

Sensitivity of MPC Performance to Component Scaling in a Battery–Hydrogen Storage System

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ABSTRACT

With the increasing share of volatile renewable energies, there is a growing need for flexible storage systems to balance fluctuations between generation and demand. Multi-energy systems, featuring battery and hydrogen storage systems, provide an efficient and scalable solution for this purpose. While rule-based control is primarily used in industry, model predictive control (MPC) is considered the most promising strategy for cost-optimized and safe operation. The performance of such controllers depends heavily on the capacities, power rates, and degradation behavior of the storage systems; for hydrogen systems, it can also depend on minimum switch-on/off times and ramping rates. This work aims to use sensitivity analysis to quantify the influence of variations in these component parameters on control quality. To this end, a lab-scale battery-hydrogen storage system (TU Wien) is modeled and operated using MPC to minimize grid exchange and thus increase self-sufficiency. Experimental data from electrolyzers and fuel cells were used to calibrate the model. Actual energy production and consumption data from one year are condensed into five representative weeks, serving as test cases. In a systematic study, the capacities and power rates of the components are varied. For the given lab-scale system, the maximum power of the electrolyzer has the greatest influence on control performance, followed by the battery and hydrogen storage capacity. The power of the fuel cell and battery has no limiting effect. It can thus be concluded that the electrolyzer is undersized, and the battery should have greater storage capacity to improve performance.

Keywords: Model-predictive-control (MPC), Mixed-integer linear programming (MILP), Sensitivity Analysis, Optimization

INTRODUCTION

The energy transition is increasing the share of renewable sources in electricity generation, particularly from photovoltaics and wind [1, 2]. Their volatile, intermittent feed-in requires storage to balance discrepancies between generation and demand and reduce strain on the grid [2]. Hybrid battery-hydrogen storage systems offer a solution here: batteries with high round-trip efficiency can buffer short-term fluctuations [2]. At the same time, hydrogen enables longer-term shifts thanks to its greater storage capacity [1]. Surplus electricity is converted into chemical energy (hydrogen) in the electrolyzer and later converted back into electricity in the fuel cell [3]. This creates a sector-coupled multi-energy system (MES) with multiple energy sources and control

variables [1, 3].

An energy management system is required for optimal and safe operation, which is often implemented in industry through rule-based control; state-of-the-art research, however, focuses on model predictive control (MPC). This control method uses a plant model to calculate optimal control inputs based on, e.g., forecasts of generation and demand [4]. The control quality of MPC depends mainly on the system specification (e.g., storage capacities, component power rates) and the operating behavior (e.g., system dynamics, such as minimum on/off times, ramping constraints, and selected degradation-preventing strategies) [2].

In literature, coupled design and operational optimization for given system requirements, such as a specified demand, is often proposed, leading to cost- and energy-

optimal dimensioning [2]. This raises the following question: how does a given operating control strategy for a specified plant respond to variations in system size around the design point?

For varying generation and demand, Holtwerth et al. [5] demonstrated the dependence of the MPC performance of a hybrid battery-hydrogen storage system. However, they did not investigate the sensitivity of individual design parameters to optimization; instead, they considered the overall system under varying disturbance inputs.

The investigation of design parameter variations is conducted at TU Wien's new hybrid battery-hydrogen storage laboratory, which operates in the low-kW power range. An MPC based on mixed-integer linear programming (MILP) formulations is being implemented for this system. The studied operational optimization goal is to minimize grid exchange, i.e., to shift generation and demand in time through storage management, thereby minimizing grid strain. This requires accurate models of the relevant components, in particular the electrolyzer and fuel cell. Electricity from photovoltaics and wind power is fed into the grid via rooftop systems, and test consumption trajectories can be emulated.

