Optimization-Based Control of a Battery Electric Storage System in an Energy Community under Uncertainty

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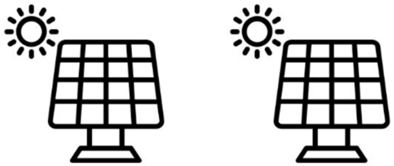
Introduction

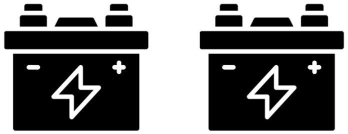
Achieving **a Net Zero Carbon Economy**

requires:

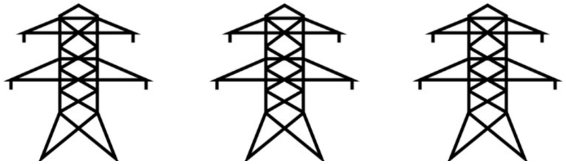
Much more renewables



Much more storage



Much more grid infrastructure



Introduction

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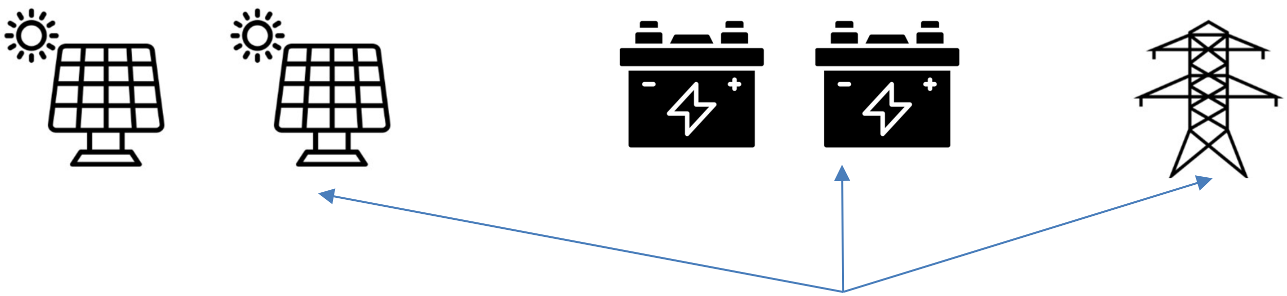
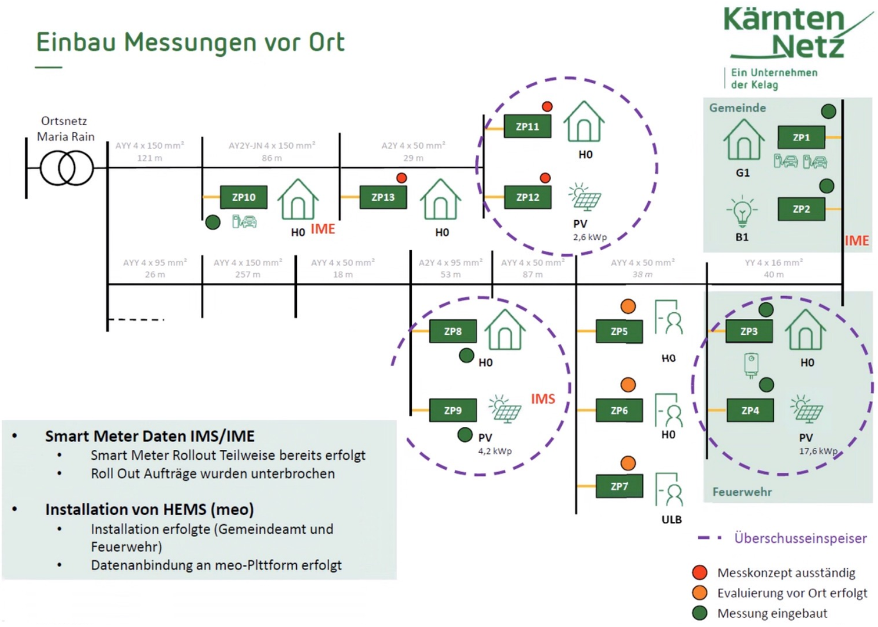


(+Energy Management*)

