Model-predictive control for testing energy flexible heat pump operation within a Hardware-in-the-Loop setting

Lilli Frison, Martin Kleinstück, Peter Engelmann

Fraunhofer Institute for Solar Energy Systems ISE, Heidenhofstr. 2, 79110 Freiburg, Germany

E-mail: lilli.frison@ise.fraunhofer.de

Abstract. Model-predictive control is a smart control technique that can unlock the potential of the building's thermal production leading to improvements in energy efficiency or energy flexibility, which is obtained by a demand responsive operation based on external grid signals. This work explains the set-up of a Hardware-in-the-Loop experiment to test an energy flexible heat pump controller under realistic conditions. The developed simple, low-cost model-predictive control algorithm can easily be integrated with a traditional heat pump controller.

1. Introduction

Future heat pump systems should interact with the electrical grid in order to balance generation and consumption of electricity and avoid peak load, which can lead to stability failures. This becomes particularly important with the increased share of the strongly intermittent renewable energy sources. Combined with thermal storage, the heat pump system can provide grid service in form of up- or down-regulation during a demand response event, i.e., consume more or less electricity. Such a demand responsive operation strategy involves the complex interaction between various conflicting objectives such as low energy consumption, grid-supportive operation and satisfaction of user comfort requirements. The resulting complex optimization problem can be solved by model-predictive control (MPC), an established control algorithm that exploits available predictions of the future behavior while solving a simplified optimization problem in an iterated moving-horizon fashion. Consequently, the closed-loop control system can correct possible forecasting errors or modeling inaccuracies.

Hardware-in-the-Loop (HIL) testing combines real building hardware with numerical simulations to evaluate the complete system under realistic settings emulated in a lab environment. Compared to numerical simulations, it avoid several modeling uncertainties of the real behavior of the plant but allows to carry out only a limited number of tests. The main aspects of HIL tests for building energy systems reported in the literature are either the test of the controller hardware and communication infrastructure while the heat generation and distribution system are emulated, cf. [1], or the evaluation and validation of single components, e.g. cf. [2, 6]. Only few consider the operation of real heat pump systems in a HIL environment and investigate the complete interaction of thermal, hydraulic, electrical and communication interfaces, cf. [3, 4, 5]. MPC for analyzing the energy flexibility potential of building heating systems, however not in form of HIL tests, has been addressed in several works, e.g., [10, 7, 8, 9].

Compared to the aforementioned publications, the focus of this article is on the implementation of a simple, low-cost MPC algorithm that can quickly be integrated with a traditional heat pump controller. To guarantee real-time operability and the simple implementation into the limited building controller hardware, a fast, gradient-based optimization algorithm has to be used. This poses challenges on the structure of the employed system model and optimization formulation, which are addressed in this work.

2. HIL testbed and communication interface

The employed HIL platform can be classified into four levels: the high-level controller, the hardware under test, the emulation system and the simulation models. The hardware under test comprises the modulating ground-source water/water heat pump with inverter technology and a water storage tank. Two circulation pumps are integrated into the heat pump on the source and sink side. The ground source for the heat pump and the heat consumer are emulated via hydraulic interfaces in two conditioning modules that provide the required temperatures to the heat pump and storage tank, respectively. The thermal behavior of the building and ground source emulators are modeled directly in Python or provided as a functional mock-up unit (FMU) using the PyFMI interface. The data acquisition via Modbus Ethernet was realized with the in-house middleware software tool Remus.

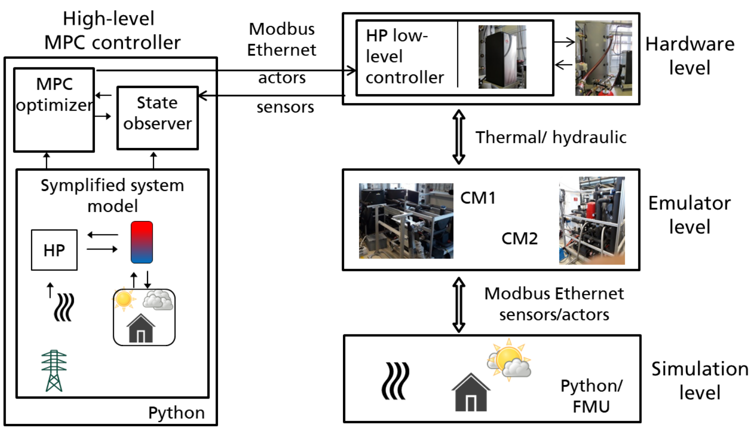

Figure 1. Structure of HIL platform in the test lab.

