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Optimizing Energy in Single-Family Homes

From Biomass Boilers to Heat Pumps

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Abstract. Many different components for heat or electricity generation have been installed in single-family homes in recent years. The efficient use of the controllable components while harvesting the volatile renewable sources and satisfying the energy consumption has become increasingly difficult. For this, we developed a modular, predictive, optimization-based supervisory control framework now deployed in hundreds of single-family homes. While initially targeting systems with biomass boilers and thermal storage, the focus has recently been extended to heat pumps. However, this shift is not straightforward, since heat pumps are typically paired with smaller buffer sizes, limiting flexibility. At the same time, heat pumps also provide new optimization potential, e.g. making use of varying electricity prices and coefficients of performance. In this contribution, we present results from real-world implementations and discuss the operational differences that arise when transitioning from biomass boilers to heat pumps. The findings demonstrate that optimization strategies must be adapted to system flexibility and storage characteristics, highlighting key requirements for the effective predictive control of residential multi-energy systems.

Keywords: Energy Management System, Model Predictive Control, Sector Coupling, Flexibility

1. Introduction

In recent years, the heating systems of single-family homes have undergone a significant transformation. Traditionally, boilers have been used for heat generation, with a gradual shift from oil and gas systems to biomass boilers. Biomass boilers are typically paired with large thermal buffers, as their relatively slow response times contrast with end users' expectations for immediate heat supply. More recently, compression heat pumps have become increasingly popular as the primary heat source for single-family homes. Compared to biomass boilers, heat pumps can deliver heat more quickly and on demand. This allows for much smaller thermal buffer storage volumes. Smaller buffers are attractive because they have lower investment costs, require less space, and reduce thermal losses when stored heat goes unused. However, larger buffers offer better operational flexibility, for example enabling the heat pump to run during periods where surplus electrical power from photovoltaics is available, where electricity prices are lower, or where a higher coefficient of performance can be achieved. Such flexibility can be used to significantly reduce operating costs. Many single-family homes now operate as multi-energy systems, integrating several energy sources, some of them volatile. These can be optimized through supervisory control systems designed to use heat and electricity as efficiently as possible within the household. If the control systems are predictive, they can also effectively employ the flexibility provided by energy storage. Looking ahead, this flexibility will also be critical for developments such as demand-side management, where a higher-level supervisory control of an energy supplier can help shift household energy demand to flatten peak loads.

1.1 Literature Review

While Mixed Integer Linear Programming (MILP)-based approaches and model predictive control (MPC) strategies for building energy systems have been extensively investigated in simulation environments and demonstrate significant potential for improving overall system performance, real-world implementations remain comparatively scarce, as discussed in [1].

Several studies have explored optimal operation and control of residential heating systems under specific configurations or objectives. For example, optimal operation of a multi-energy residential heating system including a logwood boiler, buffer storage, and solar thermal collector has been presented in [2]. Predictive operation and load shifting of heat pumps in residential buildings have also been investigated in simulation-based studies, typically assuming specific hydraulic configurations or control structures [3]. In [4], MPC is used to simultaneously reduce noise emissions and improve energy efficiency of air-source heat pumps by exploiting operational flexibility, but real-world application results are missing.

At a larger scale, energy flexibility provision through third-party control of residential heat pumps has been demonstrated in a field trial involving building clusters, highlighting the practical relevance of advanced supervisory control strategies [5]. A global optimal dispatch strategy for a combined solar thermal and air-source heat pump heating system has been proposed in [6], demonstrating the benefits of coordinated control across multiple heat sources - but only for a very limited duration of the experiments. Performance improvements through adaptive operating conditions have been investigated in [7], where a variable water temperature control strategy for air-source heat pumps in floor heating applications is shown to enhance operational efficiency and thermal comfort, for a limited duration and a specific application. These studies highlight the importance of system integration but are predominantly evaluated in simulation environments or specific application contexts with short-term experiments.

