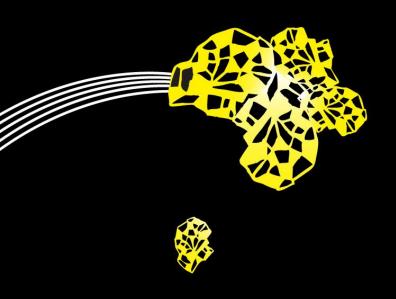
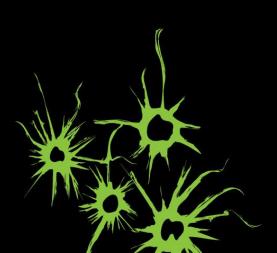
UNIVERSITY OF TWENTE.

PV AS AN ELEMENT IN A LARGER (SMART) ENERGY SYSTEM

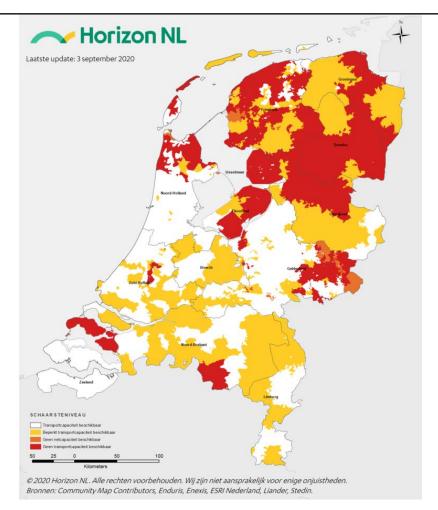
GERWIN HOOGSTEEN





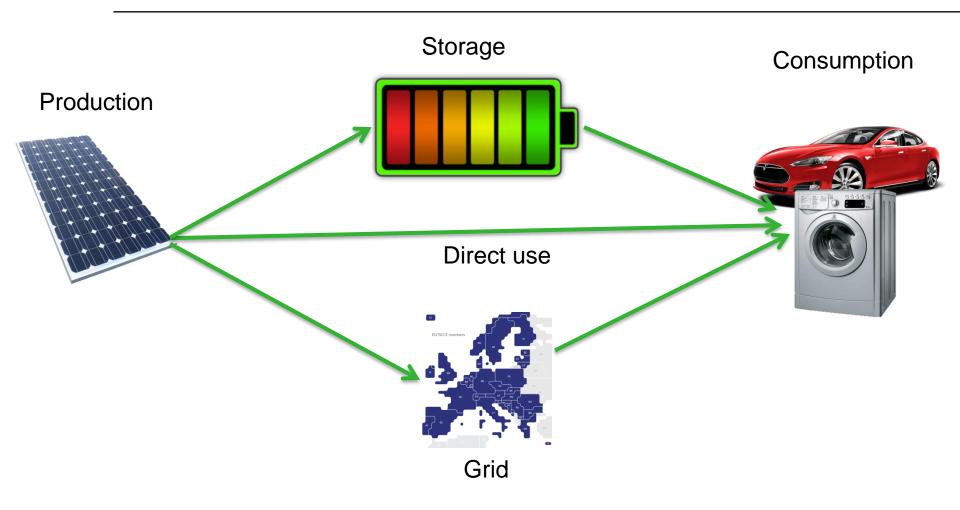
NEED FOR SMARTNESS

CONGESTED GRIDS IN THE NETHERLANDS



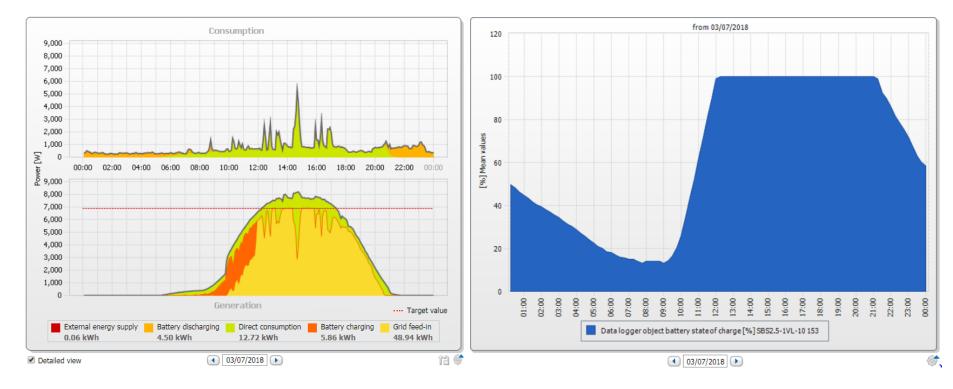
NEED FOR SMARTNESS

KEEP ENERGY LOCALLY TO AVOID GRID CONGESTION



NEED FOR SMARTNESS HOW TO CONTROL THE BATTERY STORAGE

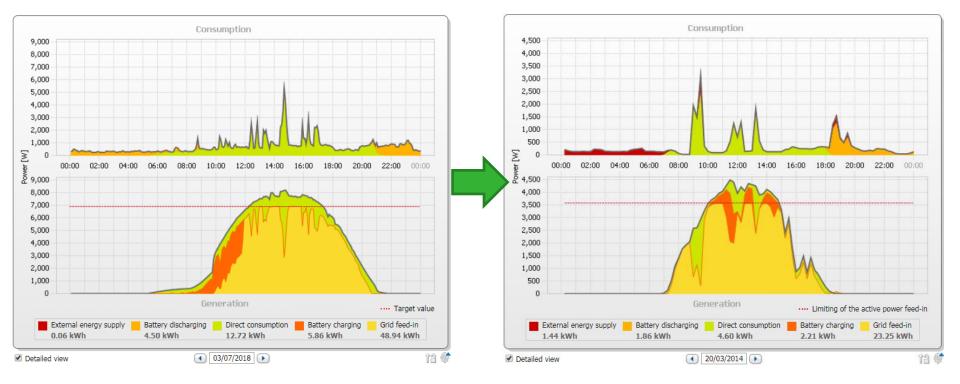
Simple "greedy" control strategies do not fit limited storage capacity



Source sma-sunny.com

NEED FOR SMARTNESS HOW TO CONTROL THE BATTERY STORAGE

Maximize storage utilization, minimize curtailment



Source sma-sunny.com

NEED FOR SMARTNESS

HOW TO CONTROL THE BATTERY STORAGE

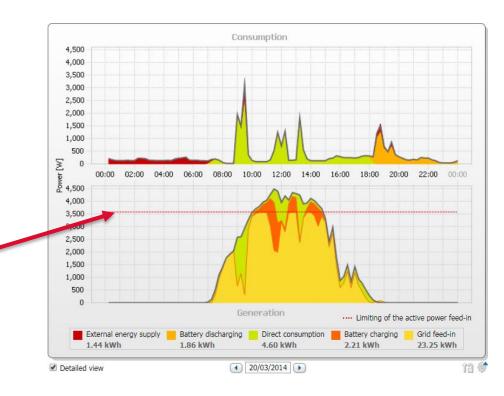
Benefits:

- Less curtailment, More renewable energy
