Performance gaps between energy system planning and operation: a study exploring the impacts of model fidelity and dispatch strategy

M Beaud[1,2], H Cai[1], A.T.D Perera [1,3], P Heer[1]

[1]Urban Energy Systems Laboratory, Empa, Dübendorf, Switzerland; [2]Chair of Automatic Control Laboratory, ETHz, Switzerland; [3]Building Technology and Urban Systems Division, Lawrence Berkeley National Laboratory, United States

E-mail: `hanmin.cai@empa.ch`

Abstract. Effective integration of renewables is essential in the energy transition, which necessitates efficient management of intermittent renewable energy generation, system cost minimization and continuous balance between supply and demand. Due to the problem's multifaceted nature, tools with a simplified representation of energy system operation are often used to ensure computational tractability, causing performance gaps between planning and operation stages. This work quantifies the gaps focusing on the impacts of model fidelity and dispatch strategy, such as the representation of physical constraints at different levels and varying forecast horizons. More specifically, a real-world case study with three energy hubs is considered. A Pareto front is first obtained considering the trade-offs between cost and carbon footprint using the *Ehub* tool, a state-of-the-art energy system planning tool. Following that, the cost-optimal and the emission-optimal designs are selected for evaluating the performance gaps, using the dispatch strategies obtained from the Ehub tool as the baseline. Results show that detailed considerations of physical constraints influence grid dependencies and fuel consumption but there are no significant impacts on resultant total costs. The cost increase due to detailed physical constraints is higher for the cost-optimal system than for the emission-optimal system. Moreover, limiting the forecast horizon to 24 hours has significant impacts on the emission-optimal system with an increase in total system cost by 20.3 %. In contrast, there is only a marginal increase of 0.8 % for the cost-optimal system.

1. Introduction

Historically, energy system operations have been centralized and hierarchical with the goal of continuous balance between energy supply and demand. Currently, the energy sector is undergoing significant structural changes due to climate change mitigation plans and there has been a substantial increase in integrating renewable energy resources into the energy system. IRENA [1] estimates that in the European Union, the share of renewables in the energy mix can increase from 17% in 2015 to 34% by 2030 cost-effectively, with renewable energy technologies primarily installed in the existing built environment. Such structural changes require additional modelling of distributed energy systems, which can be facilitated using the energy hub concept [2] that establishes a multi-energy system model consisting of diverse energy production, conversion, storage and network components. State-of-the-art energy system planning tools consider model simplifications to reduce computational burdens [3]. For example, ramping limits, minimum run-time and device degradation are neglected and conversion efficiencies are assumed to be constant. Additionally, planning tools assume full knowledge of energy demands and outputs from renewables for the entire design period, whereas system operators have only partial knowledge during dispatch. Despite the simplicity being an advantage, performance gaps exist between energy system planning and operation. The main focus of this work is to explore the impacts of model fidelity and dispatch strategy on the performance gaps. More specifically, operational cost is used as the key performance indicator during the comparison.

2. Methodology

A schematic overview is depicted in Figure 1, which illustrates the overall workflow in four steps. First of all, the *Ehub* tool [3], representing state-of-the-art planning tools, is utilized for system design considering the boundary conditions of a case study system, such as heat and electricity demands. With this tool, two design solutions to a multi-objective optimization problem are obtained, considering the trade-off between minimizing financial investments and minimizing environmental impacts. The dispatch strategies obtained from the Ehub tool are considered as the baseline. Following that, a simplified Model Predictive Control (MPC) is formulated to assess the impacts of shorter weather and demand forecasts on system costs and operation patterns. While the Ehub modelling tool optimizes system operation with full knowledge of demands and Renewable Energy Sources (RES) output for the entire design period, MPC adopts a rolling-horizon optimization strategy using short-term forecast of system response and boundary conditions such as energy demands. Subsequently, a more detailed dispatch strategy is formulated to include realistic representation of physical constraints. Lastly, the performance gaps are quantified by comparing the operational costs in all cases with the baseline. The