The present work builds on the MILP-based modular energy management framework introduced in [8] and its demonstrated applications in district heating [9] and buildings [10], and employs the multi-temperature thermal buffer storage model presented in [11]. Recent simulation studies comparing MPC and rule-based control for single-family heat pump systems demonstrate considerable performance improvements achievable with predictive control [12]. Although predictive optimization has demonstrated substantial potential in building energy systems, existing research largely assumes sufficient thermal storage or building flexibility. The consequences of limited flexibility in single-family homes — and the resulting structural change in the control problem — have not been systematically investigated in real residential multi-energy systems.

1.2 Knowledge Gap and Contribution

The current optimization-based control strategy for residential multi-energy systems has been developed under the assumption of significant thermal storage flexibility. While valid for biomass-based systems, this assumption breaks down in heat pump installations with small buffer volumes and fast dynamics. Consequently, it remains unclear whether established optimization principles remain effective when system flexibility is limited and production cannot be temporally decoupled from demand.

A systematic understanding of how storage constraints fundamentally change optimization objectives and control performance — particularly under real operating conditions — is still missing. This work addresses this gap through empirical analysis of optimization-based supervisory control across heterogeneous residential systems with different flexibility structures.

The remainder of this paper is structured as follows: in Section 2, the optimization framework is described. In Section 3, implementation requirements and details on the differences in the dynamics and operation biomass boilers and heat pumps are stated, while results and challenges of the real-world implementation in single-family homes are presented in Section 4, with a conclusion in Section 5.

2. Optimization Framework

An optimization-based control framework as depicted in Figure 1 has been developed that can consider the a) energy production of various components of a multi-energy system, including biomass boilers, photovoltaic systems, solar collectors, power-to-heat devices, e.g., heat pumps and heating rods, b) energy storage in thermal buffers, and c) consumption such as domestic hot water, space heating and electrical power consumption [8]. The framework's modular design enables the optimization problem to be tailored to the given system configuration, making it particularly suitable for residential applications. For this purpose, a configuration file has to be provided to the optimization framework, including descriptions of the multi-energy system's components, reference values, cost parameters and controller settings such as sampling time and prediction horizon.

To exploit system flexibility, forecasts of the weather, the volatile energy generation and the heat and electricity consumption are required. Weather and electricity price forecasts are obtained from an external source, while other predictions are computed within the framework using a multi-linear regression (MLR) approach as described in [13]. Using these forecasts, a mixed-integer linear programming (MILP) optimization problem is solved, and the resulting schedules for the heat-producing components are transmitted to the controllable devices.

The objective function includes both actual costs – such as electricity and fuel – and virtual costs, for example penalties for the biomass boiler switching on and off, or for deviations of the thermal buffer state of charge (SoC) from predefined operating ranges. Default parameters for the different costs have been derived from simulation studies and changes in the parameters can be applied via the system configuration file mentioned above.