- Avoid grid congestion
- Maximize self-consumption

Question:

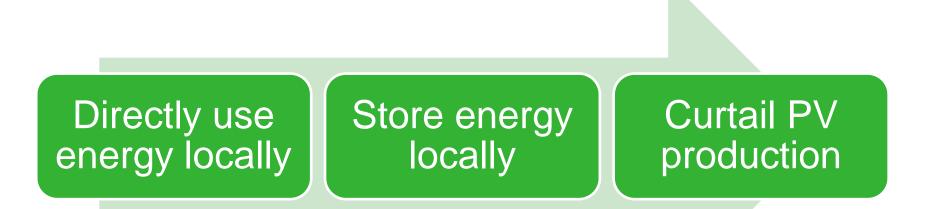
How to determine the level?

The lower the better But not too low!



Source sma-sunny.com

ENERGY MANAGEMENT



Main idea: Avoid grid congestion by utilizing energy locally!

- 1. Use demand response to match production and consumption
- 2. Use battery storage to maximize self-consumption
- 3. Only curtail if really possible

Requires clever use of battery storage.

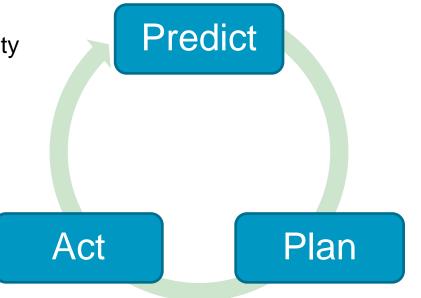
ENERGY MAANGEMENT

TRIANA CONCEPT

- Control actions affect future flexibility
- Thus, act based on the future

Model Predictive Control

- Shape future energy profile
- Make trade-offs between
 - Short-term and long-term



ENERGY MAANGEMENT

ROBUST CONTROL

Uncertainty in PV power production prediction

- The height of the power peaks
- The timing of these peaks

Total energy better predictable?

