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Estimating photo-voltaic power supply without smart metering infrastructure

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Detecting hidden dependencies in the power grid

- Since 2010, installed capacity of PV power plants is dramatically increasing in the EU (in Germany, 2010: +7GWpeak, 70% increase of installed capacity) [SaintDrenan2011]; PV power provisioning is highly fluctuating!
- Power provisioning = power demand
- Sept 2010: unexpected imbalance of +7GW for several hours. Distribution system operators underestimated the amount of power provided by new PV plants
- In Germany, 75% of all PV power plants are not measured directly [SaintDrenan2011]
- Monitoring stability of the grid state is essential (snapshot provisioning)
- However, SmartMeter infrastructure is not deployed
- Incentives for Demand/response mechanisms should be based on the surplus/shortage of energy available in the grid (i.e., the current/expected price)

Detecting hidden dependencies in the power grid

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Do we have to connect every PV plant to the SmartGrid communication infrastructure?

- The smart grid is often seen to come with huge data transfers
- current perspective: IP networks for data transmissions
- Introduces new threats in terms of security

Problem: currently, the grid is not ready for these kind of transmissions

- techniques like ripple control widely deployed
- amount of data that can be transmitted is limited
  → reduce communication overhead, i.e., by aggregating data
- In general, communication is one-way only
  → two-way communication required

Detecting hidden dependencies in the power grid

Challenge: Detect hidden dependencies within PV grid data

- reduce communication overhead
- Cooperation with local energy provider: analyze grid data of Power plants, in particular photovoltaic power plants
- Tool: "Approximate Buchberger-Möller Algorithm" [Heldt2009] [Kreuzer2010]
  - Aims to find a formula that describes polynomial dependencies between data
  - The algorithm can even cope with missing and inaccurate values

Detecting hidden dependencies in the power grid

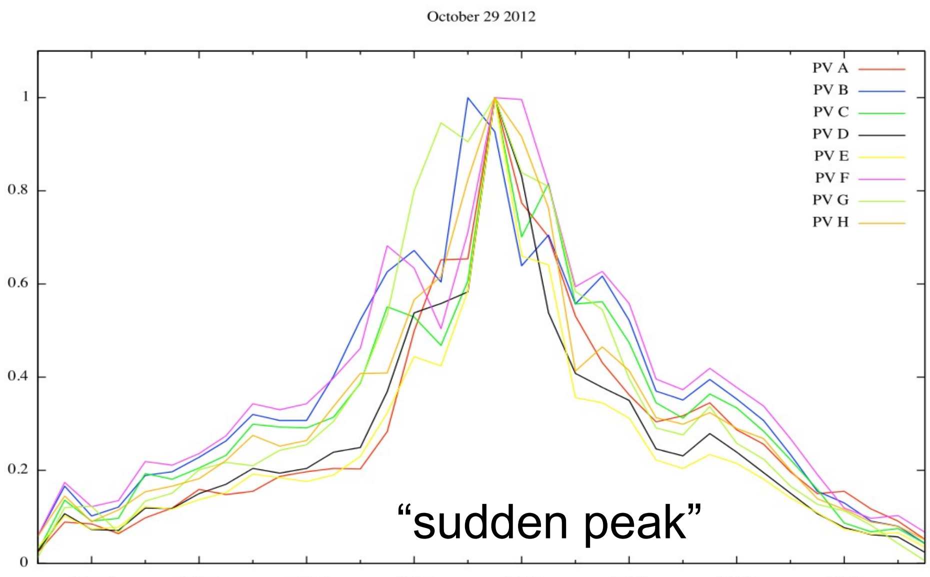
Is it possible to derive overall power provisioning of all PV plants based on a **subset** of these plants (i.e., the plants that can be directly measured?)

- Therefore, a **grid-specific formula** is derived for each energy provider.
- Overall PV grid status can then be derived by simply inserting current data of the **subset** of PV plants into the formula