***Software solutions to efficiently manage energy at a local level (household, office, microgrid)**

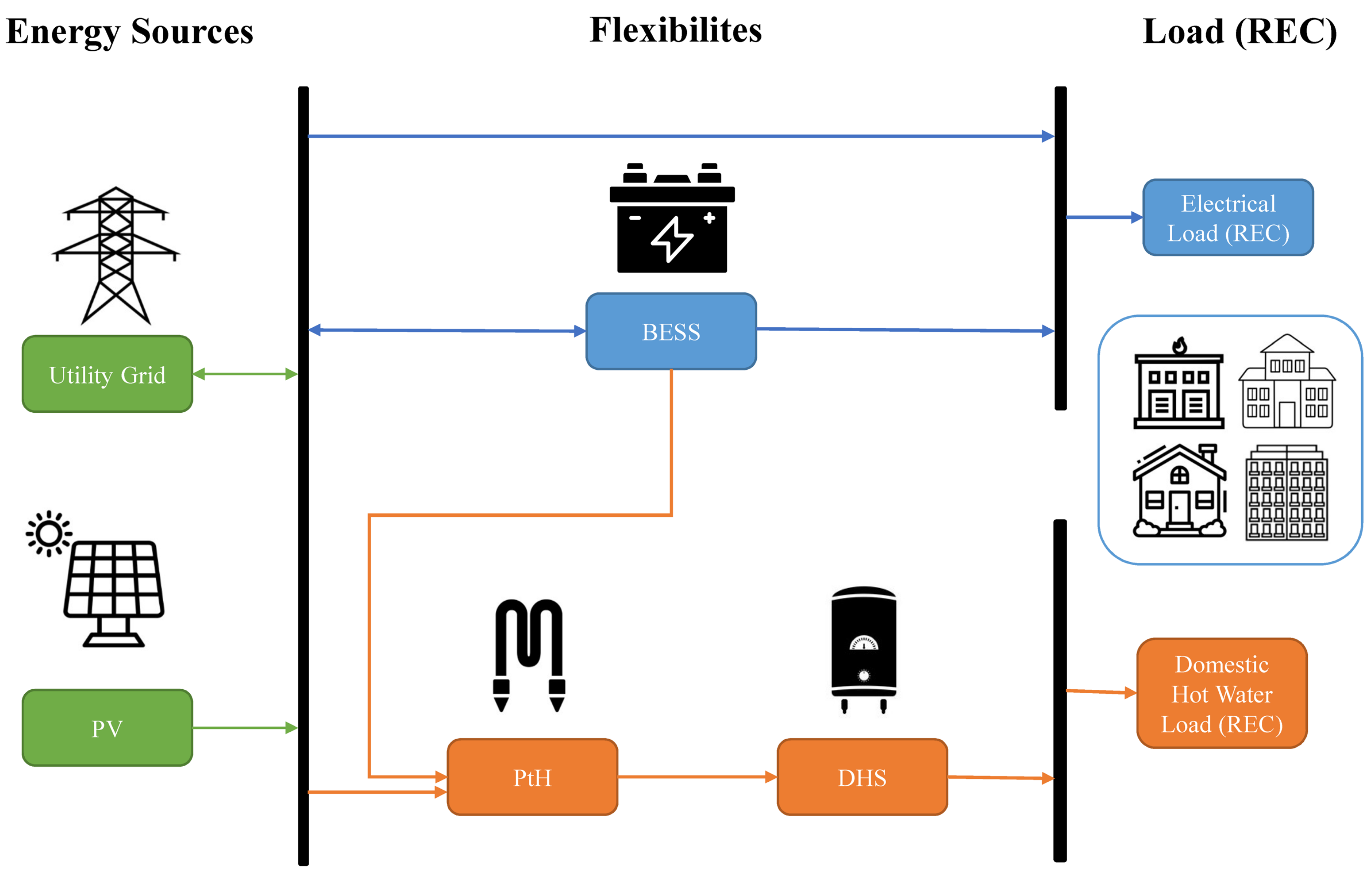
Introduction

- Maria Rain, Kärnten (AT): 3 PV Systems, 9 Homes with Battery System, fire-fighter station with a lot of need for hot water
- Investments are already done; see Cosic et al. (don't consider investment costs of technologies)



Energy System

GOAL :Satisfy the energy demand in Maria Rain at the lowest possible cost (or CO2 emissions).

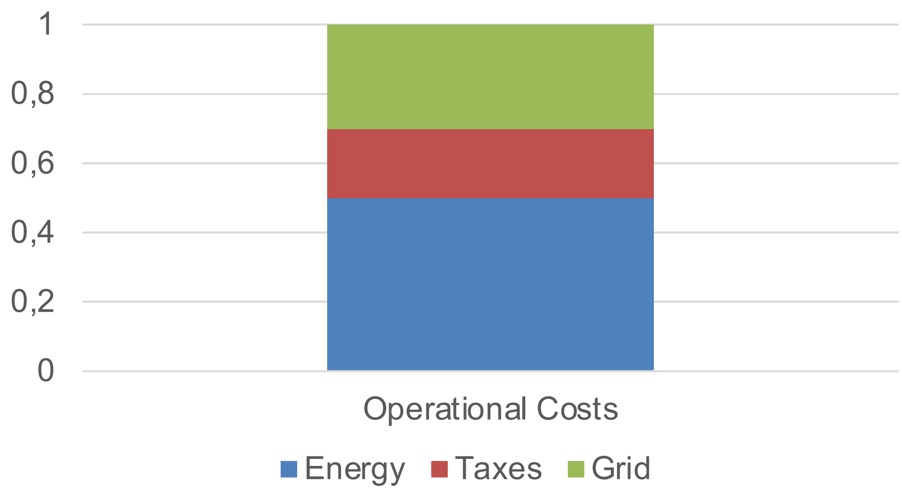


Microgrids vs. Energy Communities

Microgrids
- **Technical** Framework
- Grid-connected / Islanded
- Cluster of interconnected loads
- Microgrid controller (hardware+software)
- **Benefits**:
  1) Reduced Energy Costs

+

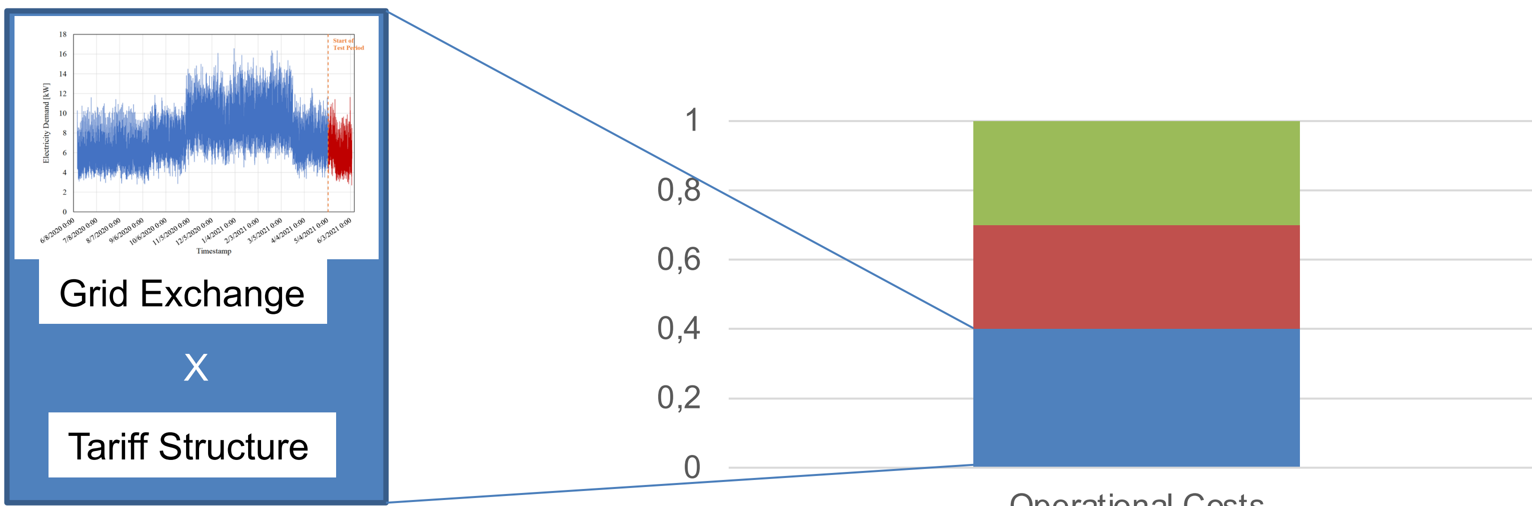
Energy Communities
- **Legal** Framework
- EU Clean Energy Package
- Activate citizen participation
- For billing only (contractual)
- **Benefits [1]**:
  1) Reduced Grid Fee
  2) Reduced Taxes