- (More) robust to above problems
- Control storage, PV and other devices as peaks happen
- Avoid need for complex models
 - Weather prediction errors > PV generation model errors

ENERGY MANAGEMENT

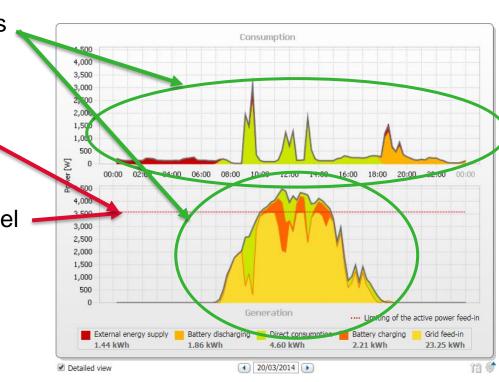
CONTROL STEPS

Prediction and planning

- 1. Predict load and generation profiles
- 2. Optimize storage profile
- 3. Determine the power level

Real-time control

- 1. Charge/discharge battery using level
- 2. Curtail PV if needed

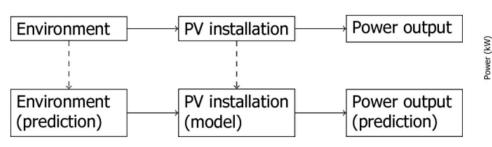


ENERGY MANAGEMENT

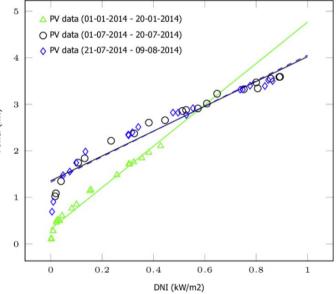
HOW TO PREDICT PV

PV predictions using multivariate linear regression

- Only irradiance data and PV output data
- No need for panel type, angles, etc
- Limited historical data, adapts to seasons

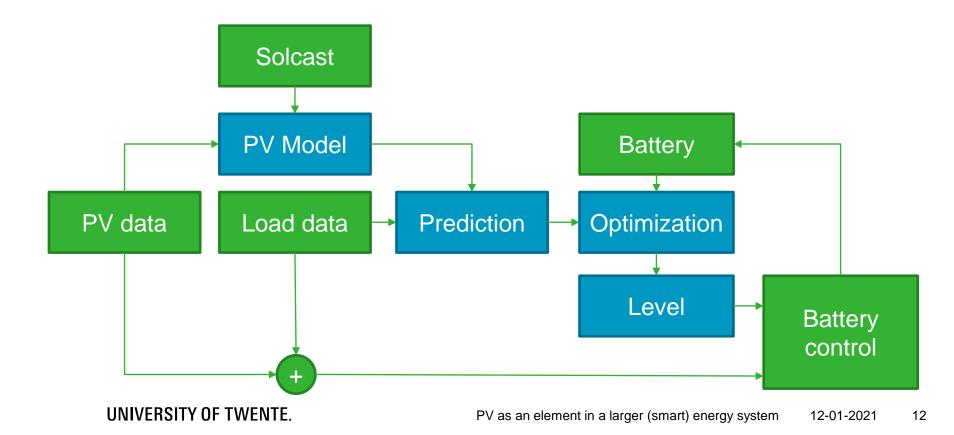


M.E.T. Gerards and J.L. Hurink, "PV predictions made easy: flexibility through simplicity," CIRED 2019 Conference Proceedings, AIM, Madrid, Spain, 2019