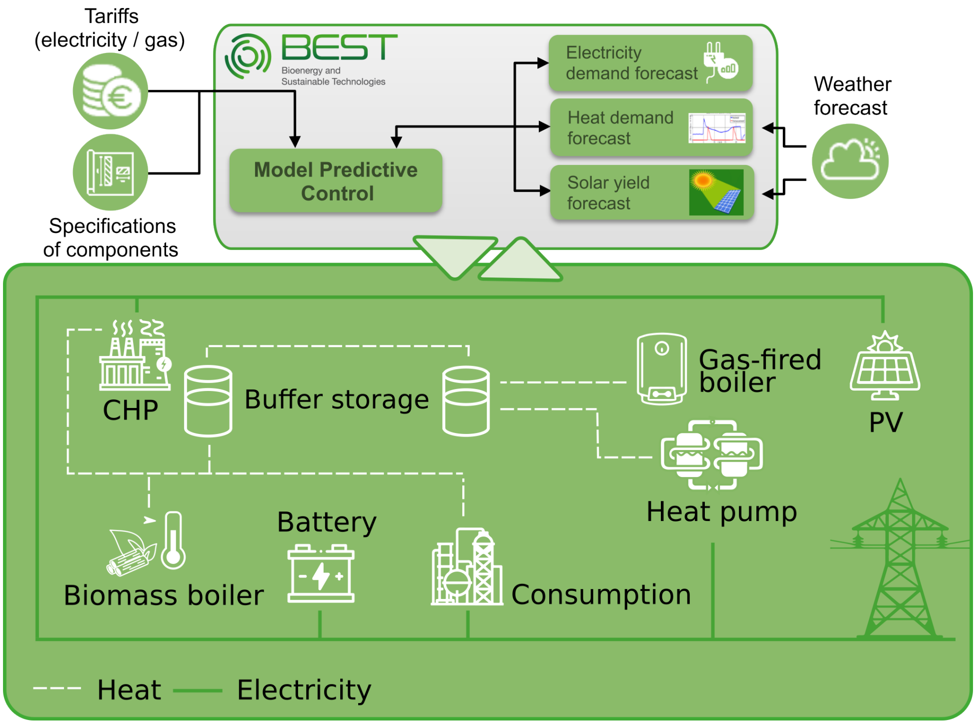


Figure 1. *Optimization-based supervisory control for multi-energy systems*

For the heat pump, the coefficient of performance (COP), which depends on ambient and feed temperatures, is configured according to manufacturer data and used within the optimization.

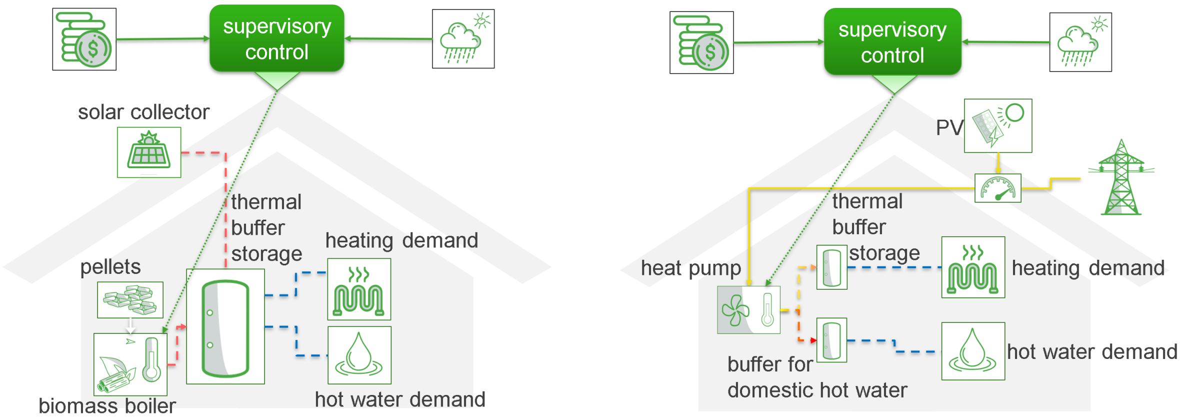
The optimization framework is implemented in Julia [14] and deployed for this application in a Docker container on a Raspberry Pi with 8GB RAM. Thus, the optimization runs locally and only needs internet access for forecast updates. In case of connection loss, the weather forecasts are trusted for a predefined time before switching back to a conventional, rule-based control strategy. In addition, safety checks are active which monitor the system performance and revert to the rule-based control strategy if predefined thresholds are exceeded, e.g., if a buffer temperature exceeds a certain limit. While the optimization framework is scheduled every 15 minutes with a sampling time of 15 minutes, the low-level checks are performed every minute.

The implementation is currently operational in hundreds of single-family homes. While most installations still use biomass boilers, first results with heat pumps have been obtained under varying hydraulic configurations – both with and without thermal buffers, and with different buffer sizes, revealing specific differences in their operational characteristics, which will be discussed in the following section.