→ #SmartMeters that have to be deployed can be reduced

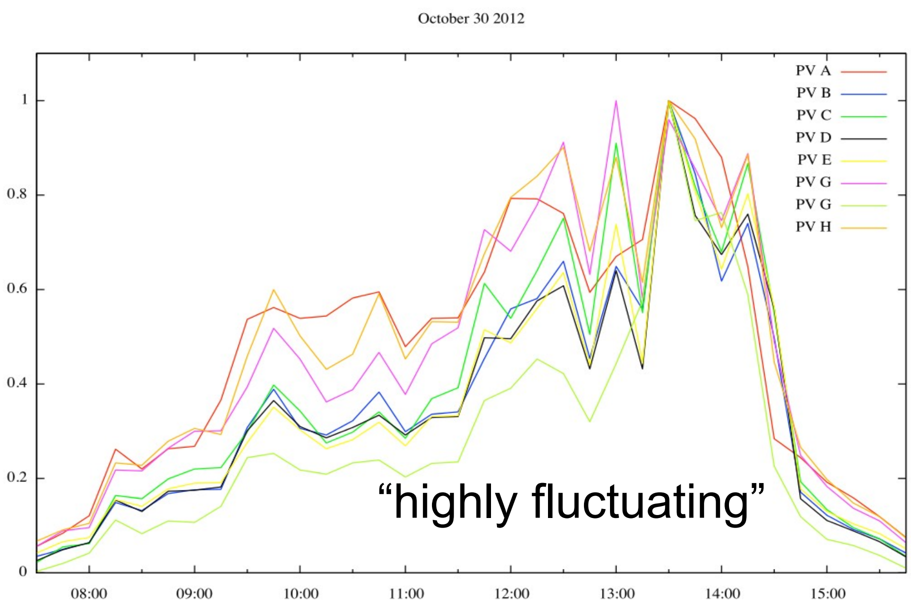
→ no extra costs in terms of communication