The main contributions of this publication are:

- Modeling of lab-scale system components of electrolyzer and fuel cell
- Numerical experiments with actual generation and demand data for five representative weeks of a year
- Analysis of control quality depending on variations in storage capacities and maximum power rates of components

The remainder of the paper is structured as follows: first, the use case is presented, *TU Wien's* hybrid battery-hydrogen energy storage lab. The electrolyzer and fuel cell are then characterized, followed by the generation and demand curves. The energy management system, a MILP-based MPC, is then introduced. Then, the sensitivity of the control quality to variations in storage capacities and maximum power rates is investigated. The paper concludes with a summary and outlook.

MATERIAL & METHODS

The investigation of variations in design parameters is conducted by modeling and controlling the use case using a MILP-based MPC approach, adapted from [6].

Use Case

The system comprises a battery and a hydrogen energy storage system, consisting of an electrolyzer, a hydrogen storage tank, and a fuel cell, as shown in Figure 1.

The difference between generation (P_{gen}) and demand (P_{de}) in the energy system is compensated for by storage,

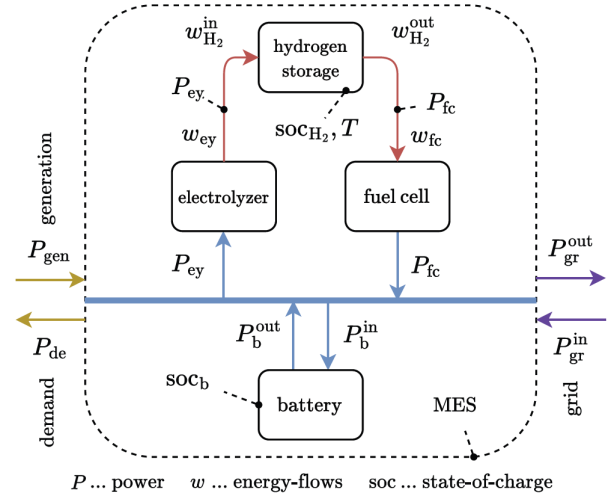


Figure 1. Hybrid battery-hydrogen energy storage system flow diagram with battery (b), electrolyzer (ey), hydrogen storage (H_2) and fuel cell (fc) adapted from [6].

and the grid balances the remaining energy discrepancy ($P_{\text{gr}}^{\text{in}}, P_{\text{gr}}^{\text{out}}$). The battery is defined by its state-of-charge (soc_b), which changes according to

$$\text{soc}_{b,t+1} = \text{soc}_{b,t} + \frac{\Delta t}{C_b} \begin{cases} P_{b,t}^{\text{in}} \cdot \eta_b, \text{ charge} \\ -P_{b,t}^{\text{out}} / \eta_b, \text{ discharge} \end{cases} \quad (1)$$

with charging and discharging power rates ($P_b^{\text{in}}, P_b^{\text{out}}$), respectively, as well as capacity (C_b) and efficiency (η_b). The time span between consecutive time steps (t) and ($t + 1$) is denoted as (Δt). The hydrogen storage state-of-charge (soc_{H_2}) is modeled analogously,

$$\text{soc}_{H_2,t+1} = \text{soc}_{H_2,t} + \frac{\Delta t \cdot \eta_{H_2}}{C_{H_2}} (w_{H_2,t}^{\text{in}} - w_{H_2,t}^{\text{out}}), \quad (2)$$

with hydrogen flow entering and exiting ($w_{H_2}^{\text{in}}, w_{H_2}^{\text{out}}$), respectively, as well as capacity (C_{H_2}) and efficiency (η_{H_2}). The power balance links all power values according to

$$P_{\text{gen}} - P_{\text{de}} + P_{\text{gr}}^{\text{in}} - P_{\text{gr}}^{\text{out}} - P_b^{\text{in}} + P_b^{\text{out}} + P_{\text{fc}} - P_{\text{ey}} = 0. \quad (3)$$

Figure 2 shows the relationship between the input power of the electrolyzer (P_{ey}) and the hydrogen produced (w_{ey}). Figure 3 shows the function between the hydrogen entering the fuel cell (w_{fc}) and the electrical power generated (P_{fc}). The maximum efficiencies for the electrolyzer and the fuel cell are 56% and 53%, respectively. These efficiencies were measured to account for all losses.