[1] https://energiegemeinschaften.gv.at/vorteile-von-energiegemeinschaften/

Electricity Tariffs (Energy Costs)

- The energy costs are typically calculated by multiplying the **a rate (e.g., c€/kWh)** with a quantity of energy.
- There are 4 major electricity tariff structures:
  1) Flat Tariff – constant rate [c€/kWh] over the whole contractual period
  2) Time-of-Use – variable rate [c€/kWh] depending on the time of the day; or type of day
  3) Demand Charge – an additional power rate [€/kW] penalty multiplied with the highest peak demand; especially prevalent in industry (USA)
  4) Real-time-Pricing – Spot market prices are passed down to the consumer; see Norway



Energy Costs

Methods

Economic Model Predictive Control

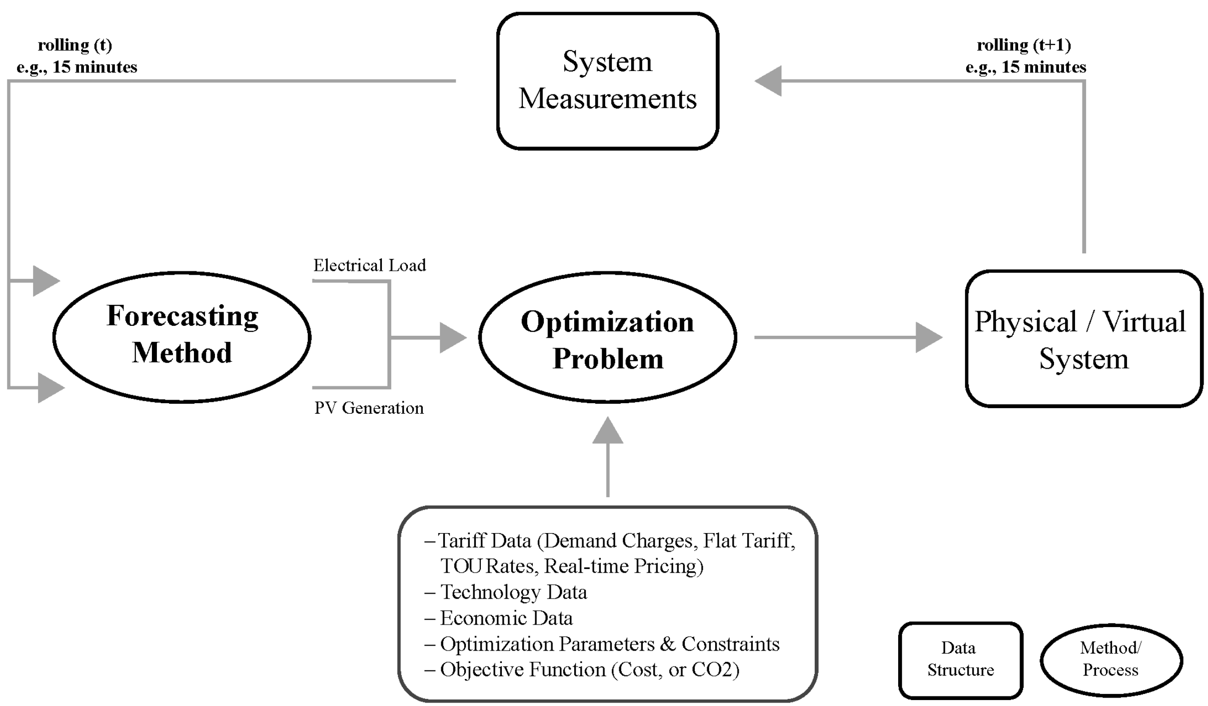
1. Model + Predictive + Control in loop:

- **Model** of the System: State and Input Variables
- **Predict** the future state variables of the System Model
- **Control** by updating the state variable of the real system