3. From Biomass Boiler to Heat Pump: Theory

In the following discussions, the differences in the multi-energy systems are discussed using the system setup shown in Figure 2 and stated in Table 1.

At first glance, replacing a biomass boiler with a heat pump as the primary heat source appears conceptually straightforward, since in both cases the supervisory controller must ensure that sufficient thermal energy is available to meet predicted demand. However, the fundamentally different dynamic and thermodynamic characteristics of the two technologies lead to substantially different control requirements. Table 2 sum-



(a) *Boiler Configuration* ***(b)*** *Heat Pump Configuration*

Figure 2. *Typical boiler and heat pump configurations*

Table 1. *Typical System Setup with Biomass Boiler or Heat Pump*

Biomass Boiler System	**Heat Pump System**
Nominal Maximum Thermal Power: $8\,\mathrm{kW}$ to $12\,\mathrm{kW}$	$8\,\mathrm{kW}$ to $13\,\mathrm{kW}$
Storage: Large stratified buffer tank $(800\,\mathrm{L})$	Small mixed buffer tank for heating $(300\,\mathrm{L})$, separate buffer for domestic hot water
Optional Components: Solar thermal collector	Photovoltaic (PV) system

marizes the key technological differences between biomass boilers and heat pumps. These differences directly translate into distinct optimization objectives.

Biomass boilers exhibit slow response dynamics with limited modulation capabilites and load-dependent efficiencies. Consequently, large and stratified thermal buffer storages with high thermal capacity are required to store excess heat, bridge boiler start-up phases, and reduce on/off cycling. Because heat production cannot be adjusted rapidly, boiler should be scheduled in advance based on forecasts of heat demand and renewable energy availability to achieve optimal performance. In practice, however, they are often operated reactively, i.e. they are switched on when certain temperature thresholds have been reached.

System performance therefore strongly depends on prediction accuracy: Forecast errors can lead to inefficient operation, unnecessary cycling, or temporary supply deficits. As a result, uncertainty in demand and generation forecasts represents a central challenge in the control of biomass-based energy systems.

In contrast, heat pumps allow fast switching and efficient modulation and are typically paired with smaller, weakly stratified / mixed buffer storages with significantly lower thermal capacity. While stratified buffers could also benefit heat pump systems, they are not yet widely adopted in practice. As a result, storage plays a different functional role: While biomass-based systems prioritize storing energy to decouple production from demand and to ensure minimum runtimes of the biomass boiler, heat pump systems primarily aim to provide the required feed temperature when needed.

Table 2. *Comparison of Biomass Boilers and Heat Pumps*

Biomass Boiler	Heat Pump
Reaction Time:	
Slow response dynamics	Fast on/off switching and rapid response
Modulation and Efficiency:	
Limited modulation capabilities and load-dependent efficiencies	Highly efficient modulation with a variable COP, $f(T_{\mathrm{ambient}}, T_{\mathrm{feed}})$
Temperature Differences:	
High temperature differences ($T_{\mathrm{feed}} - T_{\mathrm{return}}$)	Low temperature differences ($T_{\mathrm{feed}} - T_{\mathrm{return}}$)
Buffer Storage:	
Stratified buffer with high thermal capacity	Mixed buffer with low thermal capacity

In addition, heat pump efficiency strongly depends on operating conditions, particularly the temperature difference between heat source and heat sink. Lower feed temperatures increase the coefficient of performance (COP), while lower ambient temperatures decrease it. Operating the thermal buffer at higher feed temperatures may increase the stored energy, but reduces the COP, leading to higher electricity consumption and operating costs. Thus, unlike biomass systems, where energy storage is the main objective of the optimization, heat pump systems require careful management of operating temperatures to balance efficiency and thermal availability.

