FLEXHP – FORECAST-DRIVEN, AI-ENHANCED CONTROL STRATEGIES FOR FLEXIBLE HEAT PUMP OPERATION

Bernhard KLING[1], Magdalena WOLF[1], Constanze RZIHACEK[1], Patrick WAGNER[2], Sara LOPEZ[2], Markus RESCH[2], Martin PACZONA[3]

Introduction

The building sector accounts for approximately 30 % of Austria's final energy consumption and therefore offers significant potential for reducing energy demand and greenhouse gas emissions. Heat pumps (HPs) play a central role in this transition, as they combine high thermal efficiency with the capability for sector coupling between electricity and heat supply. As of 2024, around 530 000 heat pumps are installed in Austrian buildings, representing a substantial and largely untapped flexibility resource for the electricity system.

Despite this potential, most heat pumps are still operated using simple temperature-based control strategies originally designed for fossil boilers. Advanced predictive strategies, such as model predictive control, are well documented in academic literature but rarely applied in practice due to the considerable modelling effort, limited data availability, and computational constraints [1-3].

The project *FlexHP* addresses these challenges by integrating physics-based models of heat pump and building behaviour with data-driven, AI-supported forecasting methods. The overarching objective is to develop the conceptual foundation for a building-level energy management system capable of optimising heat pump operation in a forecast-driven manner while also incorporating external influences such as price signals or grid-relevant indicators.

Methodological Approach

A comprehensive forecast of building energy flows requires reliable models for all components within the system boundary, defined here as the building including on-site photovoltaic (PV) generation. Models for PV and battery storage are taken from existing research, while FlexHP focuses on detailed modelling of the heat pump and the building's thermal dynamics.

Physics-based models are validated using high-resolution measurements from a real demonstration building (LivingLab Stinatz). These validated models are then combined with a machine-learning framework trained on historical operational data to derive short-term forecasts of thermal demand and electrical consumption.

The heat pump model predicts the coefficient of performance (COP) as a function of evaporation and condensation temperatures. Four commonly used refrigerants (R407C, R290, R600a, R1234ze) are considered. Based on the building's heating load, the required thermal output of the heat pump is determined, from which the corresponding electrical power demand is derived via the COP.

Model development is carried out in IPSEpro, employing thermodynamic property data and mass and energy balances. The simulation model is shown in Figure 1. A multiparameter study was conducted to systematically vary evaporation and condensation temperatures, as well as the isentropic compressor efficiency. From the resulting characteristic surfaces, regression functions were obtained that allow computationally efficient integration of heat pump performance into the AI-based forecasting system.

[1] BOKU University, Muthgasse 107, 1190 Vienna, Austria, +43 1 47654 89315, magdalena.wolf@boku.ac.at, short.boku.ac.at/buildings
[2] Forschung Burgenland, Europastraße 1, 7540 Güssing, Austria, +43 664 612 7302, markus.resch@forschunginnovation-burgenland.at
[3] Novotek Austria GmbH, Pallstraße 2, 7503 Großpetersdorf, Austria, martin.paczona@novotek.com

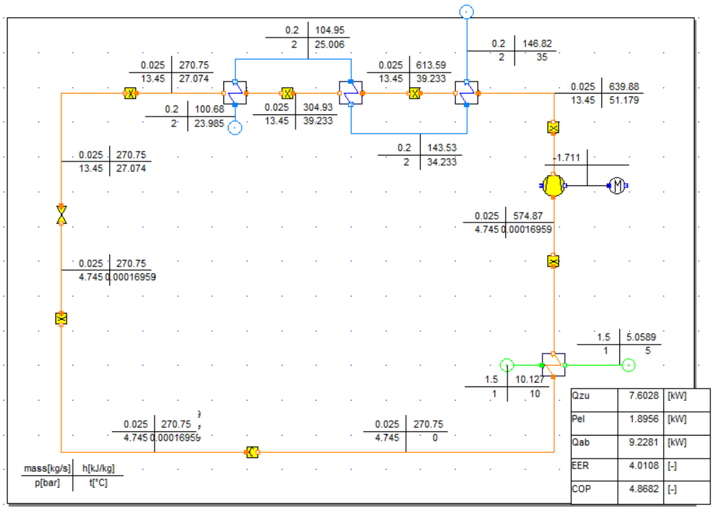

Figure 1: Design of the heat pump model in IPSEpro on components level

Results and Application

The outcome of the modelling phase is a set of mathematical COP models that can be directly embedded into a predictive control algorithm. The multiparameter study confirms that the primary drivers of heat pump performance—source and sink temperatures—exhibit strong nonlinear effects. For each refrigerant, analytical regression equations (Equations 1 – 4) were derived, providing accurate and computationally efficient COP predictions across a wide operating range. These results form the basis for reliable forecasts of the electrical energy demand associated with heat pump operation.

R407C:

$$\mathrm{COP} = 10.8213 + 0.2768 \cdot \mathrm{T_{Evap}} - 0.2526 \cdot \mathrm{T_{Cond}} + 0.002607 \cdot \mathrm{T_{Evap}^2} + 0.00197 \cdot \mathrm{T_{Cond}^2} - 0.004252 \cdot \mathrm{T_{Evap}} \cdot \mathrm{T_{Cond}} \quad (1)$$

R290:

$$\mathrm{COP} = 10.2121 + 0.2495 \cdot \mathrm{T_{Evap}} - 0.1771 \cdot \mathrm{T_{Cond}} + 0.00208 \cdot \mathrm{T_{Evap}^2} + 0.001146 \cdot \mathrm{T_{Cond}^2} - 0.003057 \cdot \mathrm{T_{Evap}} \cdot \mathrm{T_{Cond}} \quad (2)$$

R600a:

$$\mathrm{COP} = 10.7852 + 0.2121 \cdot \mathrm{T_{Evap}} - 0.2014 \cdot \mathrm{T_{Cond}} + 0.001602 \cdot \mathrm{T_{Evap}^2} + 0.001381 \cdot \mathrm{T_{Cond}^2} - 0.002479 \cdot \mathrm{T_{Evap}} \cdot \mathrm{T_{Cond}} \quad (3)$$

R1234zE:

$$\mathrm{COP} = 10.7564 + 0.2211 \cdot \mathrm{T_{Evap}} - 0.2041 \cdot \mathrm{T_{Cond}} + 0.001684 \cdot \mathrm{T_{Evap}^2} + 0.001431 \cdot \mathrm{T_{Cond}^2} - 0.002652 \cdot \mathrm{T_{Evap}} \cdot \mathrm{T_{Cond}} \quad (4)$$

T_{Evap} … Evaporation temperature [°C]

T_{Cond} …Condensation temperature [°C]

COP … Coefficient of performance [-]

Outlook

The next phase of the project will focus on validating the heat pump models using the LivingLab measurement dataset. In parallel, a multizone RC model of the building will be developed in Python and later integrated with the existing forecasting framework. This combined model will enable comprehensive assessment of building-level thermal flexibility and support the development of AI-enhanced control strategies for grid-adaptive heat pump operation.

Literature

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