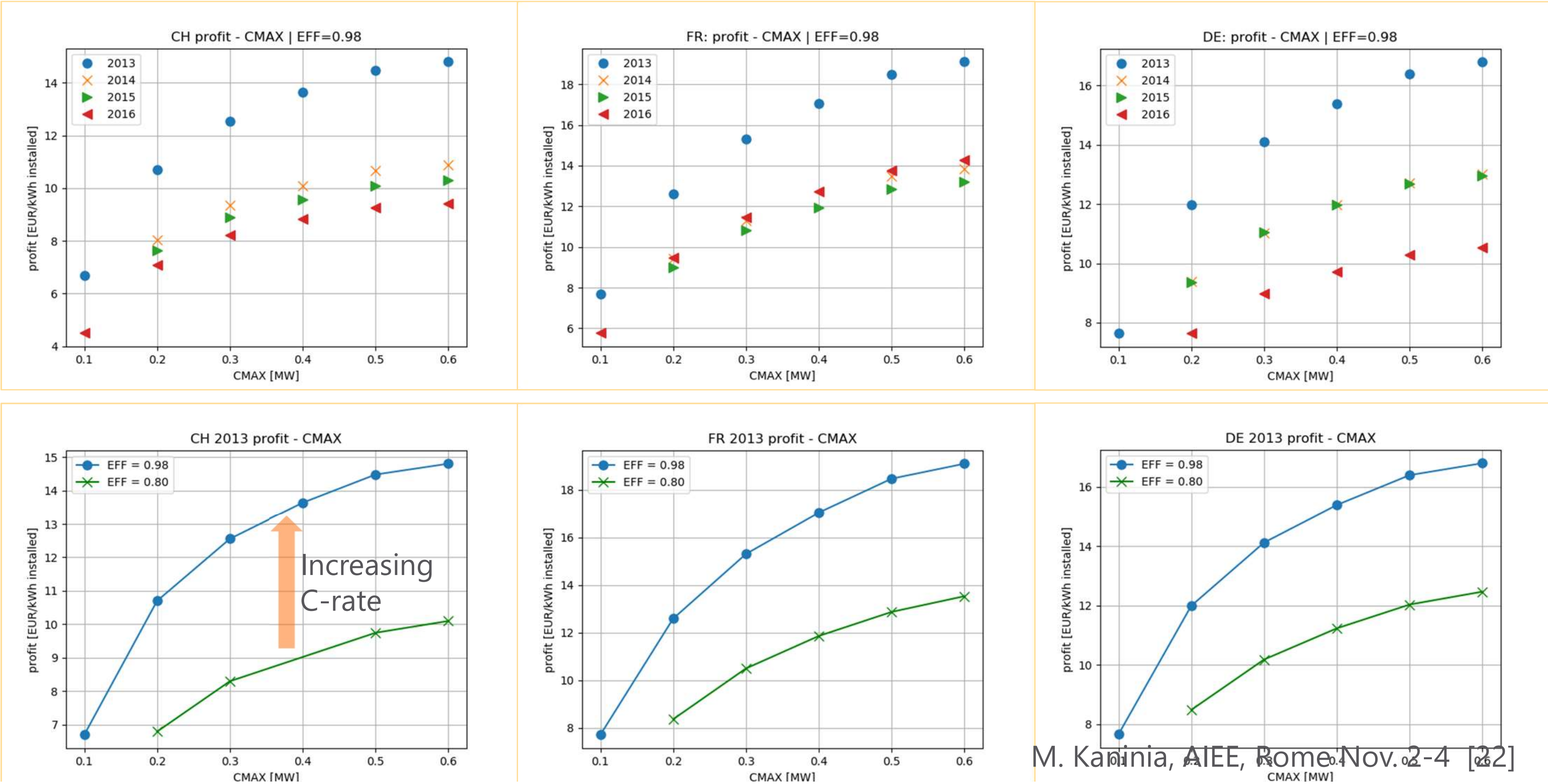




Results - 6: Sensitivity analysis, profit versus **C-rate**

- Decreasing marginal value of C-rate

Ideal efficiency (98%)



Conclusions

What is the maximum profit that a «black-box» ESS can extract via arbitrage from the spot market?

01 ESS not financially viable in EPEX-SPOT zones (years 2013-2016) based on energy-arbitrage only

02 Volatility is beneficial for ESS (price-taker)

03 Maximum calculated yearly profit (ideal ESS): €20/year (FR, 2013)

04 Assume no degradation, lifetime = 10 years (optimistic): Still not competitive to current state-of-the-art