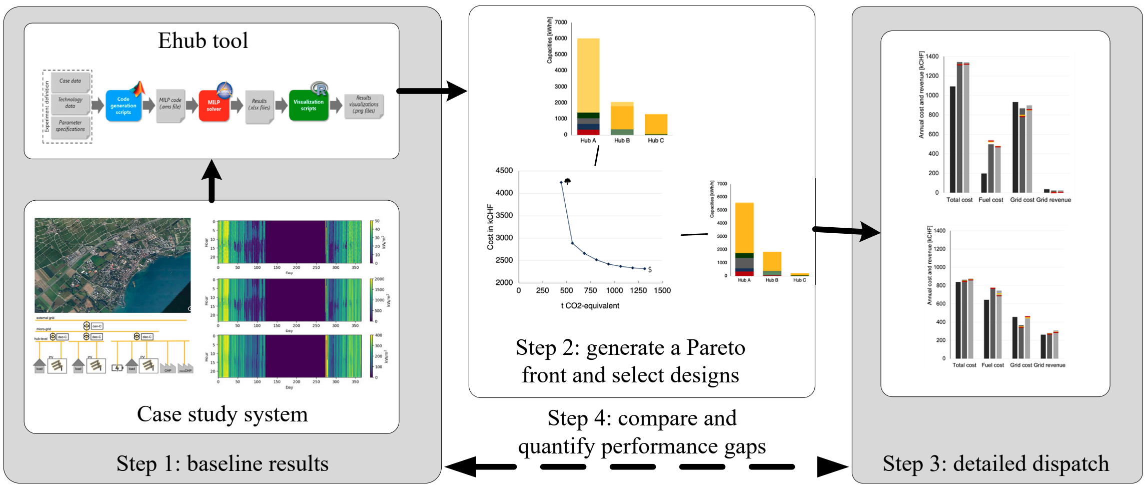


Figure 1: Workflow of system design and generating baseline results using the Ehub tool, the selection of system designs, the investigation into detailed dispatch and the evaluation of performance gaps. Steps 1 and 2 together provide two system designs that supports the investigation into detailed dispatch in step 3.

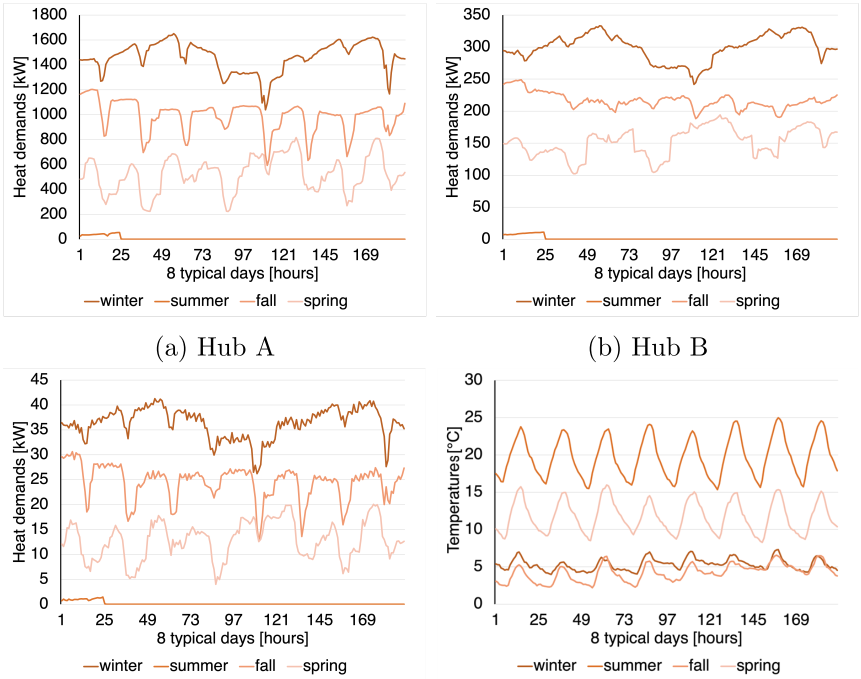
Optimal Control Problem (OCP) for the MPC is formulated compactly in Equation 1. It concerns the optimal operation of all energy generators and storage systems to minimize system costs within the horizon considering constraints on load, supply, generator capacity, and ramping rates.