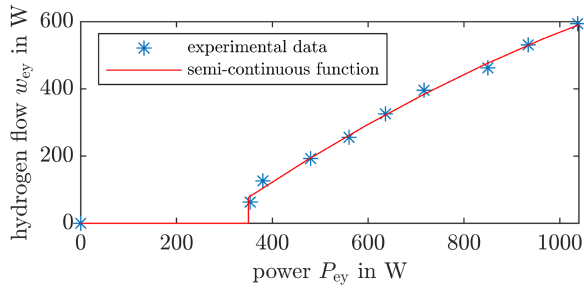


Figure 2. Fitted experimental data for semi-continuous non-linear electrolyzer function linking power (P_{ey}) in W and energy equivalent hydrogen flow (w_{ey}) in W.

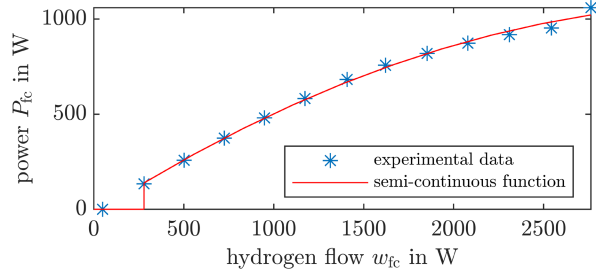


Figure 3. Fitted experimental data for semi-continuous non-linear fuel cell function linking power (P_{fc}) in W and energy equivalent hydrogen flow (w_{fc}) in W.

Parameters & Data

The energy system is specified based on the component sizes, as shown in Table 1. These are hereinafter referred to as the design point.

Table 1. TU Wien's Hybrid Energy System - Properties

Battery System		Hydrogen System		Unit
Property	Value	Property	Value	
C_b	2.6	C_{H_2}	14.3	kWh
$P_b^{\max}$	500	$P_{ey}^{\max}$	1040	W
		$P_{fc}^{\max}$	1020	W
$\text{soc}_b^{\min}$	0.2	$\text{soc}_{H_2}^{\min}$	0.1	-
$\text{soc}_b^{\max}$	0.8	$\text{soc}_{H_2}^{\max}$	0.9	-
η_b	0.9	η_{H_2}	1	-

The optimization goal of providing storage flexibility is tested using five representative weeks. These are obtained as the best approximation of the entire year and are listed in Table 2. Actual photovoltaic and wind production data, as well as energy consumption data, from Austria for 2023 are used [7].

It was rescaled that on average over the year, this results in a generation of $\bar{P}_{\text{gen}} = 1000$ W and a demand of $\bar{P}_{\text{de}} = 750$ W, i.e., a surplus of $\bar{P}_{\text{gen}} - \bar{P}_{\text{de}} = 250$ W of energy that is fed into the system.

Table 2. Representative Periods [7]

Name	Time period (2023)	Residual $\bar{P}_{\text{gen}} - \bar{P}_{\text{de}}$	Factor
Week 1	13.03-19.03	344 W	9.03
Week 2	19.06-25.06	679 W	8.16
Week 3	02.10-08.10	425 W	14.50
Week 4	23.10-29.10	37 W	10.83
Week 5	27.11-03.12	-290 W	9.48
average	01.01-31.12	250 W	52

Control Engineering

This chapter is based on [4]. Model predictive control (MPC) utilizes a design model (MILP formulations) to predict future system behavior based on the current state and a sequence of future control inputs and disturbance predictions over a prediction and optimization horizon N_{pred} , as shown in Figure 4.

