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Heat Pumping Technologies

MAGAZINE

Smart Controls and AI for Next-Generation Heat Pump Efficiency

Vol.43 No.2/2025
A HEAT PUMP CENTER PRODUCT

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Foreword

Digitalization at the Heart of Europe's Energy Future

By Bernd Windholz, Thematic Coordinator, Efficient Buildings and HVAC Technologies, Center for Energy, AIT, Austrian Institute of Technology, Austria

The digitalization of Europe's energy system is accelerating – amongst others, driven by the EU action plan – to unlock the full potential of flexible energy generation and consumption. Digital technologies enable system optimization, operational savings, and savings in network infrastructure [1]. ***In view of these possibilities, the digitalization of the energy system has become a political priority, linked to the EU's Digital Decade 2030 programme*** [2]. ***With the initiatives towards digitalization, heat pump technology is also undergoing transformation.***

According to the IEA's Net Zero by 2050 report, a total of 1.800 million heat pumps have to be installed in buildings worldwide to provide more than half of the heating needs. It is a tenfold increase compared to the level of 2020 [3].

Yet it's not just the number of heat pumps that is changing – it's how they operate. As the current volume of the HPT Magazine shows, by means of digitalization, future heat pump systems can achieve higher efficiency, increase reliability, and put the user more at the focus of operation.

Results of the recently finished IEA HPT Annex 56 *Digitalization and IoT for Heat Pumps* highlight this shift. Forty-four examples of Internet-of-Things services (IoT) were categorized and described in detail [4, 5]. Amongst the available market solutions are

- **Heat pump operation optimization**: E.g., Energy Machines "EMV", an online service with analysis of functionality and performance from live measurements of the heat pump COP, energy production, and cycle efficiency. It is an alternative measurement to energy meters, but also extends beyond the limitations of those, as even more information can be extracted from the thermodynamic cycles [6].

- **Predictive maintenance**: E.g., Smart guard, an IoT solution for remote diagnostics for heat pumps to guarantee efficient and safe operation of the heat pump and facilitate maintenance workflows. The remote diagnostics are carried out both automatically and manually by trained service personnel. In particular, the detection of faulty heat pumps is done by an automated algorithm [7].
- **Provision of flexibility**: E.g., tiko power, a system which allows the service provider to switch on/off heat pumps, helping the grid operator to maintain frequency and stability. Energy consumption characteristics of the heat pumps are determined, amongst other parameters, depending on local weather conditions. Remote control is done within defined boundaries to ensure the comfort of the inhabitants and prevent lifetime reduction of the heat pump [8].

The IEA HPT Annex 56 provided early insight into the digital maturity of connected heat pumps across Europe. The shortly started IEA Project 67 *Digital Services for Heat Pumps* builds on this and identifies specific digital solutions for heat pumps across their entire lifecycle – from product design and testing to integration, operation, and maintenance – including, e.g., modelling, hardware-in-the-loop tests, and augmented reality [9]. Therefore, IEA's HPT TCP further helps ensure the maximum service life of heat pumps and their components, as well as the lowest possible operating costs and usability for heat pump operators.

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Column

Advancing Industrial Heat Pumps through Value Chain Collaboration

By Benjamin Zühlsdorf, Innovation Director, PhD, Danish Technological Institute

Industrial heat pumps are recognized in the "Net Zero by 2050 – a roadmap for a global energy transition" by the International Energy Agency as the main technology to be implemented until 2030 to replace fossil fuel boilers. To reach climate targets, 15 % of industrial process heat below 400 °C in light industries should be covered by heat pumps, and achieving this will require a rapid increase in adoption, with an average of 500 MW of installed capacity every month worldwide between 2021 and 2030.

Accelerating industrial heat pump deployment through value chain collaboration
Traditional heat pumps have proven successful in buildings and district heating, but the complexity rises as industrial heat pumps are integrated into industrial processes, and so does the need for collaboration. Bringing together technology providers, system integrators, industrial end users, and research institutions has consistently proven crucial for overcoming technical challenges and accelerating the market readiness of industrial heat pump solutions.

Raising the bar through collaborative research
Funded research and development projects require value chain collaboration as a prerequisite, and this collective approach consistently has led to solutions that are both innovative and practical for industrial needs. In recent years, industry collaboration has significantly raised the bar for industrial heat pumps. The results from IEA HPT *Annex 58 High-Temperature Heat Pumps* have first and foremost shown that industrial heat pumps are undergoing a rapid development towards supply temperatures well above 100 °C and a variety of applications. The results did, however, also demonstrate that collaborative R&D projects involving the entire value chain have been a key driver behind most of the developments that are successfully transforming the market.

From shared knowledge to large-scale impact
While value chain collaboration is a key enabling factor within individual research projects, it is also important to establish forums for ongoing knowledge exchange. Fortunately, when looking over the landscape of conferences held across the heat pump industry, we see industrial heat pumps gaining more and more attention.