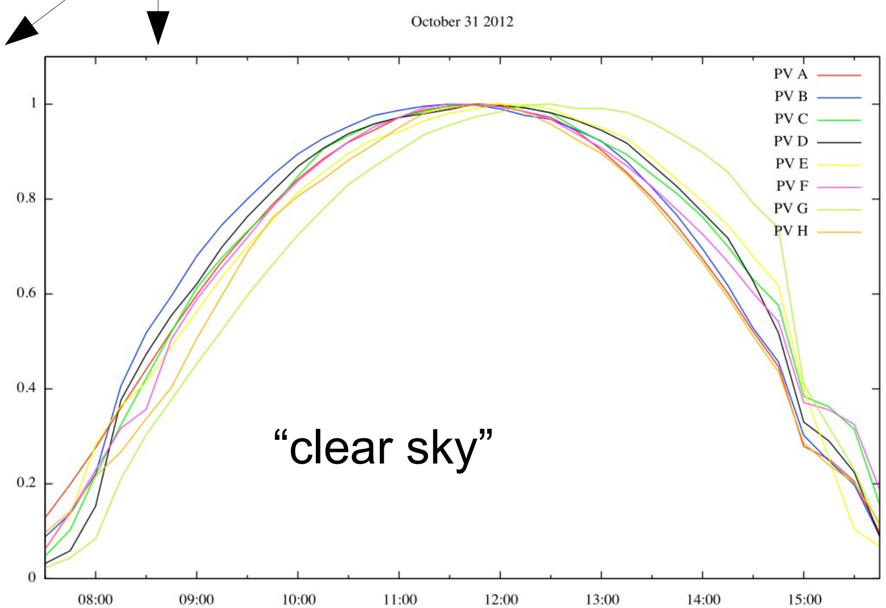
Training & validation set



Day 1: training set

Days 2 and 3: validation set

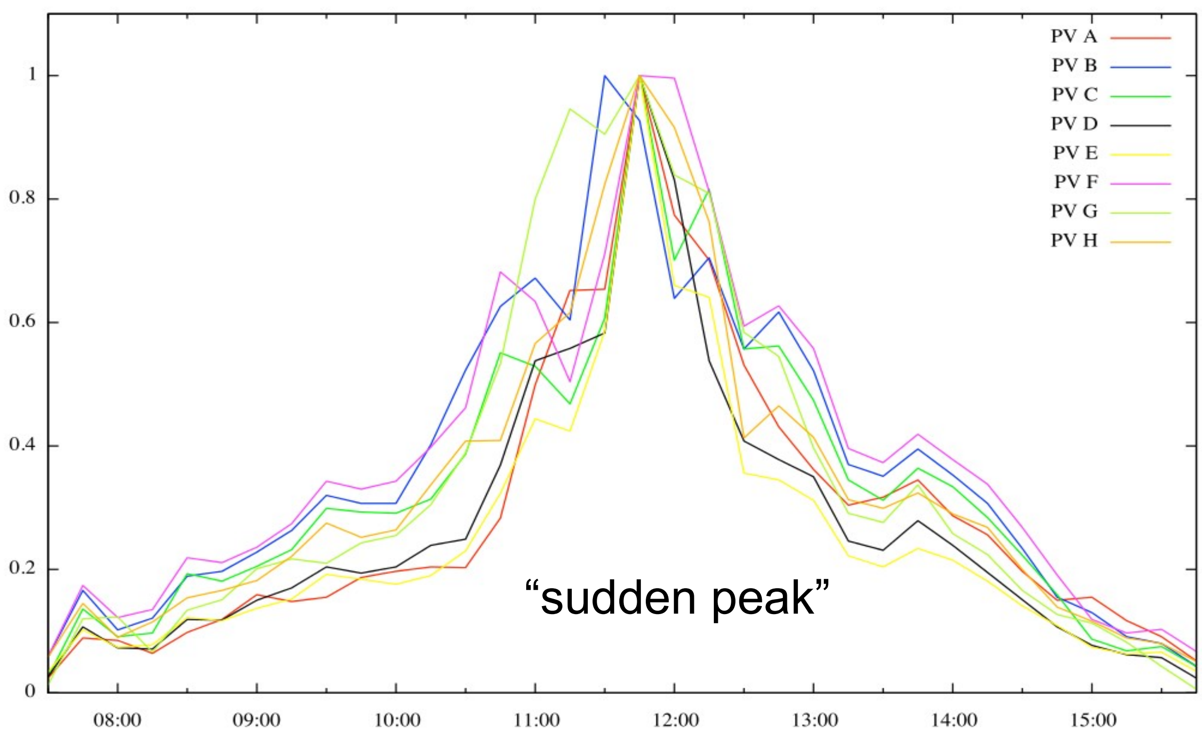




Training & validation set

Day 1: training set

October 29 2012



One of the formulas derived:

$$f_F = -1.04x_Ax_B + 0.62x_C^2 + 0.40x_G^2 - 1.2x_Bx_G - 1.38x_Cx_H - 0.81x_Gx_H + 3.31x_H^2$$
$$+ 0.37x_A + 1.43x_B + 0.81x_C - 0.06x_G - 1.52x_H + 0.02 \in \mathbb{R}[x_A, x_B, x_C, x_G, x_H]$$

Methodology

1. Data selection:
Divide data into two sets, a **training set** and a **validation set**. In our case, we took the data of one day for training and the other two days for evaluation.

2. Target selection:
Divide the set of PV plants (A,B,C,D,E,F,G,H) into two groups, a group of **source data** (A,B,C,G,H) that will provide the input data X and a group of **target data** (D,E,F).

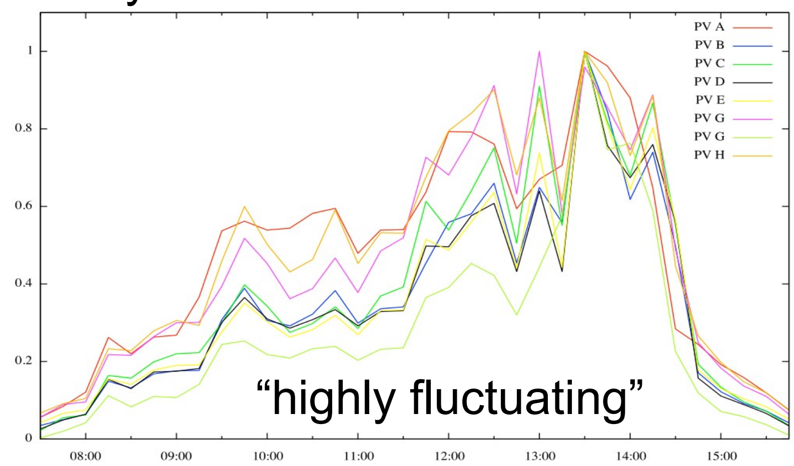
3. Preprocessing:
Filtering and normalization. We removed the values for those times, where the PV plants did not produce any energy.

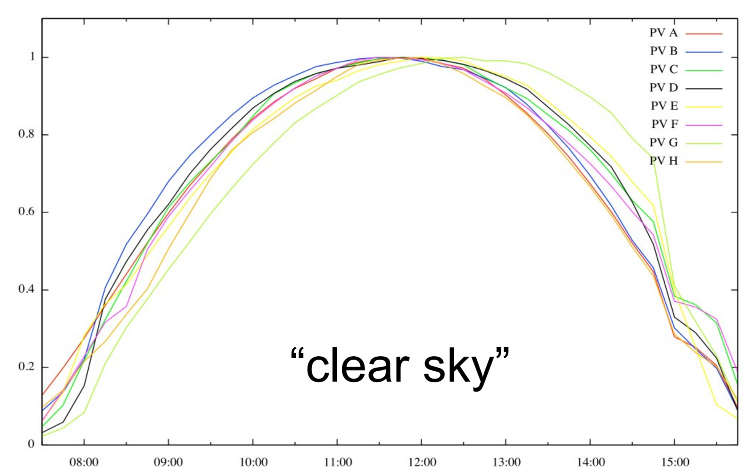
4. Model building:
Use the training data as input for the extended ABM and obtain a set of polynomials G, the set of model candidates.