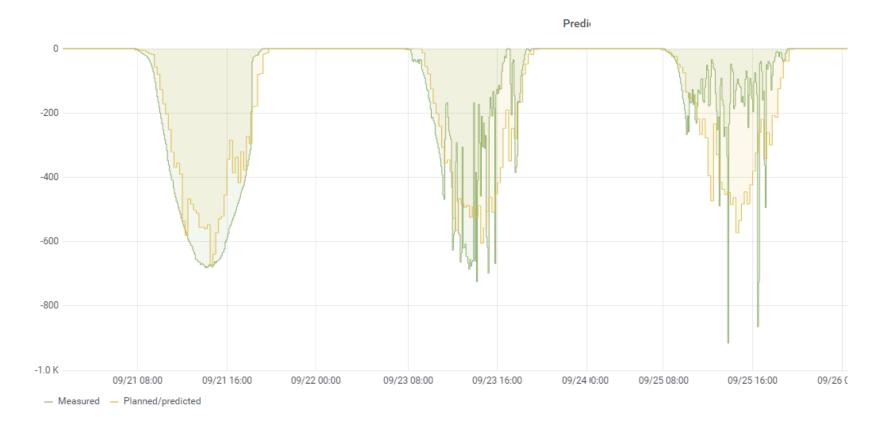


RESULTS ROBUST CONTROL

• Life test with over a year, but with a virtual battery



RESULTS EXPERIENCES



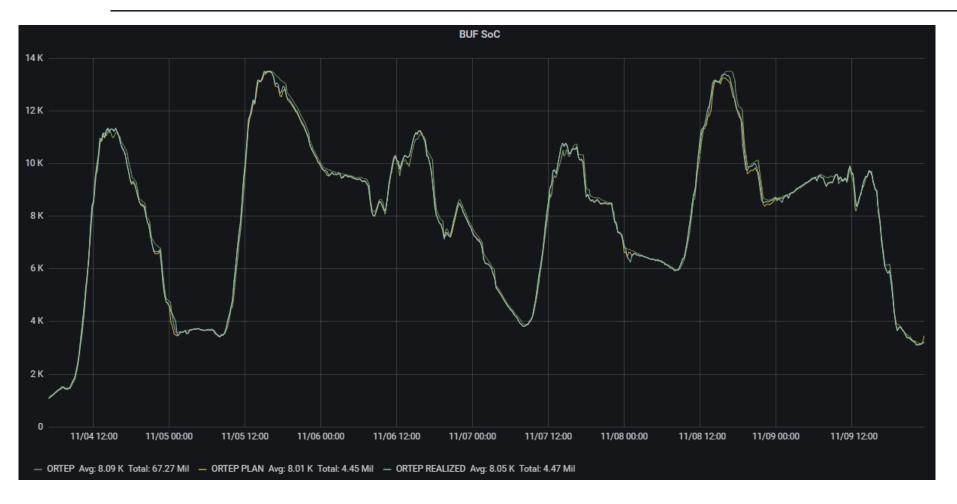
RESULTS WITHOUT CONTROL



RESULTS WITH CONTROL



RESULTS BATTERY SOC



RESULTS OVERALL RESULTS

- Reduced stress on the grid, reduced peaks
- Energy import/export not too far off Greedy (optimal)

$$\frac{\sum_{t=1}^{T} measurement_t^2}{T}$$

	Smart	Greedy	No Bat.
Euclidean Distance	162078	260488	414666
1% percentile [W]	-114	-61	-665
5% percentile [W]	-57	0	-459
95% percentile [W]	190	308	365
99% percentile [W]	318	483	935
Imported electricity [kWh]	657	613	1089
Exported electricity [KWh]	76	34	503

RESULTS PV PREDICTIONS

Deviation from the predicted solar power (15 min intervals)

	1 st percentile	5 th p.tile	95 th p.tile	99 th p.tile
Day-ahead deviation [W]	-421	-190	384	581
Intraday deviation [W]	-345	-141	284	447
Day-ahead deviation % of PV capacity	-46.0	-20.7	42.0	63.4
Intraday deviation % of PV capacity	-37.7	-15.4	31.0	48.8

Deviation from the predicted solar energy (daily)

	1 st percentile	5 th p.tile	95 th p.tile	99 th p.tile
Day-ahead deviation [kWh]	-1.78	-0.73	2.48	3.21
Intraday deviation [kWh]	-0.82	-0.36	1.44	7.85
Day-ahead deviation % of PV capacity	-21.0	-8.7	29.3	38.1
Intraday deviation % of PV capacity	-9.7	-4.2	17.0	21.9

CONCLUSION

- Design control with limited flexibiliy in mind
- Ensure robustness to prediction errors
- Clever control + PV generation can help the grid!

Future work:

- Track and fix the observed bias in PV predictions
- Utilize machine learning in a hybrid, efficient, manner

QUESTIONS