3. MPC implementation

The structure of the simplified system model for testing MPC in the HIL test bed is depicted in Figure 2. The heat pump is connected in parallel with a storage tank. The water for space heating is injected into the top of the storage tank while the return water for the heat pump is taken from the bottom. The ground source and heat consumer are emulated in the lab in two conditioning modules. The low-level heat pump controller is in charge of keeping the heat pump supply temperature to the storage tank close to the set-point T_{HP} by selecting an appropriate compressor frequency. The high-level MPC controller determines T_{HP} as well as the heat pump operation times in order to facilitate a grid-supportive operation. Thermal management of the pump speeds and valves is done by the corresponding low level controllers.

3.1. Model description

3.1.1. Heat pump model The heating power $\dot{Q}_{\mathrm{HP}} = \dot{m}_{\mathrm{HP}} c_p (T_{\mathrm{HP}} - T_{S_N})$ is calculated from the difference between return temperature to the heat pump T_{S_N} and and the supply temperature

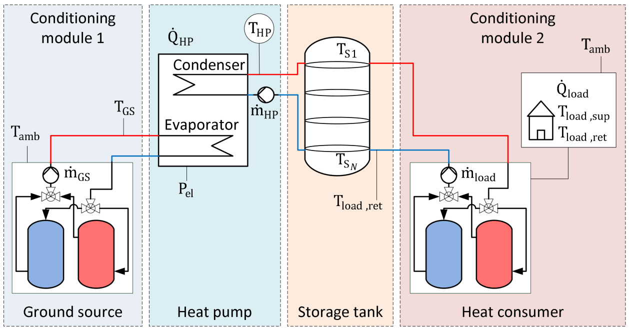

Figure 2. Simplified test bed model for MPC with additional conditioning modules.

from the heat pump to the tank T_{HP} where the mass flow is set constant to $\dot{m}_{\mathrm{HP}} = 0.583$ and the specific heat capacity of water is assumed to be $c_p \approx 4181\,\mathrm{J/kg\,K}$. The used electricity $P_{\mathrm{el}} = \dot{Q}_{\mathrm{HP}}/\mathrm{COP}$ is expressed as the ratio of heat produced $\dot{Q}_{\mathrm{HP}}$ and the heat pump's coefficient of performance (COP).

The COP is expressed as a 2nd-order polynomial and fitted with manufacturer data as per standard EN14511. For variable compressor speed heat pumps, the polynomial comes in the form of:

$$\begin{aligned}\mathrm{COP} = {} & c_0 + c_1 \cdot T_{\mathrm{HP}} + c_2 \cdot T_{\mathrm{GS}} + c_3 \cdot f_{\mathrm{comp}} + c_4 \cdot T_{\mathrm{HP}} \cdot T_{\mathrm{GS}} + c_5 \cdot T_{\mathrm{HP}} \cdot f_{\mathrm{comp}} \\ & + c_6 \cdot T_{\mathrm{GS}} \cdot f_{\mathrm{comp}} + c_7 \cdot T_{\mathrm{HP}}^2 + c_8 \cdot T_{\mathrm{GS}}^2 + c_9 \cdot f_{\mathrm{comp}}^2.\end{aligned}$$

As it can be seen the COP shows a non-linear behavior over compressor speed f_{comp} as well as sink and source temperatures T_{HP} and T_{GS}.

3.1.2. Storage model The employed stratified storage model, cf. [11], with $N_{\mathrm{layer}} = 4$ layers is based on nodal energy and mass flow balances for the temperature evolution of each layer i with mass m_i accounting for transmission losses to the exterior $\dot{Q}_{\mathrm{loss},i}$, heat conduction between layers $\dot{Q}_{\mathrm{cond},i}$ and mixing introduced during charge and discharge cycles:

$$m_i c_p \frac{dT_{S_i}}{dt} = -\dot{Q}_{\mathrm{loss},i} + \dot{Q}_{\mathrm{cond},i} + \dot{Q}_{\mathrm{HP},i} - \dot{Q}_{\mathrm{load},i} + \delta_i^+ \dot{m}_i c_p (T_{S_{i-1}} - T_{S_i}) - \delta_i^- \dot{m}_{i+1} c_p (T_{S_i} - T_{S_{i+1}}).$$

The effective mass flow $\dot{m}_i = \dot{m}_{\mathrm{HP}} - \dot{m}_{\mathrm{load}}$ is positive if energy enters from layer $i-1$, i.e. $\dot{m}_{\mathrm{HP}} > \dot{m}_{\mathrm{load}}$, in which case the parameter $\delta_i^+ = 1$ (otherwise $\delta_i^+ = 0$). A negative effective mass flow from layer $i+1$, i.e. dominance of the load mass flow and thus cooling of layer i, is taken into account by parameter δ_i^-.