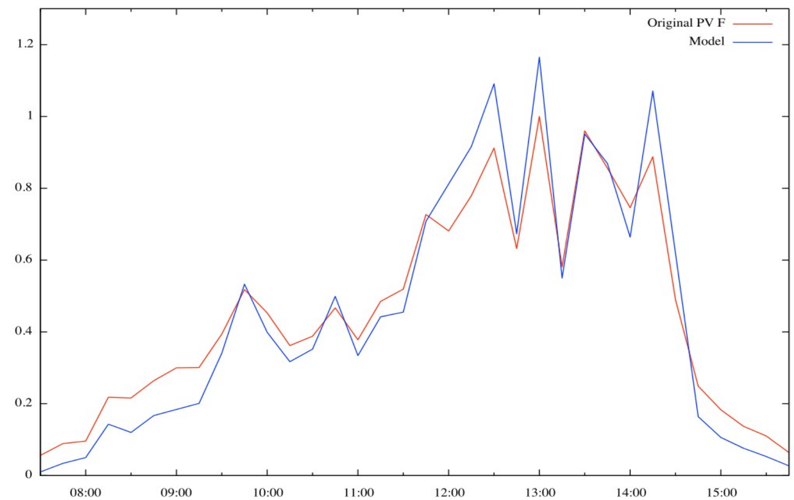
5. Model selection:
Using the validation source data, evaluate each polynomial and compute its residual error with respect to the validation target. Select the polynomial with the least residual error.

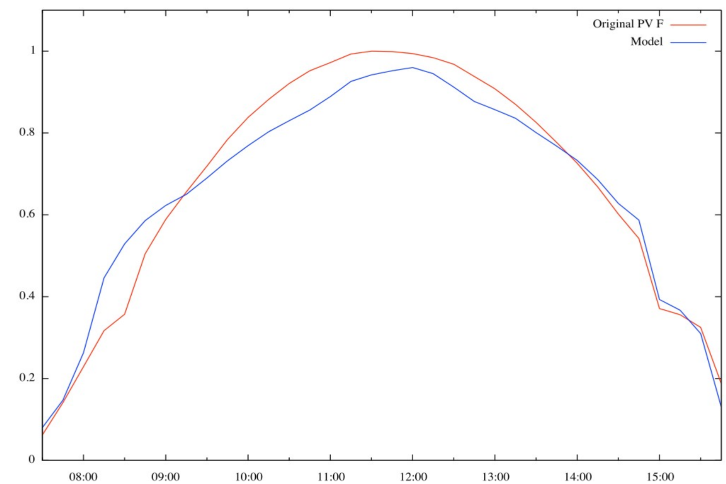
Results

Days 2 and 3: validation set









Results

All $\binom{8}{m}$ combinations were tested. Each row contains the results of modeling *m* PV stations in terms of the remaining $8 - m$ PV stations.

m	**Best error**	**Avg. # models**	**Avg. mean error**	**Avg. best error**
1	0.21	56.0 (20.8)	1.7 (3.7)	4.4 (8.0)
2	0.89	47.6 (15.0)	2.8 (6.0)	11.7 (32.3)
3	1.54	36.6 (10.6)	4.5 (10.7)	30.3 (140.4)
4	2.28	25.1 (6.2)	12.5 (59.9)	105.4 (901.0)
5	4.77	15.8 (3.3)	161.8 (1456.6)	1354.7 (13767.4)

Conclusion & Future Work

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- First results show that there are interdependencies between power provisioning patterns
- Snapshot provisioning
  - SmartGrid infrastructure requirements can be reduced
  - No knowledge of PV plant parameters needed
- Power flow analysis, taking hidden dependencies into account
- Apply results to power provisioning forecast approaches
  - analysis purely based on power provisioning patterns obtained from PV plants
  - does not depend on any other, additional data
    no information on weather conditions, irradiation, geographical locations etc. are required

References

- [SaintDrenan2011] Saint-Drenan, Y. M., S. Bofinger, B. Ernst, T. Landgraf, and K. Rohrig. “Regional Nowcasting of the Solar Power Production with PV-Plant Measurements and Sattelite Images.” In Proc. ISES Solar World Congress, 2011.

- [Heldt2009] Daniel Heldt, Martin Kreuzer, Sebastian Pokutta, Hennie Poulisse: Approximate computation of zero-dimensional polynomial ideals. J. Symb. Comput. (JSC) 44(11):1566-1591 (2009)

- [Kreuzer2010] Kreuzer, M., and H. Poulisse. “Subideal Border Bases.” Mathematics of Computation 80, no. 274 (2010): 1135.