TBC

$$h_\theta(X_j) = y_j$$

$$E_{j=1;t+1}^{stored} = E_{j=0;t+1}^{stored} \quad \forall\, t > 0$$

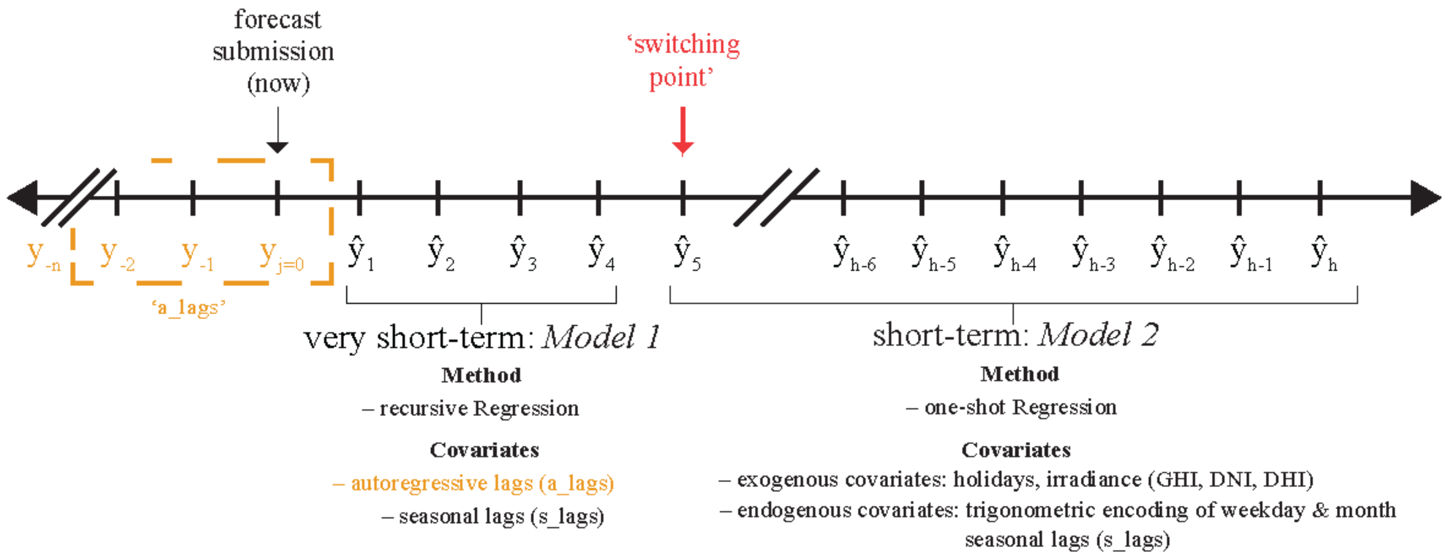


Predictive – Multi-Step Forecasting

- Features vary in importance over the forecast horizon:
- Division of the forecast horizon **h** into *very short-term* and *short-term*
- Learning a separate model for those two horizons, and concatenating their output

$$s = \underset{s}{\operatorname{argmin}}\left[\mathrm{ES}_{1:s}^{Model\ 1};\ \mathrm{ES}_{s:h}^{Model\ 2}\right]$$

$$\hat{y}_{1:h} = \left[\hat{y}_{1:s}^{Model\ 1};\ \hat{y}_{s:h}^{Model\ 2}\right]$$



Model – System Optimization

- At each t, the following cost minimization is solved as a Multi-Integer Linear Program with an index of **j**

OF

$$C = \sum_{j=0}^{h}\left(C_j^{utility} - P_j^{sales}\right) = \sum_{j=0}^{h}\left(E_j^{grid} * s_j^{purchase} - \left(E_j^{exportBESS} + E_j^{exportPV}\right) * s_j^{sales}\right)$$

Subject to:

Electrical Energy Balance Constraint

$$E_j^{grid} + E_j^{onsitePV} + E_j^{onsiteBESS} = E_j^{load} + E_j^{BESSfor} + E_j^{PtH}$$

Heat Energy Balance Constraint

$$H_j^{PtH} + H_j^{DHSfrom} = H_j^{load} + H_j^{DHSfor}$$

“Continuity” Constraints

$$E_j^{in} \leq E_j^{XOR} * N$$

$$E_j^{stored} = \left(Cap_{ES} * E_{init}^{stored}\right) + E_j^{in} + E_j^{out} - E_j^{loss} \qquad t = 0$$

$$E_j^{out} \leq \left(1 - E_j^{XOR}\right) * N$$

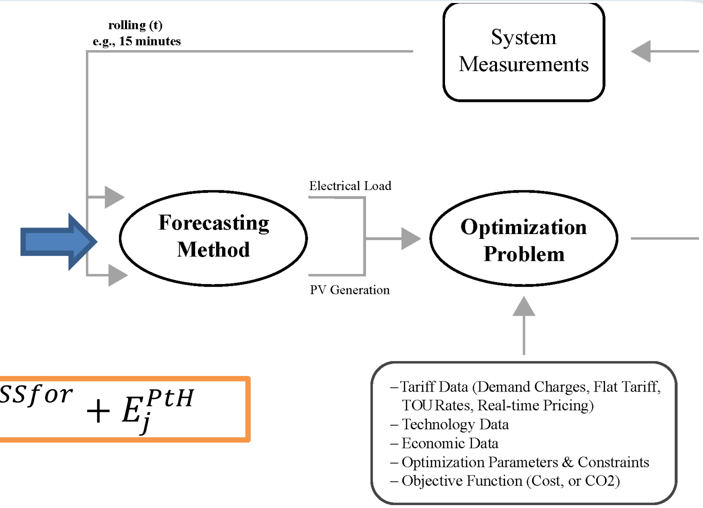
$$E_j^{stored} = E_{j-1}^{stored} + E_j^{in} + E_j^{out} - E_j^{loss} \qquad \forall t > 0$$