This is something we experience ourselves at the High Temperature Heat Pump (HTHP) Symposium, which is held in Copenhagen every second year. The Symposium became the meeting space for the entire value chain of HTHPs and is bringing academia and industry together. Since its inception in 2017 with around 60 participants, the event has grown to 400 participants in 2024, and expectations for even more in 2026. This remarkable growth reflects the increasing interest in industrial heat pumps and the importance of collaboration and knowledge exchange as the enabler for industrial growth.

Whether the increasing awareness and momentum will be sufficient to meet the ambitious target of 500 MW of new industrial heat pump capacity every month remains to be seen. However, with the launch of the new HPT Project 68 on *Industrial High-Temperature Heat Pumps*, the IEA's TCP on Heat Pumping Technologies (HPT TCP) is committed to supporting this agenda and helping the industry move towards large-scale implementation.

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Topical Article

Increased efficiency of hybrid heat pump systems using optimal control in the redesign of a historic neighborhood's heating supply

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Karl Walther, Louis Hermans, Lone Meertens, Lieve Helsen, Belgium

This article illustrates the increased efficiency of optimally controlled hybrid heat pump systems, including air-source and ground-source heat pumps, compared to the respective single-source scenarios. The redesign of the historic neighborhood "Stijn Streuvelstraat" in Bruges / Belgium, is used as an example. Physics-based models of the neighborhood and different supply options are used for a virtual comparison of conventional rule-based controls and optimal control. The efficiency gains of hybrid heat pump systems stem from the ability of optimal control to take into account different source temperatures and the predicted building behavior.

Introduction

Decarbonizing the residential heating sector is a major challenge to achieve the energy and emission targets. For future supply systems based on Renewable and Residual Energy Sources (RES), two topologies are typically distinguished: (1) individual heat pump systems on building level, typically using ambient air or geothermal heat, and (2) collective district heating networks. For modern district heating networks, two sub-topologies are generally distinguished: (a) centrally generated heat on a high temperature level, so called 4th generation district heating networks (4GDHN), typically through renewable energies (heat pumps, biomass, etc.) or residual heat (waste incineration, industrial processes, etc.), or (b) low temperature networks, so-called 5th generation district heating and cooling networks (5GDHCN) with low-temperature heat sources (solar thermal, data centers, etc.) and decentral heat pumps on building level.

This article evaluates the increased efficiency of hybrid heat pump systems integrating air-source heat pumps (ASHPs) and ground-source heat pumps (GSHPs) for the collective heat supply in a 4GDHN compared to alternative ASHP-only or GSHP-only scenarios. The redesign of the historic neighborhood “Stijn Streuvelstraat” in Bruges / Belgium, is used as a practical demonstration case. The analyses use physics-based models of the neighborhood and the heating supply to illustrate the potential of an optimally controlled system compared to conventional rule-based controls. The article is based on experiences during the design phase of the “Stijn Streuvelstraat” project. The article uses extended content of [1].

The “Stijn Streuvelstraat” pilot in Bruges, Belgium

“Stijn Streuvelstraat” is a historical neighborhood in Bruges (Belgium) with 15 dwelling units for assisted living (see Figure 1 and Figure 2). Each dwelling unit has a living room, a sleeping room, and a bathroom on the ground floor. The attic spaces are used for technical installations. The total net heated floor area is about 1,000 m^2. Internal insulation is used for the external walls (U-value 0.27 W/m^{2}K) because the heritage character does not allow external insulation. The target of the renovation is, next to the building retrofit, to design and implement a collective heat supply system that is

- 100 % R^{2}ES-based
- Future-proof facing the effects of climate change
- Cost-efficient
- Capable of providing good indoor thermal comfort