$$
\begin{aligned}
\underset{\mathbf{P}_k,\mathbf{Q}_k\ \forall k\in\{0,\dots,N-1\}}{\text{minimize}} \quad & \sum_{k=0}^{N-1} \mathrm{C}_k^{\mathrm{gas}}\mathrm{F}_k^{\mathrm{imp}} + \mathrm{C}_k^{\mathrm{imp}}\mathrm{P}_k^{\mathrm{imp}} - \mathrm{R}_k^{\mathrm{exp}}\mathrm{P}_k^{\mathrm{exp}} \\
\text{subject to} \quad & \mathbf{P}_k^{\mathrm{T}} \cdot \mathbf{1} = \hat{P}_k,\ \forall k \in \{0,\dots,N-1\}, \\
& \mathbf{Q}_k^{\mathrm{T}} \cdot \mathbf{1} = \hat{Q}_k,\ \forall k \in \{0,\dots,N-1\}, \\
& \mathbf{X}_0 = \hat{\mathbf{X}}_t,\ \mathbf{X}_{k+1} = \mathbf{A}\mathbf{X}_k + \mathbf{B}\mathbf{U}_k,\ \forall k \in \{0,\dots,N-1\}, \\
& \mathbf{P}_k = f_1(\mathbf{F}_k^{\mathrm{gas}}),\ \mathbf{P}_k \in \mathcal{P},\ \forall k \in \{0,\dots,N-1\}, \\
& \mathbf{Q}_k = f_2(\mathbf{F}_k^{\mathrm{gas}}),\ \mathbf{Q}_k \in \mathcal{Q},\ \forall k \in \{0,\dots,N-1\}, \\
& \Delta\mathbf{P}_k \in \mathbf{\Delta},\ \forall k \in \{0,\dots,N-1\}.
\end{aligned} \tag{1}
$$

where N is the time horizon, k is the index of time step within the horizon, $\mathbf{P}_k$ and $\mathbf{Q}_k$ are the vectors of electricity and heat outputs, $\hat{P}_k$ and $\hat{Q}_k$ are the estimated electricity and heat demands, t is the time stamp, $\mathrm{C}_k^{\mathrm{gas}} \in \mathbb{R}^+$ denotes the cost of gas, $\mathrm{C}_k^{\mathrm{imp}} \in \mathbb{R}^+$ denotes the cost of imported electricity, $\mathrm{R}_k^{\mathrm{exp}} \in \mathbb{R}^+$ denotes the remuneration of electricity export, $\mathbf{A}$ and $\mathbf{B}$ describe the state evolution of the storage systems, $\mathbf{U}_k$ denotes the inputs into the storage systems, $\mathbf{F}_k^{\mathrm{gas}}$ denotes the vector of fuel consumption, $\mathrm{F}_k^{\mathrm{imp}}$ denotes the total fuel consumption, $f_1(\cdot)$ and $f_2(\cdot)$ represent the energy conversion, $\mathcal{P}$ and $\mathcal{Q}$ are the constraint sets of electricity and heat outputs, $\mathbf{1}$ denotes the vector of ones, $\Delta\mathbf{P}_k$ describes the power differentials between adjacent time-steps, $\mathbf{\Delta}$ denotes the set of ramping limits, $\mathbf{X}_0$ is the vector of the initial states (e.g., state-of-charge of batteries), and $\hat{\mathbf{X}}_t$ is the vector of estimated states. This work assumes that the electricity demand $\hat{P}_k$, the thermal demand $\hat{Q}_k$ and the initial states $\mathbf{X}_0$ are exactly known. The optimization aims at minimizing total costs subject to energy balances of heat and electricity, operational limits of all technologies and initialization, with $\mathbf{P}_k$ and $\mathbf{Q}_k$ being the decision variables. Note that slack variables are introduced wherever suitable to ensure feasibility but are omitted for simplicity.

3. Case study

The energy hubs were based on a case study carried out for the village Rolle in Switzerland and more information can be found in reference [4]. In this case study area, buildings were clustered into hubs and the multi-hub energy system represents a district-scale application, in which demands represent aggregated electricity and heat loads of a couple of hundred buildings. The heat demand patterns of hub A, B and C as well as the temperature levels during four typical weeks in all seasons are exemplified in Figure 2. Specifically, electricity and heat demands were considered inflexible in this study. The simplified MPC adopts same techno-economic characteristics as the Ehub tool and the comparison concerns the impacts of forecast horizon. The detailed MPC considers realistic representation of techno-economic characteristics, allowing assessment of the impacts of model fidelity. The remaining section describes the additional considerations that differentiate the detailed dispatch from the simplified dispatch strategy. The operational characteristics of Combined Heat and Power (CHP) was considered using a piece-wise approximation of its operational area. Additional ramping rates and minimum run-time constraints [5] were included in the detailed dispatch. Battery degradation was incorporated by considering the marginal aging cost of each battery cycle [6]. A dynamic tariff was considered with higher grid tariffs on weekdays between 7 a.m. and 8 p.m. and Saturdays from 7 a.m. to 13 p.m. with 0.27 CHF/kWh and 0.22 CHF/kWh for the rest of the time [7]. The tariffs were adjusted in magnitude to match the grid tariff assumption in the Ehub tool, which is crucial to ensure comparable results. Furthermore, the MPC implementation was conducted for prediction horizons of 4 hours, 12 hours and 24 hours. Note that perfect foresight of price, load patterns and weather conditions were assumed. Additionally, a connection to the external power grid was assumed allowing electricity import when there was insufficient energy supply within the hubs.