Model – Input Predictions as Parameters

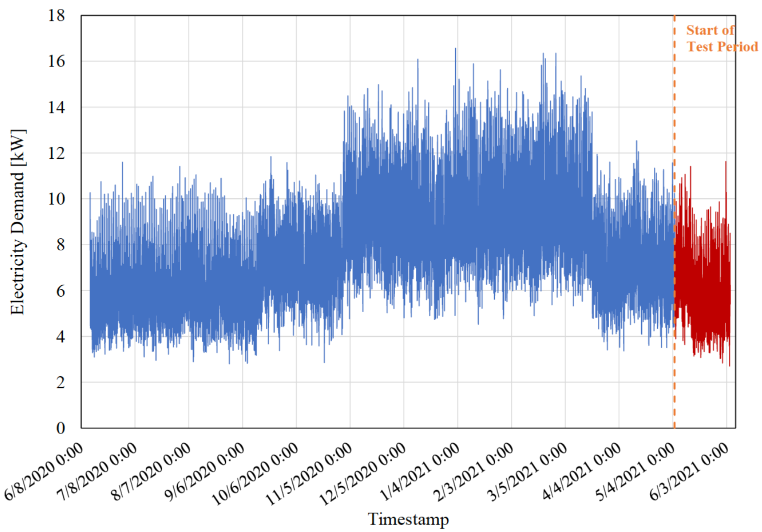
- Forecasts are Input Parameters

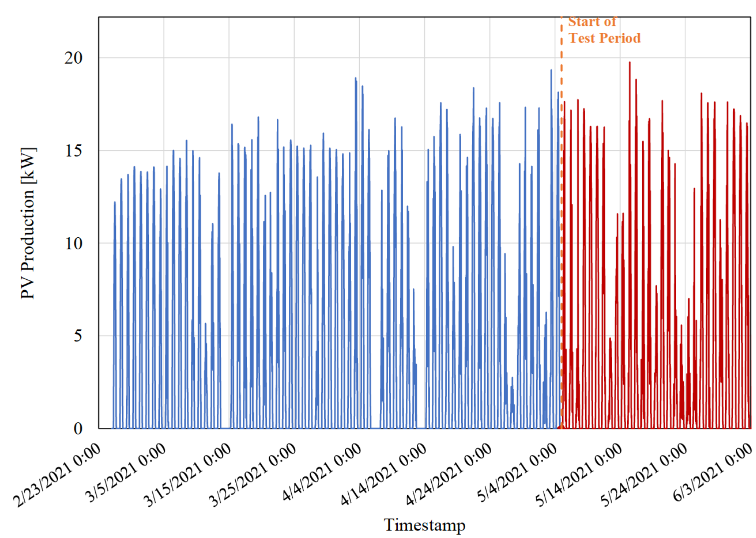
$$\boxed{E_j^{PV} = E_j^{exportPV} + E_j^{onsitePV}}$$

$$\boxed{E_j^{grid} + E_j^{onsitePV} + E_j^{onsiteBESS} = E_j^{load} + E_j^{BESSfor} + E_j^{PtH}}$$



- Train + Test Period Split – Train Data was available before operation, test was not





Model – Tariff Scenarios

Tariff Scenario	Utility Purchase Rate ($s^{purchases}$) [€c /kWh]	Utility Sales Rate (s^{sales}) [€c/kWh]	Demand Charge (s^{DC}) [€/kW]
FT	29.84	4	0
FT-DC	29.84	4	16.78
TOU	35.8 (on), 29.84 (mid), 23.87 (off)	4	0
TOU-DC	35.8 (on), 29.84 (mid), 23.87 (off)	4	16.78
RTP	29.84	Market Prices	0

- There are 4 major electricity tariff structures:
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  2) Time-of-Use – variable rate [c€/kWh] depending on the time of the day; or type of day
  3) Demand Charge – an additional power rate [€/kW] penalty multiplied with the highest peak demand
  4) Real-time-Pricing – Spot market prices are passed down to the consumer; see Norway

Uncertainty

In an open-loop environment forecast errors need to be explicitly accounted for:

- Calculate a utility exchange variable **u**

$$u_t = E_{j=1,t}^{grid} - \left(E_{j=1;t}^{exportPV} + E_{j=1;t}^{exportBESS}\right) + e_t$$

- The net error $\boldsymbol{e_t}$**:**

$$e_t^{net} = e_t^{load} - e_t^{PV}$$

$$e_t^{load} = y_t^{load} - \hat{y}_t^{load}$$

$$e_t^{PV} = y_t^{PV} - \hat{y}_t^{PV}$$

- Calculation of the costs incurred by the **per kWh rates** and **demand charge** penalty**:**

$$C_t^{rates} = \begin{cases} u_t * s_t^{purchases}, & if\ u_t > 0 \\ u_t * s_t^{sales}, & if\ u_t < 0 \\ 0, & otherwise \end{cases}$$

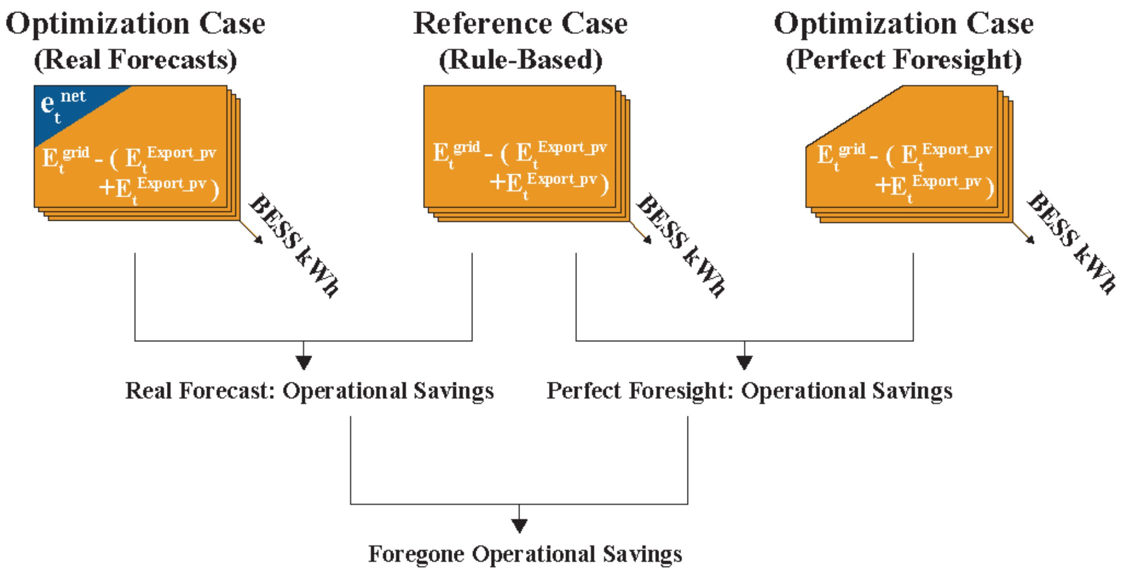
$$C^{DC} = \max(u_t) * s^{DC}$$

- Final Costs by summing the rate costs over time index **t** and adding the penalty

