AI Hackathon Challenge - Optimal Control of Microgrid

Hackathon team 9

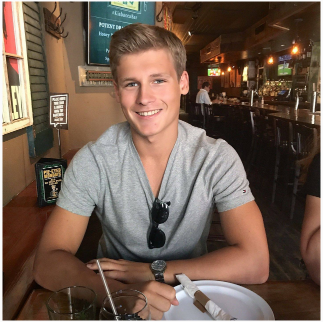
Erling Syversveen Lie og Martin Borge Heir

April, 2020

Sections

This is us

Erling Syversveen Lie



Martin Borge Heir

Both are third year cybernetics students

Sections

Team

Solution choice

Results

MPC

- We have chosen to solve the problem with MPC
- MPC is a control method for controlling a system while satisfying constraints

Modeling

- We modeled the system with the following states and inputs

$$\mathbf{x}_t = \begin{bmatrix} B_t \\ H_t \\ G_t \end{bmatrix}, \ \mathbf{u_t} = \begin{bmatrix} B_{charge} \\ B_{discharge} \\ H_{charge} \\ H_{discharge} \end{bmatrix} \tag{1}$$

Modeling

- We modeled two different cost functions. $\mathbf{P}_{spot}$ is a diagonal matrix of the prices over different time steps. $\mathbf{G}$ is a vector of the grid usage.

$$Cost_1 = \mathbf{G}^T \mathbf{P}_{spot} \mathbf{G} \tag{2}$$

$$Cost_2 = \mathbf{G}^T \mathbf{P}_{spot} \mathbf{G} + 49 * max(\mathbf{G}) \tag{3}$$

Modeling

- This gave the following equation for charging the battery and hydrogen

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \mathbf{x}_{t+1} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \mathbf{x}_t + \begin{bmatrix} 0.85 & -1 & 0 & 0 \\ 0 & 0 & 0.325 & -1 \end{bmatrix} \mathbf{u}_t \tag{4}$$

Modeling

- Equation for constraint on grid

$$G_t = \begin{bmatrix} 1 & -1 & 1 & -1 \end{bmatrix} \mathbf{u}_t - \hat{PV}_t - \hat{W}_t + \hat{C}_t \tag{5}$$

Modeling

- Inequality constraints:

$$\begin{bmatrix} 1 & 0 & 0 \\ -1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & -1 & 0 \end{bmatrix} \mathbf{x}_t + \begin{bmatrix} 0.85 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0.325 & 0 \\ 0 & 0 & 01 & \end{bmatrix} \mathbf{u}_t < \begin{bmatrix} 500 \\ 0 \\ 1670 \\ 0 \end{bmatrix} \tag{6}$$

$$\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} < \mathbf{u}_t < \begin{bmatrix} 400 \\ 400 \\ 55 \\ 100 \end{bmatrix} \tag{7}$$

Prediction

- We estimated consumption with an AR(48) model.
  - AR models are representations of stochastic processes that predicts the next timestep as linearly dependent on the signals own previous values