Figure 1: Building with 2 (out of 15) dwelling units

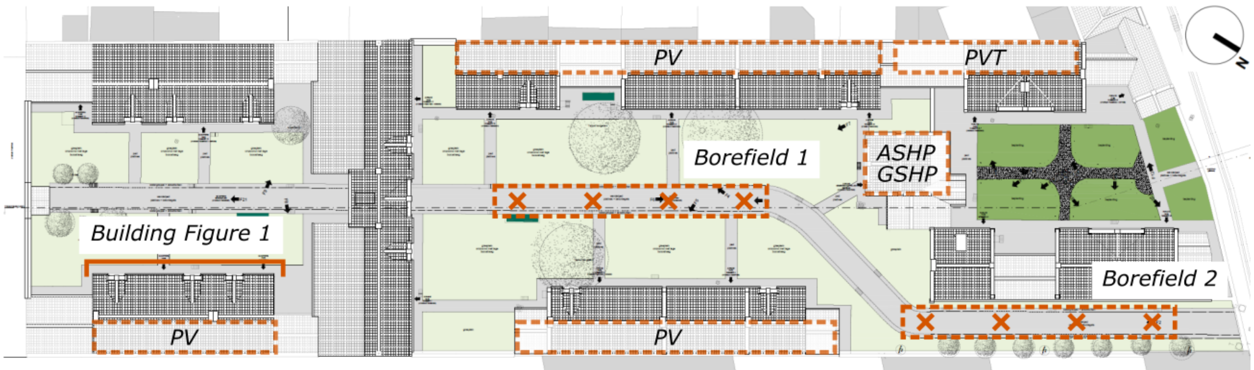

Figure 2: Site plan (source: Compagnie Costume) and technical installations

Against the background of these design goals and considering the site conditions, ASHPs or GSHPs are viable heating supply technologies. A solely ASHP-based option was not possible due to acoustic constraints. A solely GSHP-based system was excluded due to the costs of a borefield that is sized robustly enough to take into account uncertainties on the demand side, for example, through changing and extreme climatic conditions. Therefore, a hybrid heat pump supply system including ASHPs and GSHPs was designed (see Figure 2 and Figure 3). The maximum thermal capacities are 28 kW_{th} for the ASHP and 44 kW_{th} for the GSHP. Both ASHP and GSHP are modulating. Due to acoustic constraints, ASHPs are limited to a maximum of 80 % operation during night hours. The borefield is split into two parts with four boreholes with 125 m depth each. A buffer tank of 0.5 m^3 is located between the supply and demand side. A photovoltaic thermal (PVT) system enables borefield regeneration in summer. Passive cooling is possible via a heat exchanger and provides additional borefield regeneration potential in summer. Domestic hot water (DHW) is provided decentrally in each dwelling unit by an electric heater. Floor heating/cooling was selected as a room-side emission system. Temperature setpoints are defined at 21 °C (heating) and 26 °C (cooling). Each dwelling unit has a mechanical ventilation system with heat recovery.

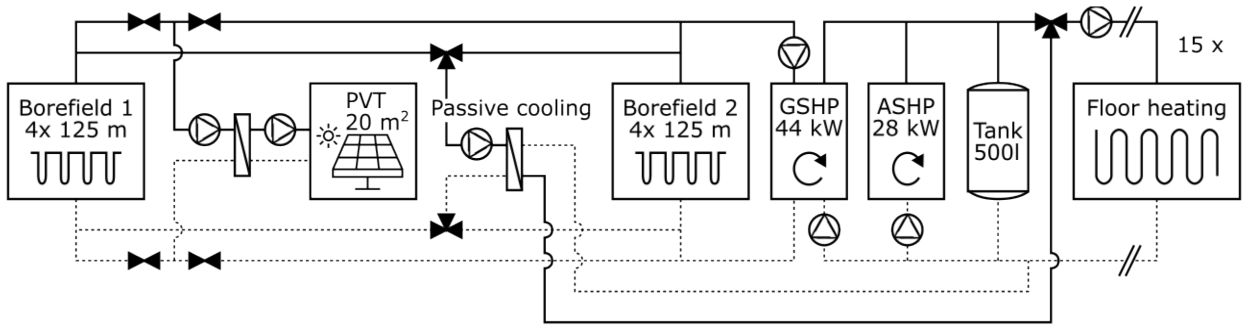

Figure 3: Simplified hydraulic scheme

Simulated efficiency gains of an optimally controlled hybrid system

As described previously, single-source heat pump systems were excluded at the design stage because of project-specific considerations. In the following, we illustrate that the designed hybrid heat pump system also reaches the best efficiency compared to single-source options. The following three scenarios are compared (**For the sake of simplicity, the PVT system (see Figure 3) is not included in these scenarios**):

- ASHP-only
- GSHP-only
- Hybrid system including ASHP and GSHP

For the comparison, a simulation study of these three different supply scenarios using a physics-based modeling approach is carried out. The 15 dwelling units with in total of 61 thermal zones (see Figure 2) and the supply system (see Figure 3) are modeled using the Modelica language. The observation period is one year. Measured hourly weather data from Leuven, Belgium, covering outdoor temperatures from −10 °C to +40 °C, is used.

The performance of each of the three supply options is compared for two control approaches: a conventional rule-based control and an optimal control. The conventional rule-based controls use a proportional integral (PI) controller to modulate the heat pumps according to the tank target temperature determined by a heating curve. In the hybrid case, a PI sequence controller is used to prioritize either the ASHP (at mild ambient conditions) or the GSHP (at cold ambient conditions). The priority switches depending on the outdoor air temperature using a hysteresis controller. The floor heating valves are regulated by PI controllers connected to the zone temperature. The optimal control uses the previously described physics-based model to predict the future building and supply system behavior. A mathematical optimizer uses these predictions to adapt the heat pump modulation degree and floor heating valves to minimize (1) the total electricity consumption (including heat pumps and circulation pumps), (2) thermal discomfort in each dwelling unit, and (3) nighttime modulation of the ASHP to reduce noise levels.