3.1.3. Heat demand profiles For a given demand profile $\dot{Q}_{\mathrm{load}}$ the resulting mass flow at the storage is given by $\dot{m}_{\mathrm{load}} = \dot{Q}_{\mathrm{load}}/(c_p(T_{S_1} - T_{\mathrm{ret,set}}))$. The supply and return temperature of the heating distribution system are denoted by $T_{\mathrm{sup,set}}$ and $T_{\mathrm{ret,set}}$, respectively, and are calculated by using a heating curve depending on the ambient temperature and the characteristics of the building heat emission system. In order to satisfy the heating demand, the temperature of the upper layer of the storage tank must be sufficiently high, i.e. $T_{S_1} \geq T_{\mathrm{sup,set}}$ whenever $\dot{Q}_{\mathrm{load}} > 0$.

3.2. MPC formulation

3.2.1. Optimal control problem The resulting optimization problem is given in the form of an economic nonlinear MPC problem with hybrid, i.e. non-continuous, dynamics in the storage modeling. It minimizes the amount paid for the needed electrical energy while ensuring that the tank water temperature is sufficiently high to be able to satisfy the heating demand. This is realized by a soft constraint formulation with constraint (4) with weighting factor w and non-negative slack variable $s(t) \geq 0$ that is only active whenever the heating demand is positive.

$$\min_{x,u,p,s} \int_0^{t_\mathrm{f}} c_\mathrm{el}(t) P_\mathrm{el}(t) + \dot{Q}_\mathrm{load}(t)/4181 s(t)^2 + 0.01 s(t)^2 \,\mathrm{dt} \tag{1}$$

$$\text{s.t.} \quad \dot{x}(t) = f(x(t), u(t), p(t)) \tag{2}$$

$$x(0) = x_0 \tag{3}$$

$$T_\mathrm{sup,set}(t) \leq T_{S_1}(t) + s(t) \tag{4}$$

$$\dot{Q}_\mathrm{HP,min}(t) \leq \dot{Q}_\mathrm{HP}(t) \leq \dot{Q}_\mathrm{HP,max}(t). \tag{5}$$

The state vector $x = (T_{S_1}, \ldots, T_{S_N})^\mathrm{T}$ holds the storage layer temperatures. The controllable input is the heat pump supply temperature $u = T_\mathrm{HP}$. The time dependent system parameters or external influences are $p = (\dot{Q}_\mathrm{load}, c_\mathrm{el}, T_\mathrm{amb}, T_\mathrm{sup,set}, T_\mathrm{ret,set})^\mathrm{T}$, i.e. the heat demand for space heating, the grid signal, the ambient temperature and the supply and the return set point temperature of the heating distribution system, respectively. The thermal capacity of the heat pump depends on T_HP and is included as time variant lower and upper bounds in constraint (5).

The quality of the solution will be evaluated by the cost $\int_0^{t_\mathrm{f}} c_\mathrm{el} P_\mathrm{el} \,\mathrm{dt}$ and by the deviation of the upper storage layer temperature from the load set-point temperature $\int_0^{t_\mathrm{f}} (T_\mathrm{ret,set} - T_{S_1})_+ \,\mathrm{dt}$ where $(T_\mathrm{ret,set} - T_{S_1})_+ = \begin{cases} T_\mathrm{ret,set} - T_{S_1} & \text{if } T_{S_1} < T_\mathrm{ret,set} \text{ and } \dot{Q}_\mathrm{load} > 0 \\ 0 & \text{else} \end{cases}$.

3.2.2. Relaxation of hybrid formulation State-dependent discontinuities arise from the temperature dependent lower bound $\dot{Q}_\mathrm{hp,min}$, which equals 0 if the heat pump is off and a minimum output power larger than 6kW otherwise, and the upward or downward direction of the mass flows between different layers in the storage model. In order to apply a gradient-based solver, the discontinuous formulations must be relaxed by using sub-optimal heuristic rules, e.g. a post-processing step to meet the lower heat pump bound and the simplifying assumption that the building load mass flow is smaller than that of the heat pump.