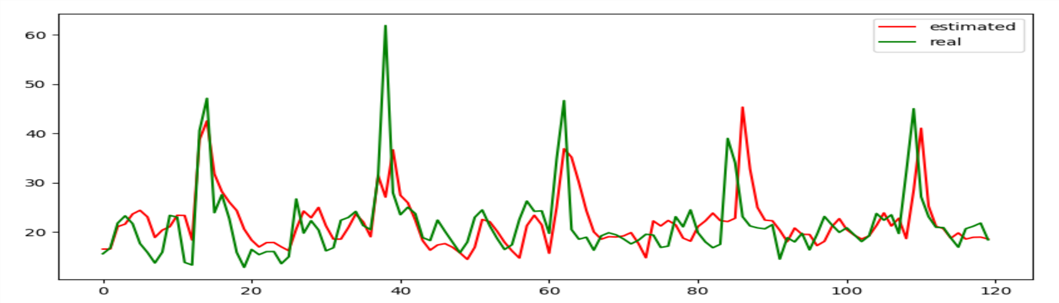


Figure 1: True vs estimated consumption

Prediction

- We estimated wind production simply by applying the wind power curve

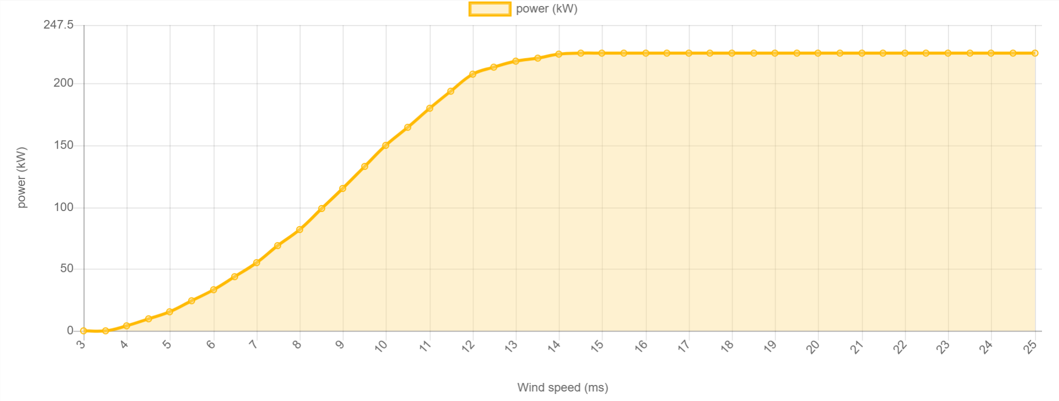


Figure 2: Ideal wind power curve

Prediction

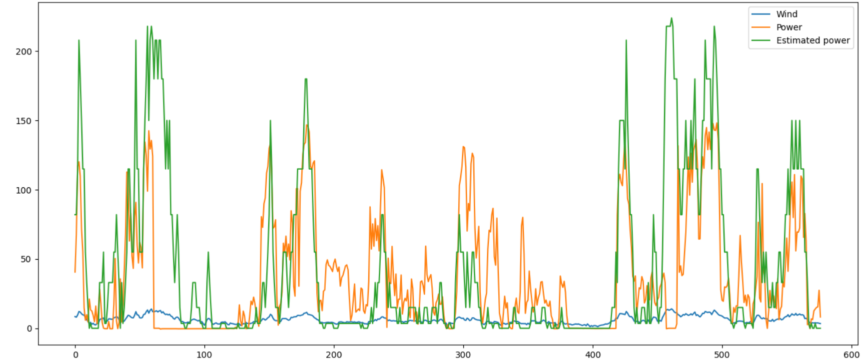
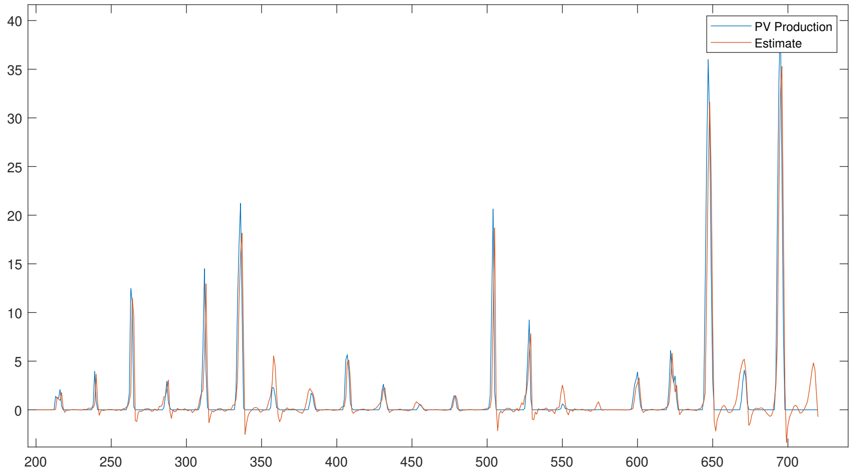


Figure 3: True vs estimated wind production

Prediction

- PV we also modeled as an AR(48) process



Sections

Result without prediction

- The system worked well when we tested with the actual stochastic values.
- On the training set, starting from 01/02-2020 we achieved a reward of 1811.
- On the test set, which starts at 01/02-2021 we achieved a reward of 11174.