Figure 4 illustrates the heat pump behavior of the three supply options (ASHP-only, GSHP-only, Hybrid) for conventional rule-based control (left column) and optimal control (right column). The selected 2-day period has a high ambient temperature swing between 0 °C and 20 °C (see Figure 4-a). The ground temperature is in the range of 8 °C to 10 °C.

With conventional rule-based control (Figure 4, left column), the heat pumps are activated at night (see Figure 4-b-i) when the zone temperatures drop below the heating setpoint (see Figure 4-c-i).[1] In the hybrid scenario, only the GSHP is used. Due to the inertia of the floor heating system, the zone temperature drops about 0.5 °C below the heating setpoint.

With optimal control, the heat pump behavior differs significantly between the three scenarios: in the ASHP-only case, the optimal controller, 'aware' of the higher heat pump COP at higher outdoor temperatures, solely operates the heat pump during the day ('ASHP-only' in Figure 4-b-ii). This 'preheating' behavior avoids heat pump operation at night, leading to the highest indoor temperatures among the three scenarios, up to 23 °C (see Figure 4-c-ii). In the GSHP-only case, the heat pump operation is much smoother with the highest compressor power around midnight ('GSHP-only' in Figure 4-b-ii). In the hybrid case ('Hybrid' in Figure 4-b-ii), the optimal controller selects the two heat pumps according to the source temperatures: the ASHP is operated during the day and the GSHP at night.

The maximum compressor power with a conventional rule-based control is between 7 kW and 9 kW. In all optimally controlled scenarios, the maximum compressor power used is significantly lower (between 3 kW and 5 kW). This underlines the ability of optimal control to shift operation to periods with higher source temperatures (see ASHP-only case), and to avoid peak operation with high supply temperatures and lower COP (see GSHP-only scenario). Moreover, in all optimally controlled scenarios, the heating setpoint of 21 °C is significantly better maintained than with conventional rule-based control due to the ability of optimal control to anticipate the floor heating inertia and avoid excessive temperature drops.

[1] The heat pump is activated when the storage tank temperature drops below a threshold (not depicted in Figure 4).