(a) Hub A (b) Hub B

(c) Hub C (d) Temperature

Figure 2: Temperature patterns and corresponding heat demand patterns in all energy hubs.

4. Results

This section first presents the results of system designs followed by discussing the control results in all cases, where the same system designs were used. A variety of technologies were considered in system design, namely Ground Source Heat Pump (GSHP), Photovoltaic (PV), micro-CHP, CHP, Thermal Photovoltaic (PVT), gas boiler, water-based thermal storage and batteries. A range of designs with diverse cost and emission levels were obtained using the Ehub tool. For a concise discussion of performance gaps, the rest of the paper focuses on two Pareto-optimal solutions when implementing MPC-based dispatch: the cost-optimal system and the emission-optimal system, as shown in Figure 3.

The cost-optimal design represented a system design with a highly-dispatchable capacity (large gas-fuelled CHP units) and a high share of RES in power supply. The emission-optimal design featured a system design with high shares in both the heat and the power supplies, large batteries and thermal storage within all energy hubs. More specifically, Hub A operated a large and a micro-CHP. Each of the three energy hubs operated a GSHP and PV in the cost-optimal design. In the emission-optimal design, Hub A relied heavily on PVT that produced electricity and heat simultaneously. In the emission-optimal design, all energy hubs operated large storage devices as shown in Table 1. In contrast, only the largest Hub A operated a short-term storage and Hub B operated a negligible thermal storage in the cost-optimal design. In both designs, the energy hubs also partially relied on gas boiler. With the system designs presented in Figure 3, the simplified MPC and the detailed MPC were implemented and the comparison with the baseline is exemplified for Hub A in Figure 4.

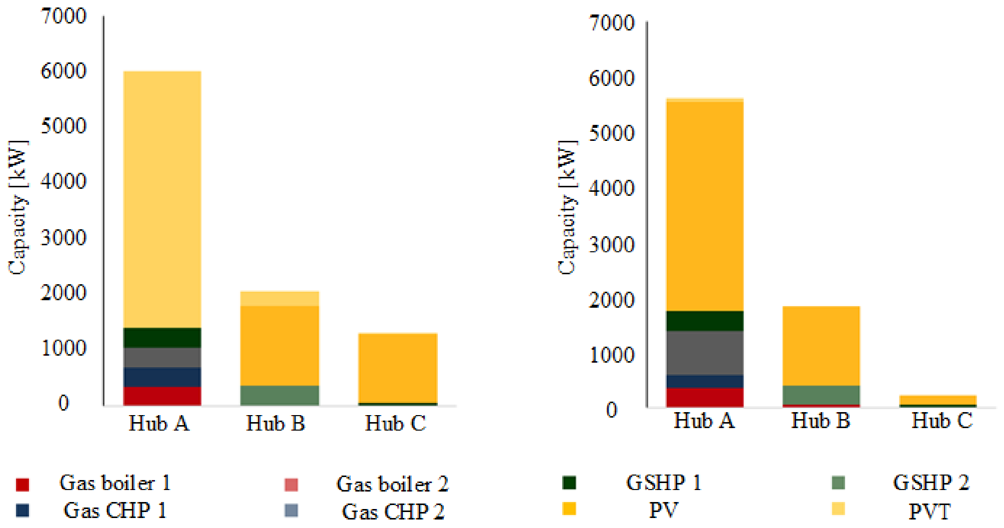
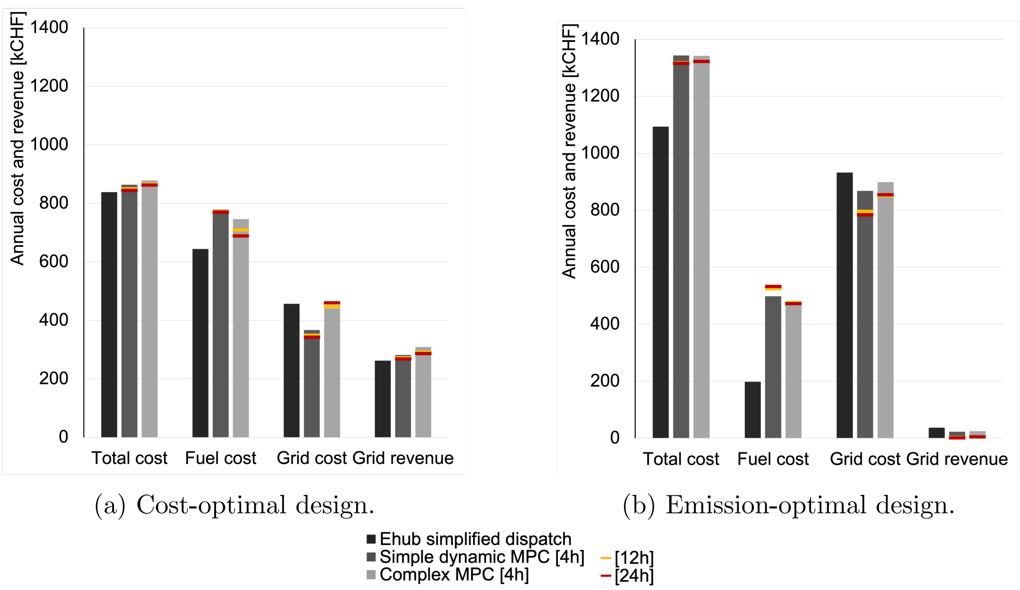