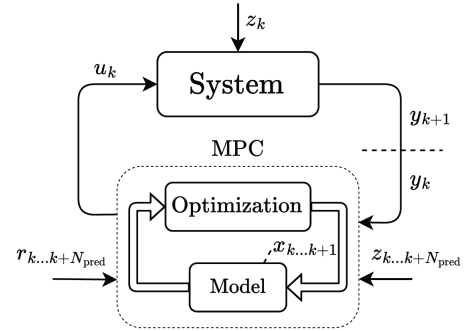


Figure 4. Model predictive control loop with control variable u , system state x , system output y , disturbance z and reference value r for discrete time step k over prediction horizon N_{pred} adapted from [4, 6].

At each discrete time step k , an optimization problem minimizes a cost function J , in this case, the energy exchange with the grid, according to

$$\min. J = \min. \sum_k^{k+N_{\text{pred}}} \frac{(P_{\text{gr},k}^{\text{in}} + P_{\text{gr},k}^{\text{out}})}{(\bar{P}_{\text{gen}} - \bar{P}_{\text{de}})}. \quad (4)$$

This optimization is subject to system dynamics and input and state constraints, described as equality constraints $h(x, u) = 0$ and inequality constraints $g(x, u) \leq 0$. Here, the system output y_k includes the system state x_k , comprising the states-of-charge of the battery and hydrogen storage, as well as grid exchange, as seen in equations (5) and (6).

$$y_k = [x_k \quad P_{\text{gr}}^{\text{in}} \quad P_{\text{gr}}^{\text{out}}]_k^T \quad (5)$$