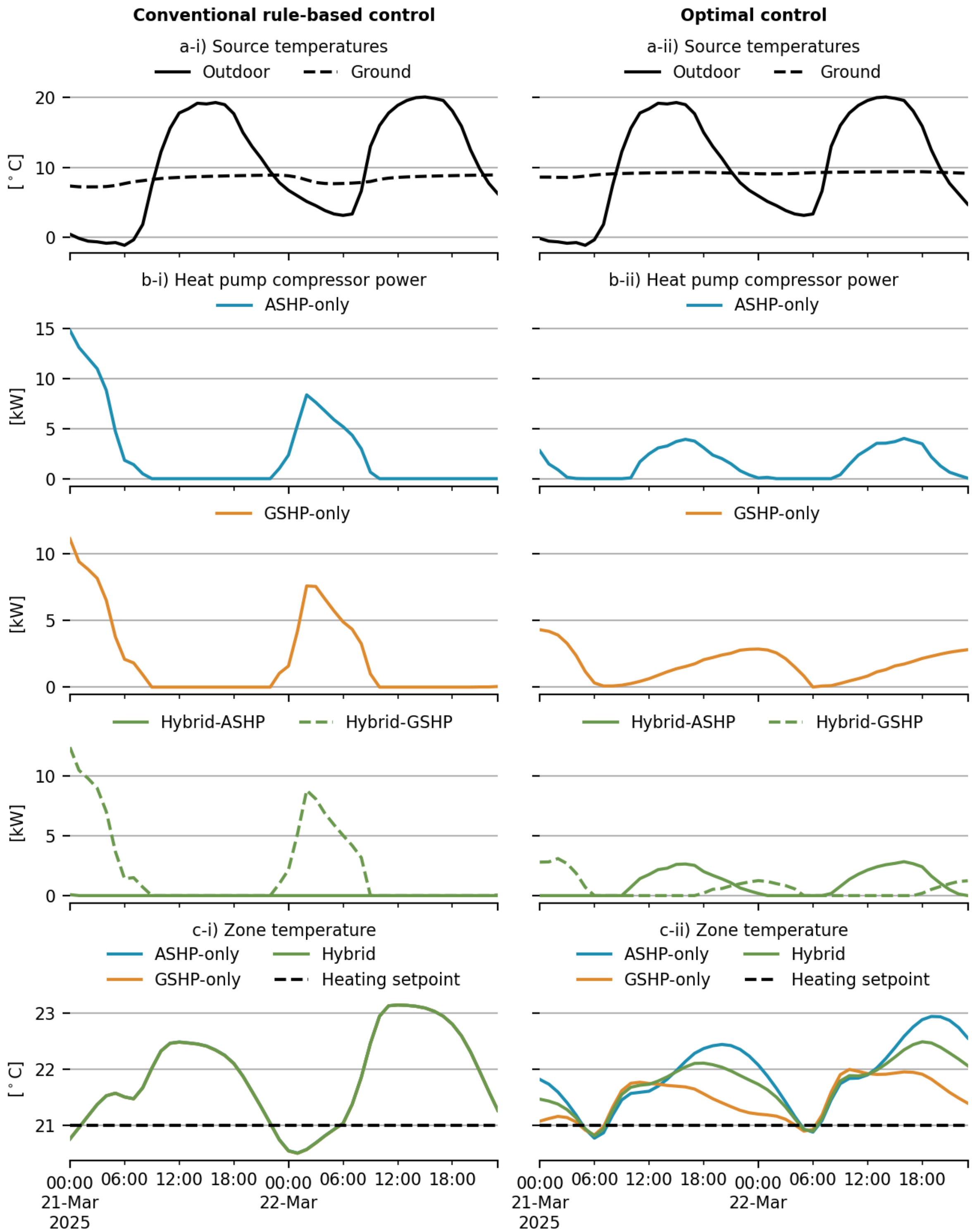

Figure 4: System behavior of ASHP-only, GSHP-only, and hybrid options for a 2-day period

Figure 5 compares the total annual performance, including the annual heat generation, the electricity consumption, and the Seasonal Coefficient of Performance (SCOP, annual condenser heat / annual electricity used). The comparison highlights that the optimally controlled system yields lower heating demand (−8% to −10%) and lower electricity demand of the heat pump compressor(s) (−24% to −32%). The savings are achieved through the integrated optimal control of the floor heating valves and the operational management of the heat pumps by taking into account the Coefficient of Performance (COP) dependent on source temperatures (air and ground).

An important aspect of the comparison is how the different supply options are ranked.
With the conventional rule-based control, the ASHP-only option has the lowest SCOP of 3.9, significantly below the optimally controlled system, because the rule-based control activates the heat pump at night (see Figure 4-b). The difference in the GSHP-only option is smaller and achieved by avoiding peak operation with high supply temperatures. With optimal control, the hybrid case reaches the highest SCOP of 5.6, compared to the ASHP-only option (SCOP=5.2) and the GSHP-only option (SCOP=5.4), because the operation of both heat pumps is optimally distributed according to the source temperatures and the corresponding COP.

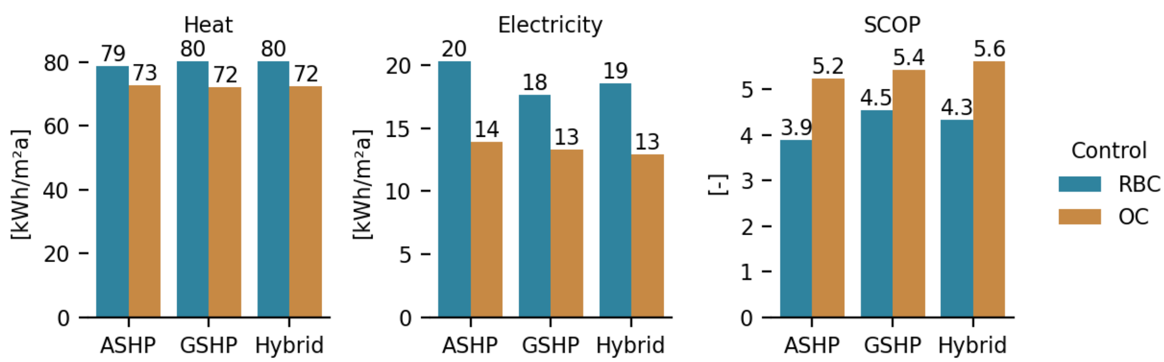

Figure 5: Heat demand, electricity demand, and SCOP of ASHP-only, GSHP-only, and hybrid supply options (sum of ASHP and GSHP in hybrid case, space heating only, no DHW).

Conclusions

This article uses physics-based models to analyze the increased efficiency of optimally controlled hybrid heat pump systems compared to the respective single-source scenarios. For the “Stijn Streuvelstraat” case study, the hybrid system reaches the highest SCOP of 5.6 compared to the GSHP-only option (SCOP=5.4) and the ASHP-only option (SCOP=5.2). The efficiency gains stem from the ability of the optimal controller to take into account the different source temperatures and the future system behavior. This highlights the advantages of optimal control as system integrator in increasingly complex supply systems. A standard conventional rule-based control can not fully exploit this potential and achieves a lower SCOP of 4.3 for the hybrid system compared to an SCOP of 4.5 for a GSHP-only system.

Beyond the increased efficiency through optimal control, using a hybrid system enables the use of smaller individual systems. A smaller ASHP has the advantage of lower noise emissions, and smaller GSHPs, particularly a smaller borefield, reduce investment costs. Finally, having two heat sources managed by an optimal controller provides resilience facing the effects of climate change. The related study in [1] also highlights the competitive life cycle costs of hybrid systems.