$$C = \sum_t C_t^{rates} + C^{DC}$$

Cost Savings

- Operate the same month with our controller (=**Optimization Case)** and a rule-based controller (**=Reference Case) –** rule-based: *e.g., if surplus pv -> charge battery*
- Operate our controller once with perfect foresight and once without for all tariff scenarios
- Carry out a sensitivity analysis to maximum energy capacity of the battery system
- Savings are calculated in comparison to the **Reference Case**, and foregone savings by comparing the savings of **perfect forecast** with those of **real forecast** runs



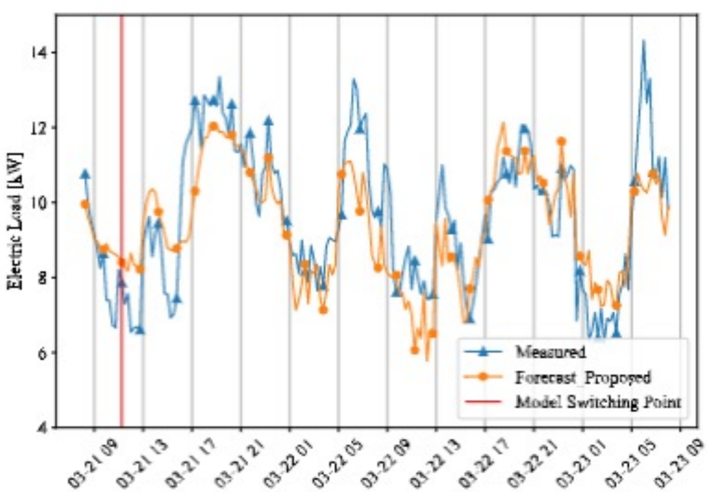
Results

Results: Forecast Quality

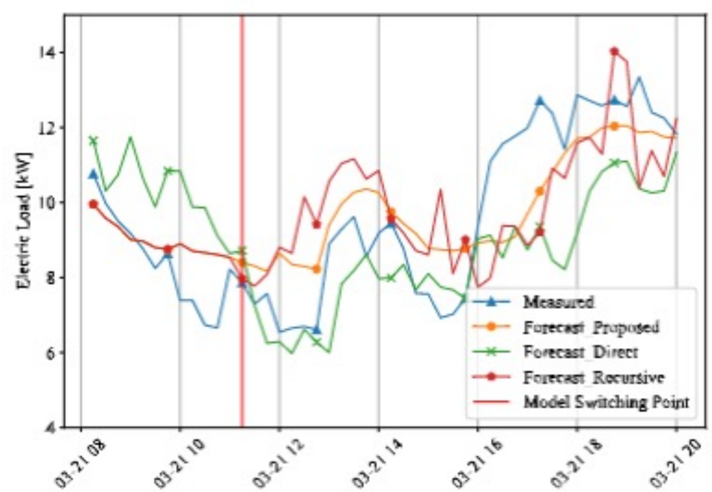
Q: How ‘good’ are the forecasts?

A: By visual and numerical inspection they are accurate, also compared to the literature

	Error Score		Computation Time	
	nRMSE	MAPE [%]	Training Time [s]	Execution Time [ms]
Recursive Method	2.30×10^{-2}	18.2	22.1	10.9
Direct Method	1.95×10^{-2}	15.2	4531.0	40.8
Proposed Method	1.87×10^{-2}	13.9	24.3	20.3



(a) Forecasts (the proposed method) 48-hours ahead



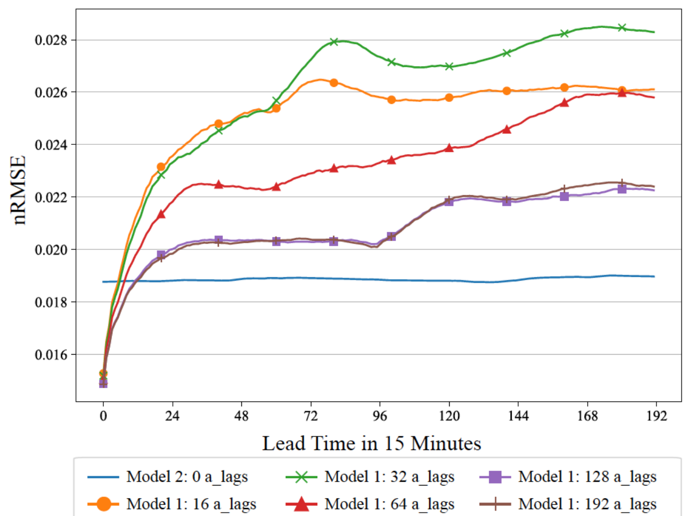
(b) Proposed method vs. ’direct’ and ’recursive’ 12-hours ahead