From an optimization perspective, the faster dynamics and electrically driven operation of heat pumps introduce additional potential for optimization. Their operation can be aligned with time-varying electricity prices or coordinated with on-site photovoltaic generation, enabling cost optimization and improved utilization of renewable electricity. However, this temporal decoupling between energy generation and heat demand is only possible if sufficient thermal storage capacity is available. At the same time, smaller storage volumes reduce the tolerance to model uncertainties and forecast errors and increase the importance of accurate system modelling.

Furthermore, heat pumps may also be operated with no dedicated thermal buffer storage. In such cases, flexibility can either be provided by moving the demand to times of high COP, or through alternative storage mechanisms, such as utilizing the building mass as a thermal reservoir.

Overall, shifting the focus of supervisory control from biomass boilers to heat pumps changes both the primary optimization objectives and the operational constraints: from maximizing energy storage and minimizing boiler cycling toward managing operating temperatures, maximizing COP, and economically scheduling electricity consumption under limited storage capacity, as summarized in Table 3.

In the following section, results from real-world implementations are presented to validate these differences in practice and to discuss the challenges arising when applying an optimization-based control framework across fundamentally different residential multi-energy system configurations.

4. From Biomass Boiler to Heat Pump: Real-World Results

Figure 3 shows the optimization results for a single-family system equipped with a large stratified thermal buffer and a biomass boiler (according to Table 1). The predicted

Table 3. *Comparison of Optimization Objectives for Biomass Boilers and Heat Pumps*

Biomass Boiler	Heat Pump
Primary Goals:	
Storing energy to reduce on/off cycling of the boiler	Providing the required operating temperature on demand
Providing energy until boiler startup is complete	Maximizing COP *(requires large storage)*
Avoiding boiler operation if solar yield is predicted while satisfying demand	Minimizing operational costs (e.g., variable electricity prices) *(requires large storage)*
Challenges:	
Uncertainties in the prediction of heat production and consumption	Model uncertainties combined with small storage volumes
	Limited optimization potential without sufficient storage capacity

solar thermal yield is incorporated into the schedule, and the biomass boiler is primarily activated during nighttime to ensure sufficient heat supply for the expected demand.

The buffer storage temperatures range from approximately $30\,°C$ to $70\,°C$ while maintaining clear thermal stratification. The lowest subplot presents the state of charge (SoC) of the thermal buffer, which is derived from temperature measurements together with predefined minimum and maximum temperature levels representing the usable thermal energy with respect to a nominal feed temperature for consumption. This SoC serves as a state variable in the optimization.

To account for the slow reaction dynamics and long startup time of the biomass boiler, a minimum SoC of $25\,\%$ is enforced to ensure sufficient stored energy during startup phases. Conversely, a maximum SoC of $85\,\%$ is defined to prevent excessive storage temperatures, particularly in the presence of model uncertainties. As shown in the figure, the optimization maintains the SoC within these limits, both in the planned schedule and in real operation. Here, the expected SoC refers to the predicted value for the optimization horizon, calculated at the current timestep. However, due to forecast uncertainties and system disturbances, deviations from the predicted SoC are inevitable. These deviations can be effectively mitigated by running the optimization every 15 minutes with updated information, allowing the system to adapt dynamically to changing conditions.

Figure 4 shows the operation of a typical system with an air-source heat pump and a comparatively small heating buffer (according to Table 1), complemented by a separate domestic hot water storage. Cost parameters in the objective function have been adapted using the configuration file, otherwise the same optimization framework has been used. In contrast to the biomass system, the heat pump operates almost continuously in order to match the estimated heat demand.