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Topical Article

Soft Fault Diagnosis and Evaluation Strategies: An Approach BEYOND the State of the Art to Reduce Emissions Associated with Heating and Cooling in the Residential Sector

DOI: 10.23697/h63c-vx93

Belén Llopis-Mengual (Spain), Francesco Pelella (Italy), Luca Viscito (Italy), Alfonso William Mauro (Italy), Emilio Navarro-Peris (Spain)

Heat pumps are essential for decarbonization, but their efficiency is often reduced by hidden 'soft faults' that can increase their daily energy consumption up to 26%. This article highlights the state of the art of methods for fault detection and diagnosis, pointing out the advantages of combining Machine Learning techniques with a large amount of synthetic data generated by models, which are calibrated on appropriate and limited experimental datasets. From a perspective of smart services for resilient operation, the presence of concurring soft faults causing deterioration in performance and energy efficiency makes the evaluation of the faults' intensities also important, to evaluate which intervention is economically and/or environmentally convenient. This innovative step is now backed by a strategic EIC-funded project, BEYOND.

Introduction: The Impact of Operational Faults on System Performance

The real-world efficiency of heat pumps, a key decarbonization technology, is often undermined by 'soft faults' like refrigerant leakage or fouling. These issues degrade performance while the system remains functional, often going undetected until they significantly increase energy consumption by up to 26% daily [1] or escalate into a complete system failure. The prevalence of these problems is significant: a study by Pigg et al. [2] found refrigerant charge issues in 69% of inspected AC units, noting that proper maintenance improved energy efficiency by an average of 9.5%.

Addressing these operational inefficiencies through Fault Detection and Diagnosis (FDD) has therefore become a critical area of research. Robust FDD techniques are essential to mitigate performance degradation, lower maintenance and energy costs, and reduce carbon emissions, ensuring that the full energy-saving potential of heat pumps is realized throughout their lifetime [3].

Methodologies for Fault Detection and Diagnosis (FDD)

Modern Fault Detection and Diagnosis (FDD) methodologies, increasingly powered by Machine Learning, are traditionally classified into three categories: quantitative model-based, qualitative model-based, and data-driven approaches [4], [5].

Quantitative, physics-based models are rarely employed due to their complexity and extensive validation requirements. Qualitative, rule-based techniques (e.g., "if subcooling is low, a fault is present") are more common, but their reliability is limited by system-specific thresholds that struggle with complex systems. Consequently, data-driven methods, which analyze historical data without relying on underlying physics, have become the primary focus for both research and industry. These approaches can be broadly classified as knowledge-based, purely data-driven, or hybrid gray-box models (as illustrated in Figure 1).
Despite this academic focus on advanced diagnostics, a clear gap remains between research and commercial application. A patent review by Pelella et al. [6] reveals that industrial innovation still focuses on simple, rule-based methods for single-fault diagnosis. Crucially, existing patents and commercial products lack the ability to precisely evaluate the *severity* of a fault, especially when multiple faults occur simultaneously. This gap highlights a significant opportunity for advanced FDD systems capable of moving beyond simple diagnosis to quantitative fault evaluation, which is essential for optimizing maintenance and system performance.

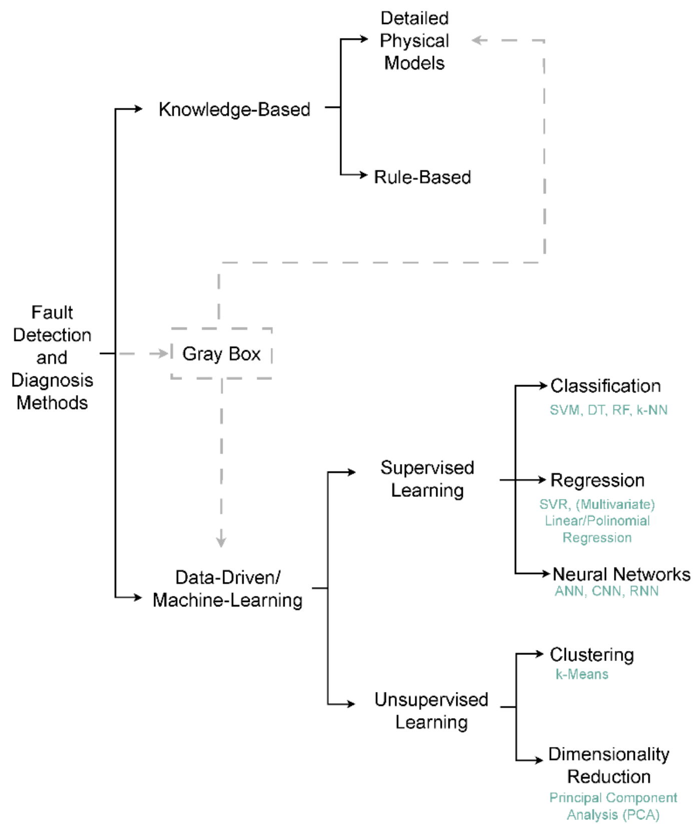

Figure 1. Classification of FDD methodologies based on recent advances.