3.2.3. Solution of the MPC problem For solving the MPC problem, the optimal control problem is transformed into a nonlinear optimization problem using direct collocation [12] on a time grid of step size 900s, which prevents an over-frequent cycling of the heat pump. The MPC algorithm as well as the system model are implemented in Python, using the symbolic differentiation framework CasADi [14] and the nonlinear programming solver IPOPT [13]. The sampling length for MPC is 900s while the prediction horizon is 24h. The solution time for one MPC iteration and for a yearly simulation takes less than 1s and half a day, respectively, on a PC with limited performance.

4. Case study

The heat pump employed in the test bed allows to modulate the thermal power output in the range of 7 to 25 kW at W10/W35. The water tank has a volume of $1\mathrm{m}^3$, which gives a maximum storage capacity of approximately 23kWh (assuming a low-temperature load supply of 35°C and a large storage over-heating temperature of 20K). Thus, the energy flexibility potential lies in the range of a few hours during one day and requires a heat pump charging operation of 1 hour at full heat pump load and almost 3 hours at optimum compressor speed. Whether the system can exploit the energy storage capacity during a demand response event and provide up- or down-regulation to the grid, depends on the heating load profile.

As current electricity prices, e.g. the variable day-ahead-price, or other grid flexibility signals do not offer sufficient variations to stimulate grid-supportive operation [15], we consider an artificial renewable energy cost signal that is based on the solar and wind energy production in Germany over the heating season (January till April, October till December) of 2018 [16]. The averaged and scaled cost signal is presented in Figure 4 with high cost in the late morning and afternoon.

In a short case study, we show how the developed MPC algorithm can exploit the flexibility potential of the heat pump storage system. The load profile features an energy-efficient office building with a maximum heating power demand of 20kW. Since the considered flexibility potential is in the range of hours, the HIL testing duration can be reduced to one type day for the considered grid signal. The employed averaged demand profile is presented in Figure 4. The resulting grid-supportive storage temperature profile as well as heat pump thermal production are illustrated in Figures 3 and 4. The energy efficient reference operation is obtained by using

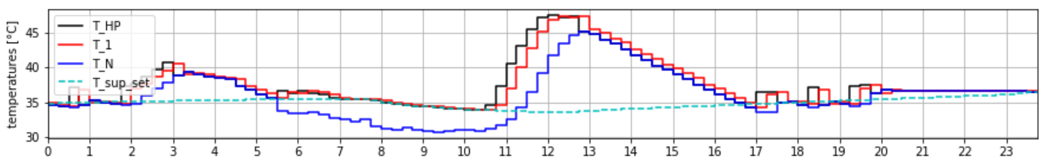

Figure 3. Charging of storage tank computed by energy flexible MPC for 24h. Upper and lower tank temperature, heat pump supply and consumer set-point temperature are plotted as red solid, blue solid, black and dashed cyan curve, respectively.

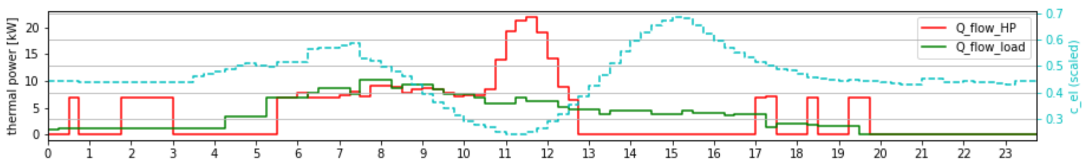

Figure 4. grid-supportive heat pump operation computed by MPC for 24h. Heat pump thermal power and heating load are plotted as red solid and green dash-dotted curve. The grid signal c_{el} is plotted as light blue-colored dashed curve.

a constant grid signal and takes into account the minimum heat pump power requirement. The flexible operation is compared to the reference strategy by computing the percentage increase or decrease factor $1 - C^{\mathrm{flex}}/C^{\mathrm{ref}}$ where C represents the considered indicator, e.g., energy usage, cost or grid support. The latter is evaluated by the grid support coefficient GSC [15], which indicates whether electricity is consumed in average at a grid pricing signal lower (GSC < 1), equal (GSC $= 1$) or higher than average (GSC > 1). The simulation results are presented in Table 1 and confirm the achieved energy flexibility resulting from the MPC. The energy efficient reference strategy, which follows the heat demand profile, can be classified as grid-neutral. To support the validity of the reduced HIL type day set-up, the comparable results for the full heating year are included.