The heating buffer exhibits nearly uniform temperatures, indicating mixed storage behaviour with a substantially smaller temperature spread than in the stratified biomass system. Overall temperature levels are also lower, reflecting operation close to the required feed temperature for consumption. However, in the presented data, buffer tem-

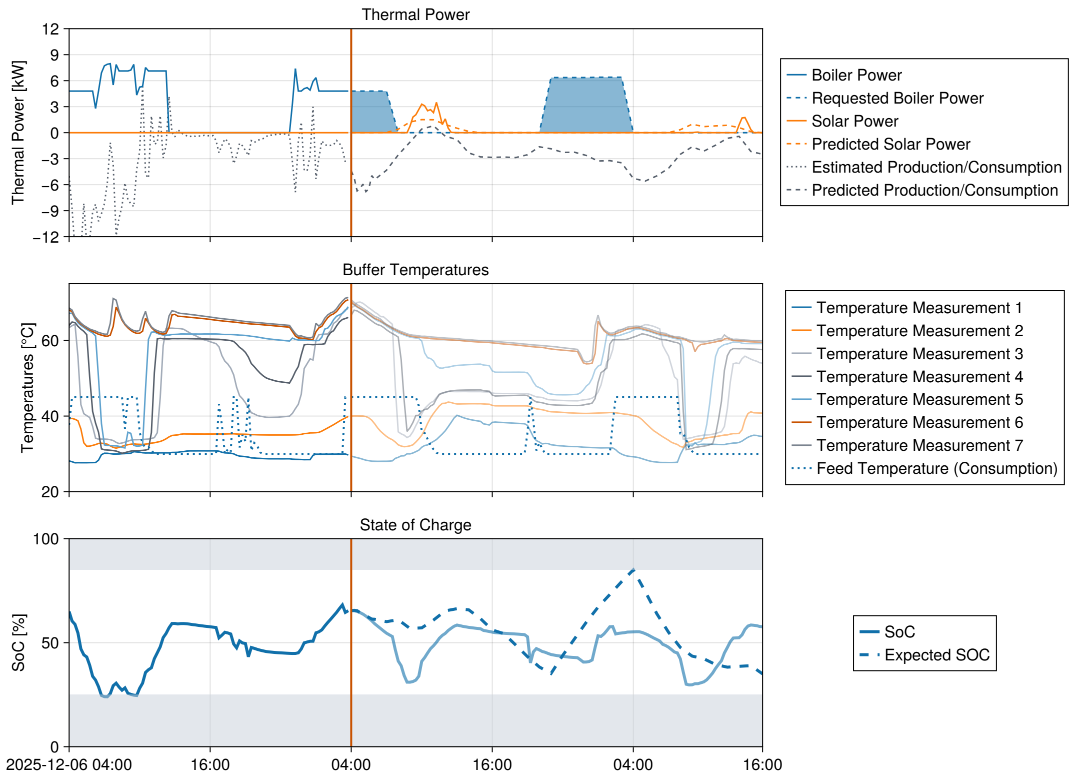


Figure 3. *Results from the single-family home with large storage and biomass boiler from real-world application. The vertical orange line represents the current timestep of the optimization; data to the left is historical data, solid data to the right is actual data from operation in-the-loop, while dashed data shows the optimization results for this timestep over the prediction horizon. The boiler is operated intermittently, the buffer has many different temperature layers and the SoC remains within the configured bounds.*

peratures are higher than necessary. This is caused by model uncertainties of the heat pump: the expected COP (dashed line) underestimates the actual COP (solid line), leading the controller to assume lower available thermal power and therefore operate at higher temperatures than required, which deteriorates the overall performance. Reducing this modelling error is part of ongoing work.

Since heat pumps are characterized by their rapid response capabilities, no minimum stored energy reserve is required and no minimum SoC is configured. Due to the small storage size, the SoC exhibits stronger fluctuations compared to the biomass system. These fluctuations are primarily driven by short-term demand variations and smaller operating temperature ranges, rather than the long-term energy buffering required for biomass boilers. Given these dynamics, the control strategy for heat pump systems must prioritize agility and precision. Specifically, a shorter sampling time is recommended to capture rapid changes in demand and operating conditions. Then, a shorter prediction horizon is preferable since a) long-term predictions (e.g., 36 hours) are unnecessary due to the dominance of short-term demand and b) shorter sampling times require shorter solve times, which is only feasible with a reduced prediction horizon. The effect of these two parameter adaptations will be investigated in future implementations.