Discussion on the advantages and limitations of Machine Learning approaches for FDD

While smart devices make field data increasingly available, it cannot be directly used for robust Fault Detection and Diagnosis (FDD). Unsupervised learning, for instance, struggles to reliably distinguish specific fault signatures from normal operational variations, as the type and intensity of any underlying faults are usually unknown and unlabeled. For this reason, supervised learning is preferred for complex FDD tasks, which require large, physics-informed datasets. A common strategy is to use limited, high-quality lab data to calibrate physics-based models that then generate extensive synthetic data for training. This approach is powerful, but its final accuracy depends on several interconnected factors: a) the ML method's generalization capabilities, b) the accuracy of the measurements, c) the chosen step of fault intensity, and d) the model's fidelity for data synthesis.

Recent literature explores these challenges. While studies by Kim et al. [7] and Ebrahimifakhar et al. [8] both demonstrated the high accuracy of SVM models, their work was either not experimentally validated or required an unfeasible number of sensors for residential systems. A recent study by Pelella et al. [9] developed a large synthetic dataset and, using a limited set of measured inputs, demonstrated that the accuracy of the measurements is strictly connected to the step in the intensity of the fault, which can be determined univocally. This is an important effect that is often not accounted for when assessing the accuracy of ML methods, strongly limiting the generality of the conclusions achieved by the studies. The work by Mauro et al. [10] created a large dataset correlating the effects on the cycle with three concurrent soft-fault intensities (FDD+Evaluation - FDD+E). Then, they imposed some long-time faults' combination (based on assumptions over statistical data from the field), simulated the corresponding condition to have virtual measurements from the simulated cycle. Then, with this set of measurements, they predicted back the faults with different methods: multi-dimensional interpolation and ML tools (Neural Networks -ANN and KNN). The accuracy of all the ML tools is good, but each of them has some indeterminacy zones, which are intrinsically related to the overlapping of effects due to different intensities of soft faults.

A recent study by Llopis-Mengual et al. [11] added to the estimation of the accuracy of the ML method, also the accuracy from the experimental data. They created a synthetic dataset from simulations under different soft-fault conditions and used this data to train a robust machine learning algorithm, a Support Vector Machine (SVM), to distinguish between different faulty states. Figure 2 shows a simple example of how this algorithm works when classifying two different fault states based on the measurement of two variables. The SVM algorithm, trained exclusively with the simulated data, was then tested using real experimental measurements from the same physical unit operating under controlled fault conditions in a laboratory.

The results were highly promising, with the algorithm successfully identifying the correct fault status (including multiple simultaneous faults) with a balanced accuracy of 82%. Nevertheless, some zones of indeterminacy of the faults remain, which cause false predictions that can not be addressed only by the use of ML.

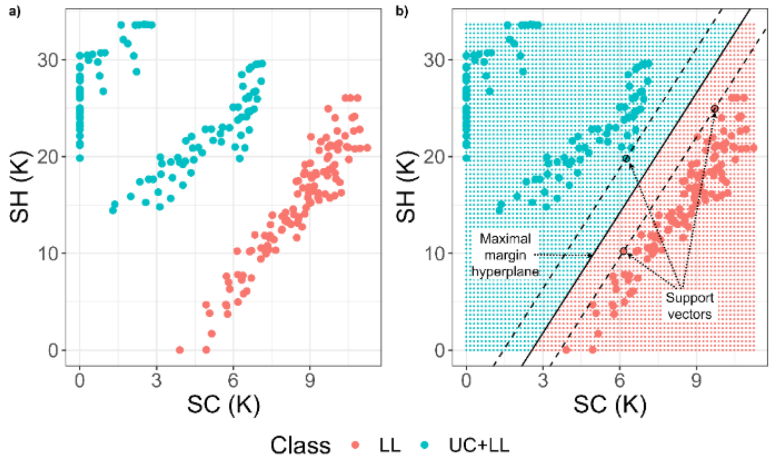

Figure 2. Figure elaborated in [7] under license CC BY-NC-ND. It shows an example of the application of a support vector classifier to distinguish tests with Liquid Line restrictions (LL) or combined LL+UC (undercharge) faults as a function of subcooling (SC) and superheat (SH).

Strategic Research Initiatives: The BEYOND Project

To enable smart maintenance services for heat pumps, it is crucial to evaluate the intensity of concurrent soft faults to assess the economic and environmental convenience of an intervention. Since current methods struggle with quantitative evaluation and solving indeterminacy conditions, the BEYOND project [12] was funded in 2024 by the European Innovation Council's (EIC) Pathfinder program to address this gap under the "Clean and efficient cooling" challenge. The challenge aims to advance novel solutions that increase operational reliability and strengthen the EU's technological leadership. More specifically, the BEYOND project's goal is to develop a novel and cost-effective method for the detection, diagnosis, and quantitative evaluation of simultaneous soft faults in residential heat pumps. The strategy involves running a massive test campaign on air-to-water and air-to-air heat pumps. A dedicated model will be calibrated and validated on these experiments to build a large dataset, which will be used to design and test a completely new algorithm, not limited to standard ML or regression techniques.