Train - February 2020

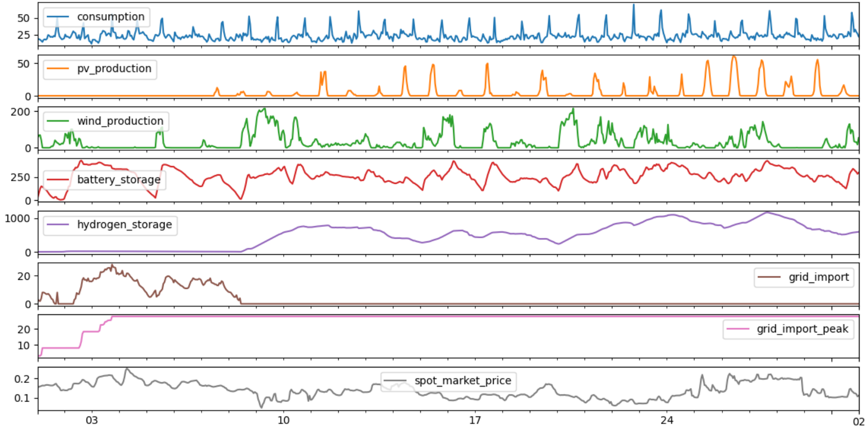


Figure 5: Performance on February 2020

Test - February 2021

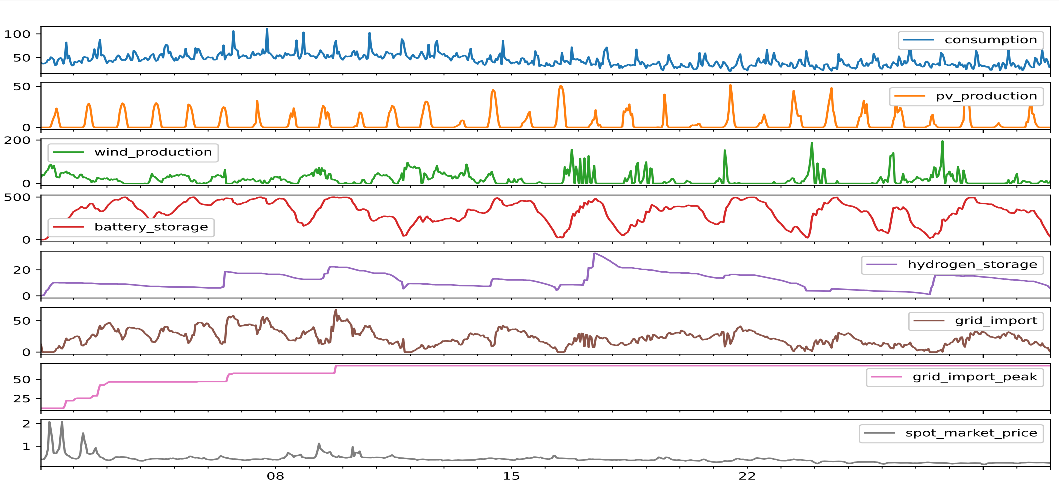


Figure 6: Performance on February 2020

Result with prediction

- When we include prediction our model unfortunately performs bad
- On the test set with estimated stochastic values we reached a reward of 18032 NOK with the MPC model
- No action at all gives 14385 NOK reward
- We felt we had to at least provide a model that performs better than no action. So we propose a solution called Night and Day model
  - Discharge battery with a rate of 25 kWh between 15 and 19 each day.
  - Charge battery with a rate of 3.57 kWh between 19 and 15.
- The Night-and-Day model achieves 13421 NOK reward on the test set.