$$x_k = [\text{soc}_b \quad \text{soc}_{H_2}]_k^T \quad (6)$$

Only the first control action u_k is applied, and the process

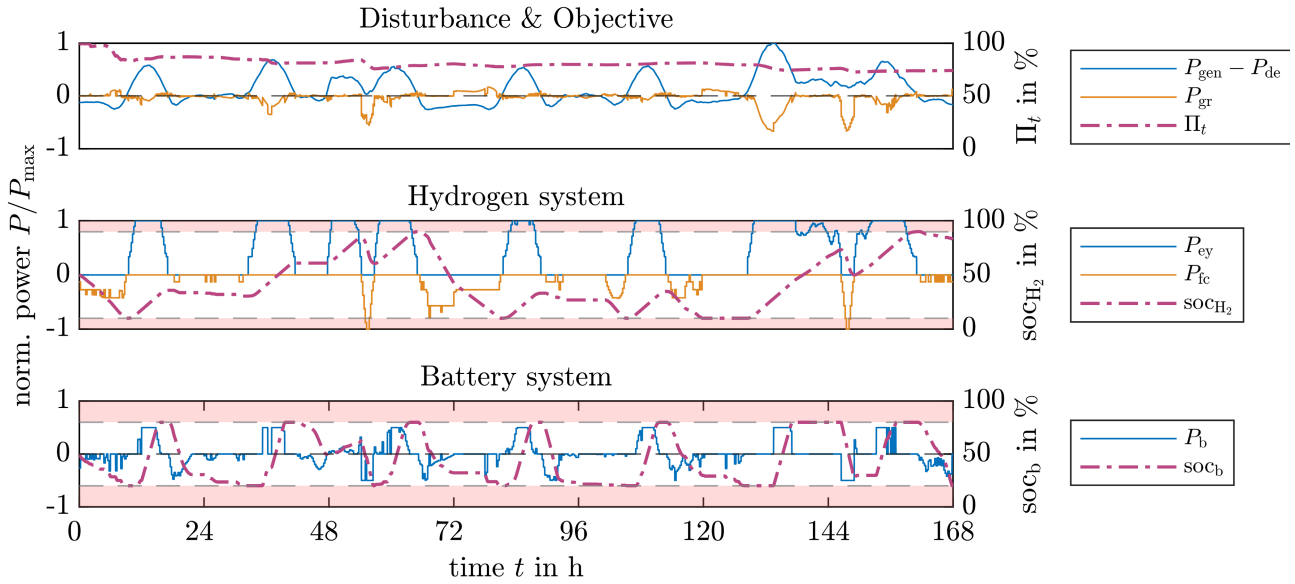


Figure 5. Exemplary process variables for week 3, 2-8.10.2023, with imposed disturbance ($P_{\text{gen}} - P_{\text{de}}$), setpoints of electrolyzer (P_{ey}), fuel cell (P_{fc}) and battery ($P_{\text{b}}^{\text{in}}, P_{\text{b}}^{\text{out}}$) power rates, states-of-charge ($\text{soc}_{\text{H}_2}, \text{soc}_{\text{b}}$) and resulting grid exchange ($P_{\text{gr}}^{\text{in}}, P_{\text{gr}}^{\text{out}}$) and performance factor (Π).

is repeated at the next step $k + 1$, using updated measurements, known as receding horizon control.

$$u_k = [P_{\text{b}}^{\text{in}} \quad P_{\text{b}}^{\text{out}} \quad P_{\text{ey}} \quad P_{\text{fc}}]^T_k. \quad (7)$$

Energy generation and demand act as a disturbance on the system; the predictions can be written as

$$z_k = [P_{\text{gen}} \quad P_{\text{de}}]^T_{k \dots k+N_{\text{pred}}}. \quad (8)$$

MPC is well-suited for constrained, multivariable systems with predictable dynamics and disturbances. To evaluate the control quality, a dimensionless metric, the performance factor, is built, according to

$$\Pi_t = 1 - \frac{\sum_{\tau=0}^{\tau=t} \frac{P_{\text{gr}, \tau}^{\text{in}} + P_{\text{gr}, \tau}^{\text{out}}}{\sum_{\tau=0}^{\tau=t} |P_{\text{gen}, \tau} - P_{\text{de}, \tau}|}. \quad (9)$$

Since there is no explicit degradation modeling as a regularization, the ramping of electrolyzer and fuel cell power is limited, as shown in Equations (10) and (11). The maximum rate of change was chosen to be $\delta P_{\text{ey}, \text{lim}} = P_{\text{ey}}^{\text{max}}/3600$ in W/s for the electrolyzer and $\delta P_{\text{fc}, \text{lim}} = P_{\text{fc}}^{\text{max}}/3600$ in W/s for the fuel cell. Therefore, extensive power changes are restricted, thereby minimizing one part of degradation [8, 9].

$$\frac{|P_{\text{ey}, k+1} - P_{\text{ey}, k}|}{t_{k+1} - t_k} \leq \delta P_{\text{ey}, \text{lim}} \quad (10)$$

$$\frac{|P_{\text{fc}, k+1} - P_{\text{fc}, k}|}{t_{k+1} - t_k} \leq \delta P_{\text{fc}, \text{lim}} \quad (11)$$

RESULTS & DISCUSSION

To evaluate the dependence of individual component size variation on system performance, the capacities of the battery and hydrogen storage tank, as well as the maximum outputs of the electrolyzer and fuel cell, are varied relative to the design point (see Table 1) over a range of -40% to +40%. For this purpose, the terminal value (168 h) of the performance factor (see Equation (9)) is evaluated for the five representative weeks. The weighted sum is then calculated using the previously determined factors for the respective representative week (see Table 2) and used for subsequent evaluations.

Figure 5 illustrates, exemplarily, the simulated process variable resulting from the optimized control input and imposed disturbance for week 3 (see Table 2) at the design point. In the upper tile, the energy residual (blue), grid exchange (orange), and performance factor (magenta, dashed) are shown. The middle tile displays the hydrogen subsystem, with normalized electrolyzer power (blue), fuel cell power (orange), and storage state-of-charge (magenta, dashed).

Analogously, the lower tile displays the battery subsystem, with normalized charging and discharging power (blue) and state-of-charge (magenta, dashed).