5. Summary and future work

This contribution presents the set-up of a HIL experiment for testing the energy flexibility potential of a heat pump system. The focus is on the development of a simple, low-cost MPC

Table 1. Increased energy usage and improvement in energy flexibility of grid-supportive operation compared to reference operation for type day and simulation of the full heating year.

test duration	single type day	heating year
energy usage increase	1.9%	0.3%
GSC improvement	15.2%	16.0%
GSC absolute values	0.84 (flex), 0.99 (ref)	0.84 (flex), 1.0 (ref)
cost saving	3.1%	5.72%

controller that is suitable for implementation in control hardware, and the set-up and evaluation of the testing sequence. The actual lab experiments are currently in operation.

Acknowledgments
The authors acknowledge the financial support by the German Federal Ministry of Economics and Energy in the project "flexControl" (project code: 03ET1359A).

References

[1] Stutterecker W, Schoberer T, Steindl G 2015 Development of a Hardware-in-the-Loop Test Method for Heat Pumps and Chillers *Proceedings of REHVA Annual Conference" Advanced HVAC and Natural Gas Technologies"* 117-24

[2] De La Cruz AT, Riviere P, Marchio D, Cauret O and Milu A 2017 Hardware in the loop test bench using Modelica: A platform to test and improve the control of heating systems *Applied energy* **188** 107-20

[3] El-Baz W, Mayerhofer L, Tzscheutschler P and Wagner U 2018 Hardware in the Loop Real-Time Simulation for Heating Systems: Model Validation and Dynamics Analysis *Energies* **11** 3159

[4] Chen K, Streblow R, Müller D, Benigni A, Molitor C and Monti A 2012 Hardware-in-the-Loop Simulationsverfahren für Hausenergiesysteme *Proceedings of the Fourth German-Austrian IBPSA Conference*

[5] Schneider G F, Oppermann J, Constantin A, Streblow R and Müller D 2015 Hardware-in-the-Loop-Simulation of a Building Energy and Control System to Investigate Circulating Pump Control Using Modelica *Proceedings of the 11th International Modelica Conference* **118** 225-33

[6] Pratt A, Ruth M, Krishnamurthy D, Sparn B, Lunacek M and Jones W 2017 Hardware-in-the-loop simulation of a distribution system with air conditioners under model predictive control *IEEE Power & Energy Society General Meeting, Chicago* 1-5

[7] Halvgaard R, Poulsen N K, Madsen H and Bagterp Jorgensen J 2012 Economic Model Predictive Control for building climate control in a Smart Grid *Proceedings of the 2012 IEEE PES Innovative Smart Grid Technologies* (IEEE Computer Society, Washington, DC, USA) 1-6. DOI=http://dx.doi.org/10.1109/ISGT.2012.6175631

[8] Masy G, Georges E, Verhelst C, Lemort V and André P 2015 Smart grid energy flexible buildings through the use of heat pumps and building thermal mass as energy storage in the Belgian context *Science and Technology for the Built Environment* **21** 800-11

[9] Péan T C, Salom J and Costa-Castelló R 2019 Review of control strategies for improving the energy flexibility provided by heat pump systems in buildings, *Journal of Process Control* **74** 35-49

[10] Fischer D, Bernhardt J, Madani H and Wittwer C 2017 Comparison of control approaches for variable speed air source heat pumps considering time variable electricity prices and PV. *Applied Energy* **204** 93-105

[11] Eicker U 2003 *Solar Technologies for Buildings* (Wiley)

[12] Rawlings JB, Mayne DQ and Diehl M 2018 *Model Predictive Control: Theory, Computation, and Design* **2** (Nob Hill Publishing)

[13] Wächter A and Biegler L T 2006 On the Implementation of a Primal-Dual Interior Point Filter Line Search Algorithm for Large-Scale Nonlinear Programming *Mathematical Programming* **106** 25–57

[14] Andersson J, Gillis J and Diehl M 2017 User Documentation for CasADi URL `http://casadi.sourceforge.net/users_guide/casadi-users_guide.pdf`

[15] Klein K, Herkel S, Henning H-M and Felsmann C 2017 *Load shifting using the heating and cooling system of*

an office building: Quantitative potential evaluation for different flexibility and storage options **203** 917-37
Characterizing the energy flexibility of buildings and districts *Applied Energy* **225** 175-82
[16] SMARD Strommmarktdaten der Bundesnetzagentur `https://www.smard.de/home/downloadcenter/`