Test with prediction - February 2021

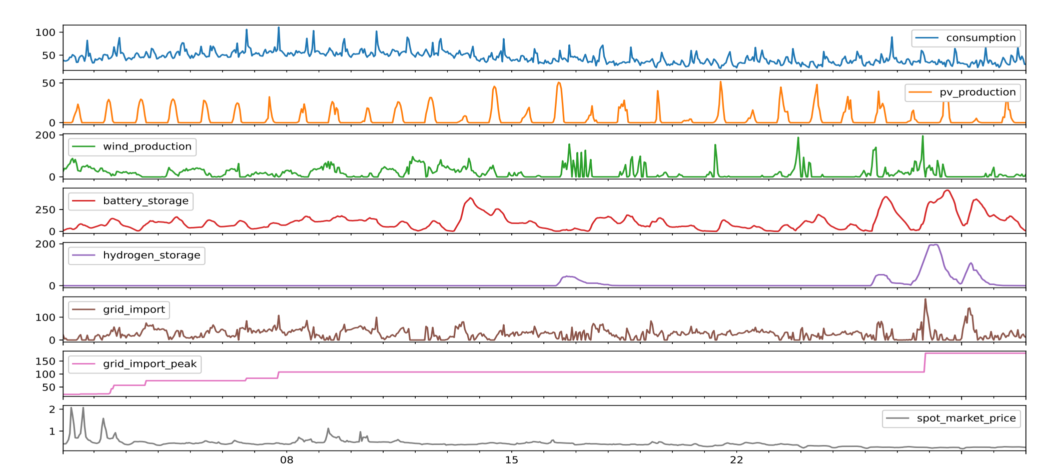


Figure 7: States for test set with predicted stochastic values

Test with prediction - February 2021

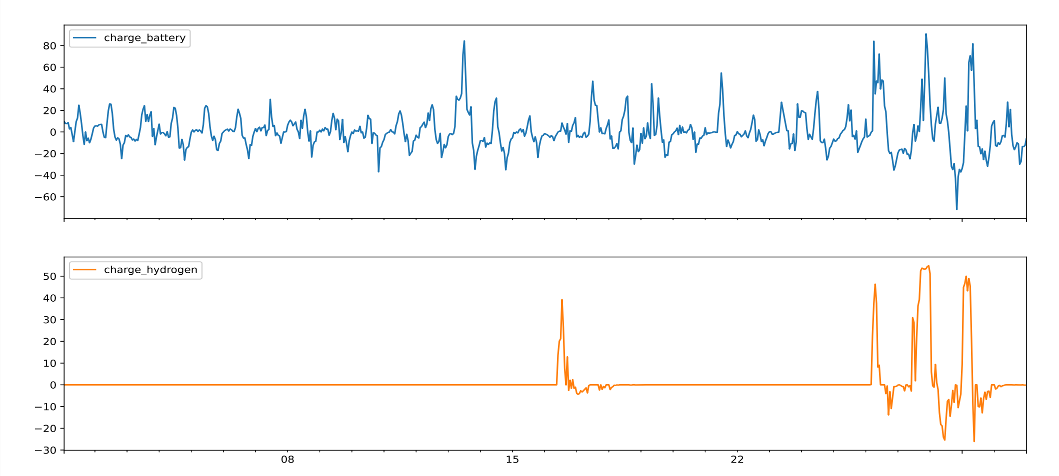


Figure 8: Actions for test set with predicted stochastic values

Test Night and day - February 2021

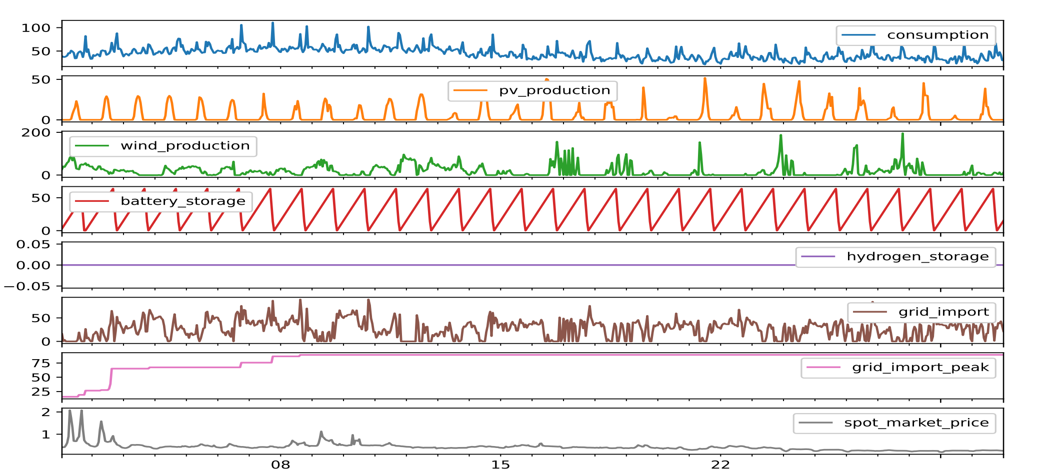


Figure 9: States for test set with night and day model

Test Night and day - February 2021

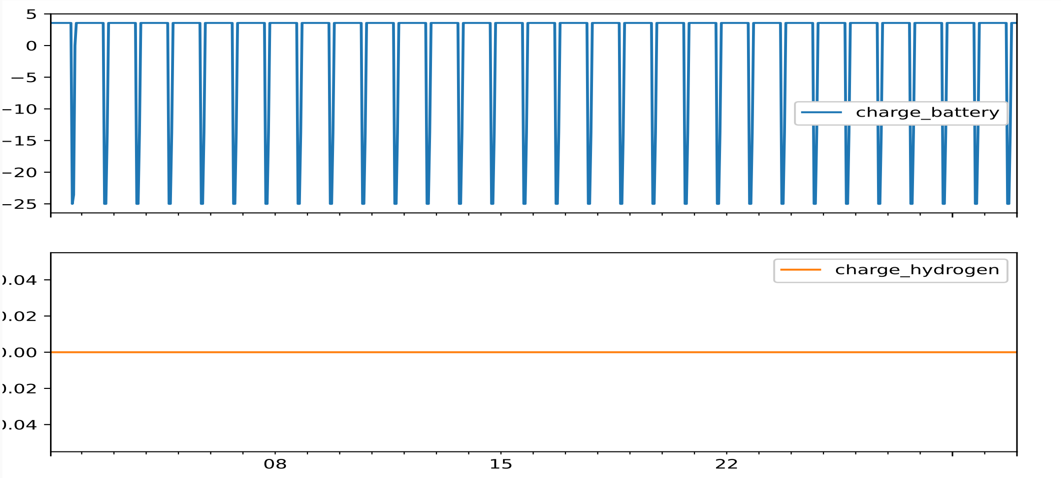


Figure 10: Action for test set with night and day model