These main differences in the resulting operating strategies of the biomass boiler and heat pump systems are summarized in Table 4.

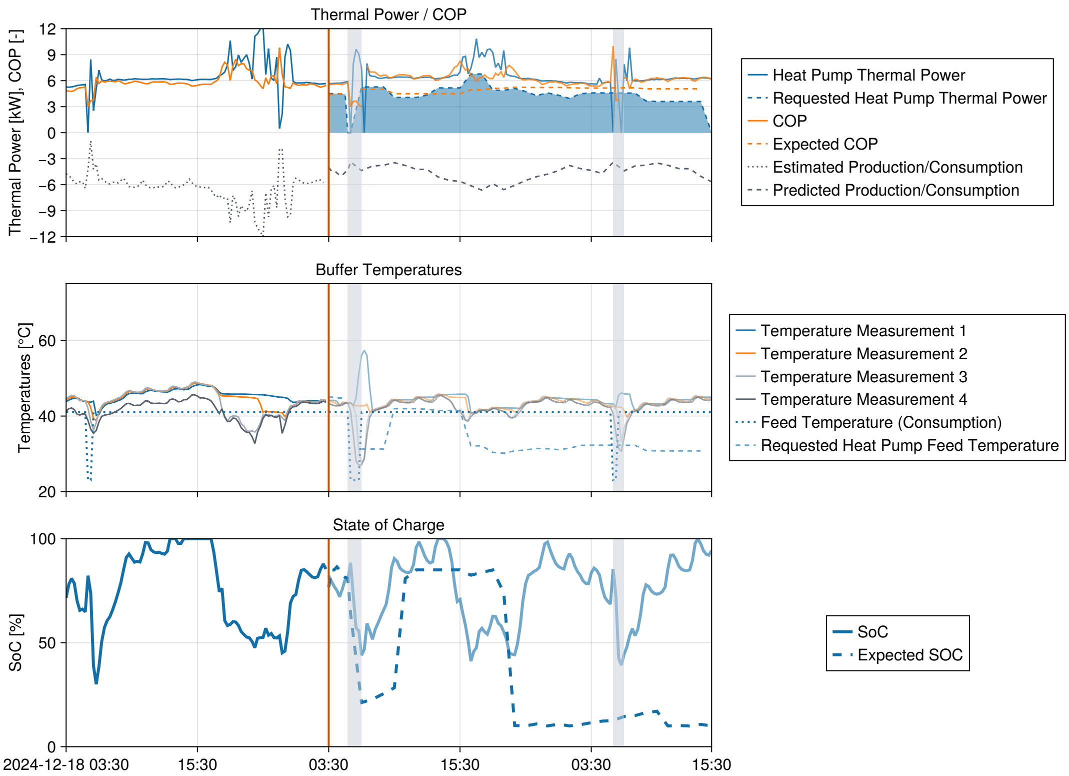


Figure 4. *Results from the system with heat pump and a small storage for heating, with a separate storage for domestic hot water. The vertical line represents the current timestep of the optimization, data to the left is historical data, while solid data to the right is actual data from operation in-the-loop, with optimization results over the prediction horizon represented by dashed lines. The heat pump is modulated and operates continuously, the buffer temperatures are mixed, and the bounds for the SoC are no longer reasonable for the operation with heat pump. Periods with grey background indicate charging of the domestic hot water storage. In the data shown, hydraulic interactions caused an unintended temperature increase in the heating buffer during these periods; this issue has since been resolved and is not considered further in the analysis.*

Overall, the expected flexibility benefits of heat pump operation - such as shifting operation to periods of low electricity prices or high photovoltaic generation - cannot be effectively exploited in the presented system due to the limited thermal storage capacity. Without sufficient buffering, or alternative storage mechanisms such as the thermal mass of the building, heat production must closely follow instantaneous demand. Under these conditions, the heat pump primarily operates as a demand-driven device rather than a flexible energy asset, which fundamentally changes the role and potential benefit of predictive optimization. Developing control strategies that exploit alternative forms of flexibility therefore remains an important topic for future work.