Results: Forecast Accuracy Trajectory

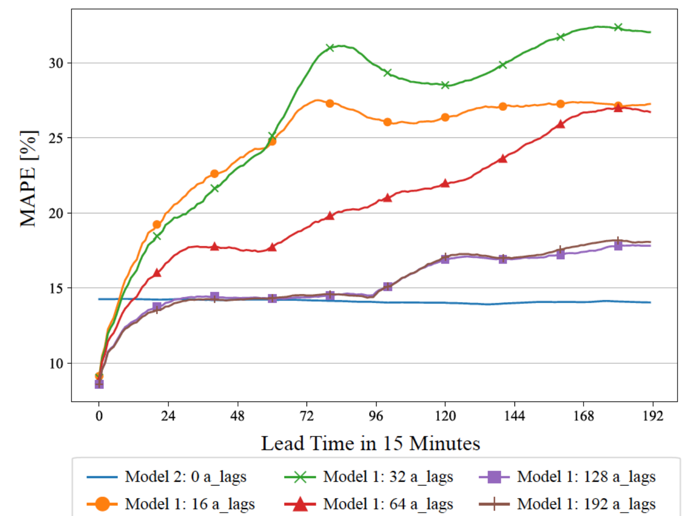
Q: Was the model switching approach warranted:

A: Yes, the error propagation of the recursive method is substantial and is truncated by the approach

	Error Score		Computation Time		Switching Point	
	nRMSE	MAPE [%]	Training Time [s]	Execution Time [ms]	nRMSE	MAPE
16 a_lags	1.89×10^{-2}	14.1	0.1	10.9	6	7
32 a_lags	1.88×10^{-2}	14.0	8.7	10.9	6	8
64 a_lags	1.87×10^{-2}	13.9	12.6	14.1	8	12
128 a_lags	$\mathbf{1.87 \times 10^{-2}}$	**13.8**	24.3	20.3	12	26
192 a_lags	1.87×10^{-2}	13.8	36.4	21.9	13	27