Figure 3: Technology mix and the corresponding capacities in energy hubs A, B and C.

Table 1: Storage system sizing in the cost-optimal design (denoted as PP1) and the emission-optimal design (denoted as PP8).

Storage	Hub A PP1	Hub B PP1	Hub C PP1	Hub A PP8	Hub B PP8	Hub C PP8
Hot water tank [kWh_{th}]	14340	2	-	147106	4275	249
Battery [kWh_{el}]	840	-	-	4907	2124	297



(a) Cost-optimal design. (b) Emission-optimal design.

Figure 4: Total operational cost of the largest Hub A calculated for the Ehub dispatch, a simplified MPC control and the MPC control with detailed physical constraints. The comparison is made for horizons of 4 hours (grey), 12 hours (yellow) and 24 hours (red).

In the cost-optimal design, reducing the forecast horizon to 24 hours only led to marginal increase in total cost by 0.8 %, since there were highly-dispatchable generator capacities. However, the reliance on CHP units increased along with more fuel consumption when grid imports were limited. Further consideration of weather-induced performance degradation of PV panels, physical constraints of gas boilers and CHP units reduced system flexibility in the cost-optimal design and the total cost increased by 2.9% compared to the Ehub tool. In the emission-optimal design, there were high shares of renewables in both heat and power supplies. The system costs and heat mismatches increased significantly when reducing the horizon. Concretely, limiting the forecast to 24 hours greatly affected the total cost resulting in an increase by 20.3 %. Detailed consideration of operational constraints further reduced system flexibility in the emission-optimal design leading to cost increase by 20.9 % compared to the baseline.

5. Conclusion

The energy systems are experiencing system-wide changes due to large-scale integration of renewables and decision makers need to consider system planning and operation holistically. The existing energy system planning tools, such as the Ehub tool, commonly consider simplified representation of the operational stage to mitigate computational burdens. This introduces performance gaps between design and operation stages. This work aims to quantify such gaps using a real-world case study system and focuses on the impacts of model fidelity and dispatch strategies. A comparison between the simplified MPC and the dispatch strategy from the Ehub tool shows the impacts of forecast horizon length. Instead of full knowledge within the entire design period, MPC implementations with horizons of 4 hours, 12 hours and 24 hours are evaluated. The performance gaps are quantified for two selected system designs: the cost-optimal design and the emission-optimal design. Results show that limiting the horizon of forecast to 24 hours has larger impacts for the emission-optimal system than for the cost-optimal system. Additionally, detailed considerations of physical constraints influence grid dependencies and fuel consumption but there are no significant impacts on resultant costs. Nonetheless, a number of limitations must be noted. The study assumes perfect foresight of load patterns and prices, which is not realistic. Future work includes examining the impacts of forecast errors. Second, the results obtained have implication on improving system design. This information feedback to the design stage needs to be further investigated. Lastly, heating demand is considered inflexible in this work and exploring their impacts on system operation can be further investigated.

Acknowledgements

This research has been conducted within the SWEET PATHFNDR project funded by the Swiss Federal Office of Energy SFOE (grant Nr. SI/502259-01).

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