5. Conclusion

This study evaluated the real-world performance of an optimization-based supervisory control framework applied to residential multi-energy systems with fundamentally different primary heat sources. The results demonstrate that control strategies developed for biomass boiler-based systems cannot be directly transferred to heat pump systems without substantial adaptation of the optimization objective. The decisive factor is the available thermal storage capacity and the associated system dynamics.

Table 4. *Operating Strategies in Real-World Scenarios for Biomass Boilers and Heat Pumps*

Biomass Boiler	**Heat Pump**
Operation Mode:	
Intermittent operation (on/off cycling)	Continuous operation with modulation
Storage Strategy:	
Stratified buffer tank	Mixed buffer tank
Maintain minimum stored energy to manage prediction uncertainty	Buffer may be depleted due to fast response capability
Reaction Time:	
Slow (requires preheating and stable combustion)	Fast (near-instantaneous heat output)
Key Objective:	
Minimize boiler on/off cycling and ensure energy availability	Maintain high COP through modulation
Provide heat from the thermal buffer until the boiler output meets the demand	Provide required feed temperature on demand

For biomass-based systems, large stratified buffer storages enable anticipatory operation and energy-oriented scheduling. The optimization therefore focuses on storing heat, reducing cycling, and maintaining sufficient reserves to compensate for forecast uncertainty. In contrast, heat pumps are typically coupled with small, weakly stratified storage volumes and exhibit fast response behaviour. Under these conditions, temporal decoupling between production and demand is limited, and the optimization shifts from energy scheduling toward temperature management and efficiency control. The smaller storage capacity also increases sensitivity to model inaccuracies, particularly in heat pump performance prediction.

Although heat pumps offer additional optimization potential through electrically driven operation, especially when considering time-varying electricity tariffs, this can only be exploited if sufficient thermal storage or equivalent flexibility is available. Results show that, in systems with small buffers, heat pumps largely operate in a demand-driven manner, substantially limiting the benefits of predictive optimization.

Future work should therefore focus on expanding usable system flexibility beyond conventional buffer storage. In particular, the thermal mass of the building represents a promising resource for longer-term load shifting. Realizing this potential requires improved modelling of building thermal dynamics, more accurate component models, and control formulations specifically designed for low-storage systems.

Overall, the findings highlight that effective optimization-based control of residential multi-energy systems must be strongly aligned with available flexibility resources.

Data availability statement

The data supporting the findings of this study have been provided by KWB Energiesysteme GmbH and are restricted due to privacy considerations, as they were collected from private single-family households, and are therefore not publicly available.

Author contributions

Astrid Leitner: Funding Acquisition, Formal Analysis, Investigation, Project Administration, Software, Validation, Visualization, Writing - original draft
Bernd Riederer: Project Administration, Investigation, Software, Writing - reviewing
Andreas Moser: Investigation, Software, Validation, Visualization
Daniel Muschick: Conceptualization, Software, Writing - reviewing & editing
Valentin Kaisermayer: Methodology, Software
Jakob Fuchsberger: Formal Analysis, Investigation
Markus Gölles: Supervision, Writing - reviewing & editing
Christopher Zemann: Conceptualization, Funding Acquisition, Data Curation, Project Administration, Resources

Competing interests

The authors declare that they have no competing interests.

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When writing this paper, ChatGPT with GPT-5.2 has been used to improve grammar and language. The authors have modified and reviewed the output carefully and take full responsibility for the content.

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