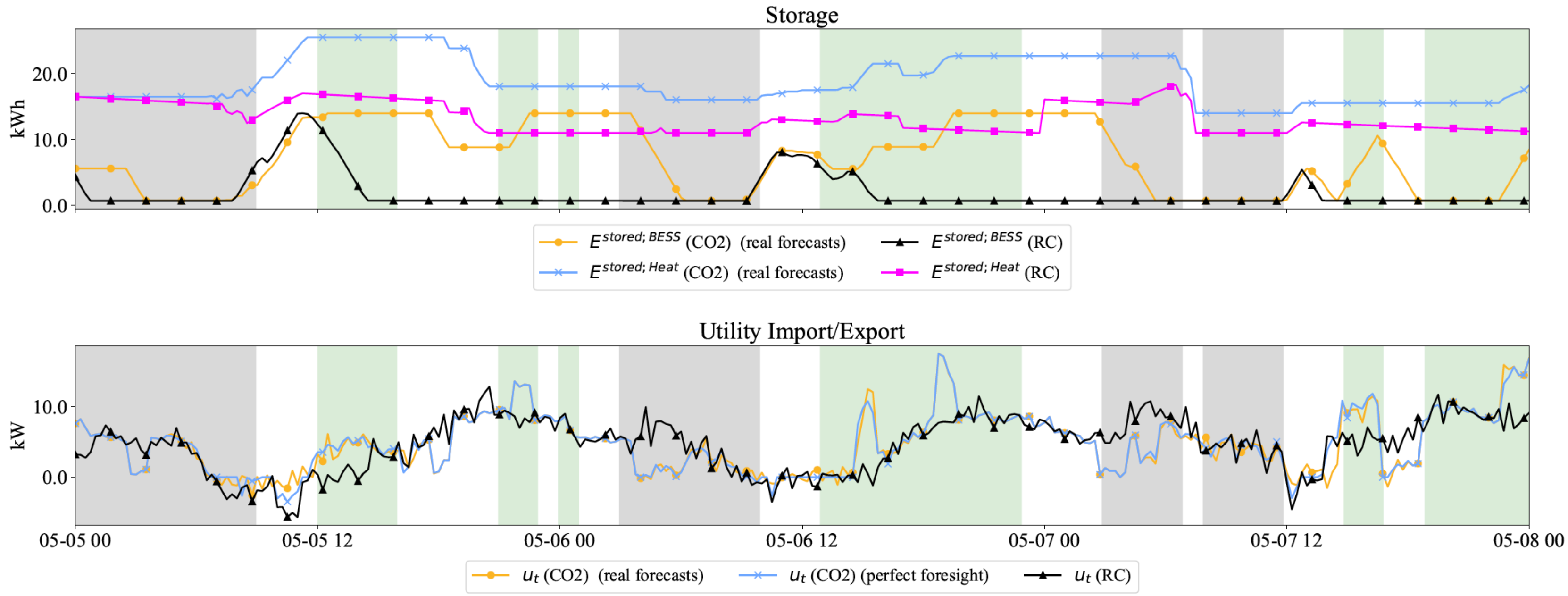
(a) Electrical Load Forecasts – nRMSE



(b) Electrical Load Forecasts – MAPE

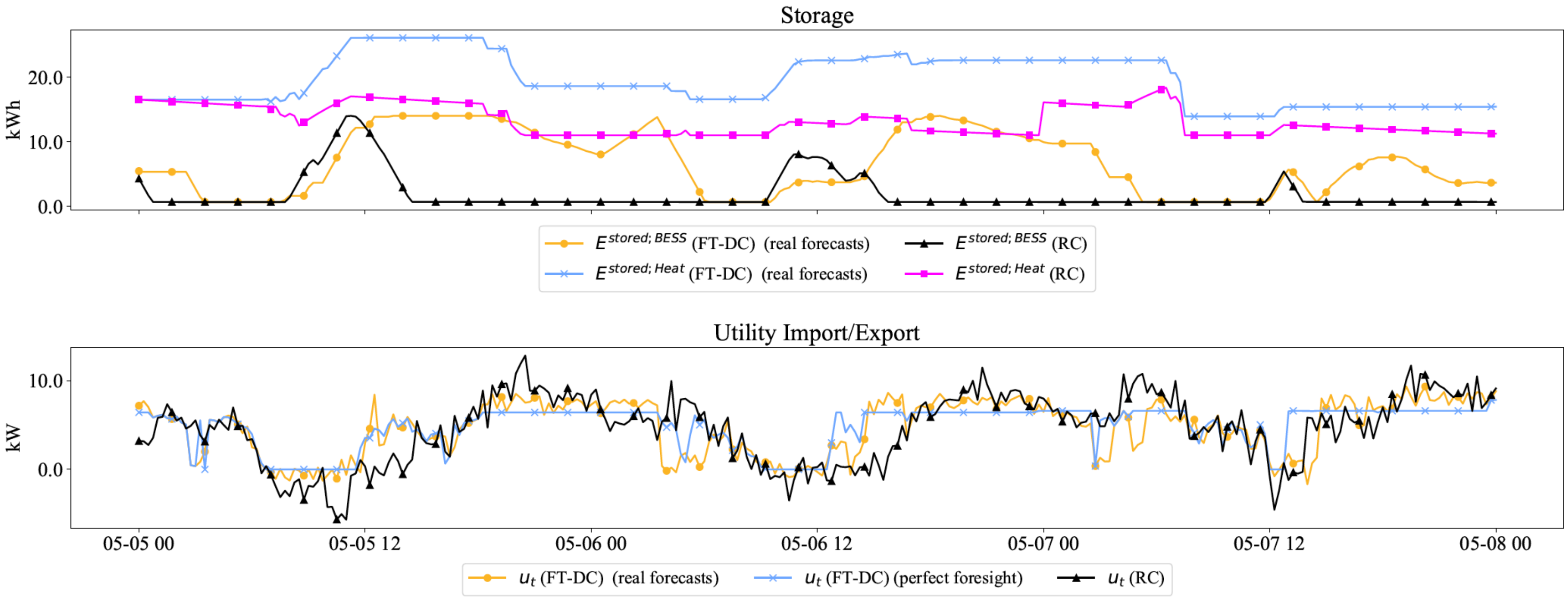
Operational Dispatch – CO2

- CO2 Minimization: We would expect that the REC **Buys when electricity is green**



Operational Dispatch – FT-DC

- Cost Minimization under Demand Charges: We would expect **peak Shaving**
- With perfect foresight, this happens
- With real forecasts we increase peaks



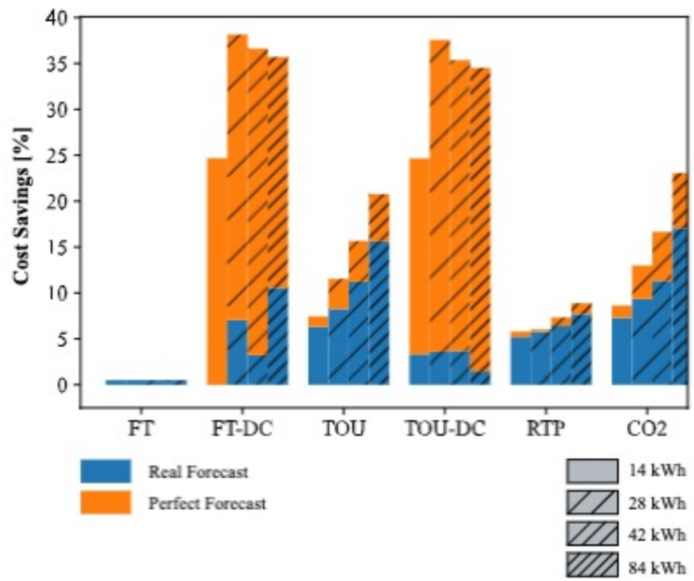
Foregone Savings & Sensitivity to BESS

Q: What are the potential savings of the controller if we had not forecast errors?

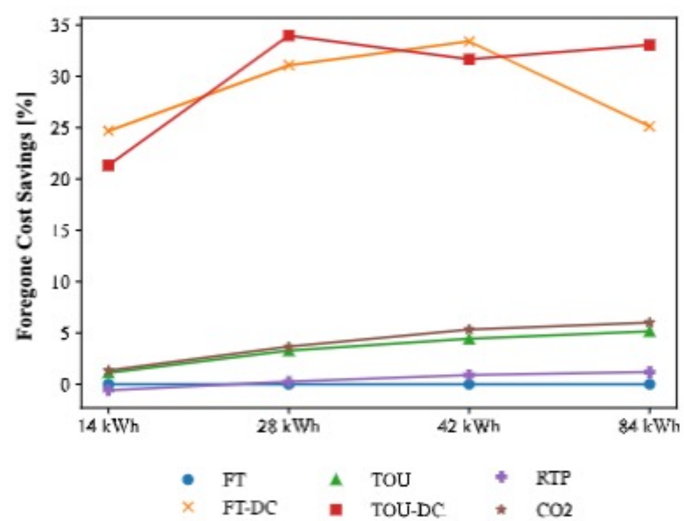
A: Significantly higher than in real operation.

Q: How do the real and perfect forecast savings evolve with greater BESS size?

A: A larger BESS size increases the discrepancy between real and perfect forecast savings



(a) Percentage operational cost savings of real and perfect forecasts.



(b) Foregone operational cost savings due to forecast errors.

Conclusions & Future Work

- Mixed-Integer Linear Program that models the sector-coupling of the electricity and heat systems within the renewable energy community
- Forecasting method allows multi-step ahead forecasting dealing with the problem of recursive approaches.
- Results indicate that without forecast errors the proposed controller can outperform a rule-based dispatch strategy by 24.7% in operational costs and by 8.4 % in CO_2 emissions
- But if the controller is used in a realistic environment, where forecasting is required, the same savings are reduced to 3.3 % and 7.3 %, respectively.
- We suggest that forecast errors are a significant cost driver that easily outweigh the benefits of a larger BESS.

- Future research in forecasting should thus focus on developing forecasting algorithms that can account for the bias in tariff structures.
- handling of forecast errors **internally** rather than through utility exchanges (hierarchical control)