The variation in battery and hydrogen storage capacities, C_{b} and C_{H_2} , respectively, influences performance, resulting in a three-dimensional surface, shown in Figure 6. The performance factor varies between 56.8% and 68.5% over the considered parameter range, with the battery having a greater relative influence on the

result ($\bar{\Delta} = 7.5\%$) than the hydrogen storage system ($\bar{\Delta} = 4.4\%$). To answer the question of which component has the most limiting effect on performance, the variations around the design point for the maximum power rates, as well as the capacities at the design point, are plotted in Figure 7. The upper tile shows the performance, and the lower tile shows its partial derivative with respect to each component sizing, over the sizing ratio relative to the design point.

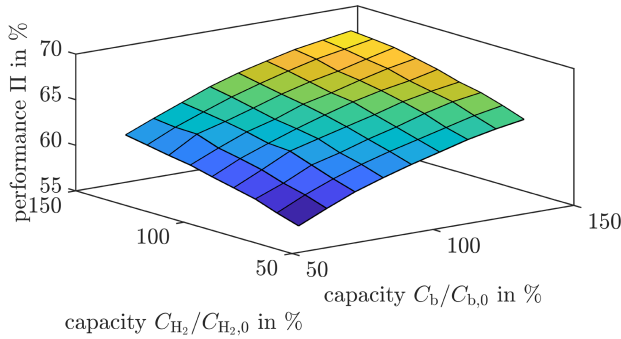


Figure 6. Performance value over battery and hydrogen storage capacity ratio variation in %.

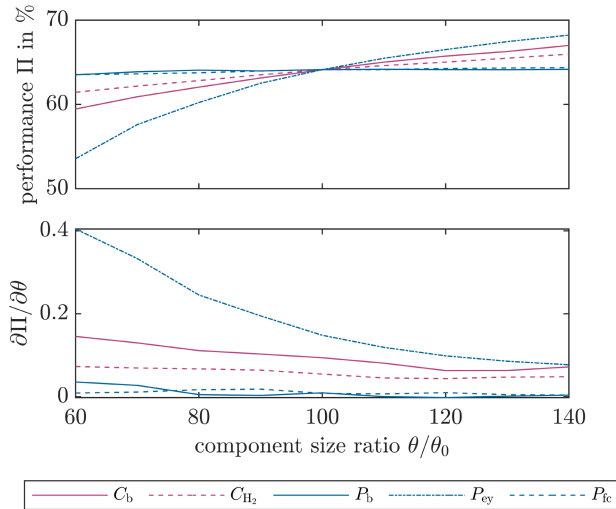


Figure 7. Upper tile: performance value; lower tile: partial derivative of performance value over component size ratio variation in %.

It can be seen that the electrolyzer has the greatest influence; this has a limiting effect, suggesting that it was undersized compared to the other storage components. This can also be explained by the fact that converting electrical energy into hydrogen and reconvert it to electricity are subject to losses due to low efficiency. Based on the determined efficiencies, an electrolyzer power input approximately four times the fuel cell power output would be appropriately dimensioned.

At maximum electrolyzer power, the capacities of

the battery and hydrogen storage tank have the greatest influence on control quality. The maximum power rates of the battery and fuel cell have no influence on the performance factor.

CONCLUSION & OUTLOOK

In this study, the performance sensitivity with respect to component sizing of a model predictive control strategy designed to minimize grid exchange and thereby increase self-sufficiency was evaluated. To this end, a simulation and optimization model based on mixed-integer linear programming formulations for a lab-scale hybrid battery-hydrogen energy storage system was developed. Here, experimental data were used to fit non-linear semi-continuous functions for the electrolyzer and fuel cell. The variation in battery and hydrogen storage capacity, as well as the maximum power rates of the electrolyzer, fuel cell, and battery, was evaluated with respect to control performance.

The results indicate that for the given lab-scale system, the electrolyzer's maximum power has the greatest influence, followed by the battery and hydrogen storage capacity. The power of the fuel cell and battery does not affect the controller's performance. It can be concluded that the electrolyzer is undersized, and the battery should have greater storage capacity to improve performance. In general, the electrolyzer power input should be approximately 4 times the fuel cell's power output, accounting for conversion losses.

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