Conclusions

Soft faults often reduce the real-world efficiency of heat pumps, a key technology for decarbonization. The use of maps of faults can be used with several techniques to try to solve FDD or even the FDDE. The use of synthetic data from models is a good approach to limit the need for experiments, and ML tools can help to solve the challenge of FDDE, combining speed and accuracy. But the accuracy of the prediction is not only related to the training phase, but also to the accuracy of measurements and of the models. Also, most importantly, the crucial aspect is that increasing the degree of freedom of the system and the concurrence of soft-faults, the number of indeterminate zones (which cannot be univocally related to the fault intensities) increases. The project BEYOND will face these challenges.

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Topical Article

The Impact of AI in Prescriptive Maintenance for Chillers and Heat Pumps

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AI-driven prescriptive maintenance is transforming the way HVAC systems are managed. By integrating real-time monitoring, predictive analytics, and automated decision-making, this approach delivers measurable gains in performance, sustainability, and reliability. No longer experimental, AI is becoming a trusted ally in the pursuit of decarbonization and operational excellence. For facilities aiming to meet energy, environmental, and financial goals, prescriptive maintenance offers a strategic pathway that aligns smart technology with long-term success.

Introduction

The HVAC industry is undergoing a significant technological transformation, driven by growing demands for energy efficiency, decarbonization, and operational resilience. Traditional maintenance strategies, reactive and preventive, often fall short in addressing the dynamic needs of today's complex mechanical systems. In response, advanced data-driven methodologies are emerging, with prescriptive maintenance standing out as a practical and highly effective solution for chillers and heat pumps, the central components of hydronic HVAC systems.

Prescriptive maintenance combines real-time system data, advanced analytics, and simulation models to forecast failures and recommend specific, actionable interventions. This paper outlines the key mechanisms behind prescriptive maintenance in commercial

HVAC systems, focusing on chillers and heat pumps deployed in critical sectors such as healthcare, office real estate, and hospitality.

Overview of Prescriptive Maintenance

Prescriptive maintenance solutions use high-frequency operational data collected through IoT-enabled components, Building Management Systems (BMS), and dedicated sensors. Through the application of machine learning algorithms and thermodynamic modeling, these platforms identify deviations from expected behavior, perform root cause analysis, and generate prioritized maintenance recommendations. Key capabilities include:

- **Continuous monitoring** using temperature, pressure, and energy sensors.
- **Anomaly detection** through multivariate statistical analysis and pattern recognition.
- **Hybrid digital twins** for predictive simulations and system optimization.
- **Decision support** through cost-risk-based maintenance recommendations.

This approach enhances system reliability, lowers lifecycle costs, and enables predictive resource allocation. As AI models are further integrated, facility teams gain access to automated insights that can be acted upon immediately, reducing the lag between detection and resolution.

System Connectivity: How it Works

For AI-enabled prescriptive maintenance to function effectively, the chiller must be integrated into the building's digital infrastructure. This involves both physical and logical connections that allow the chiller to communicate with supervisory control systems and remote analytics platforms.

Logically, the chiller's data points are tagged and normalized to align with semantic data models, ensuring consistent interpretation across various software tools. This structure enables scalable analytics and seamless integration with AI dashboards, visualization tools, and mobile maintenance applications. Key steps in the operational process include:

- **Asset connection** to IoT infrastructure.
- **Data acquisition and trending** via IoT platforms.
- **Remote monitoring** through a centralized command center, with critical alarm tracking and connectivity checks.
- **AI analysis**, using predefined algorithms to detect opportunities and risks, interpreted by technical experts.
- **Customized reporting**, including health diagnostics or component-specific alerts.

The system identifies early indicators of potential issues (e.g., abnormal refrigerant temperatures, pressure anomalies, waterflow irregularities), interprets the data to determine degradation levels, and assesses potential impacts such as increased energy consumption or component stress. Based on this, tailored recommendations are generated (e.g., preventive maintenance, upgrades, or replacements).

Technical Applications for Chillers & Heat Pumps

AI enables a wide range of applications that improve the long-term performance of HVAC equipment. Among the most impactful use cases are:

1. **Health Diagnostics & Fault Detection**
   AI-powered diagnostics interpret real-time performance data to detect early signs of system degradation. Predefined algorithms classify symptoms and recommend targeted corrective actions, reducing downtime and improving reliability.

2. **Refrigerant Leak Characterization**
   Continuous monitoring of critical parameters enables early detection of refrigerant leaks. Subtle deviations in pressure, superheat, or temperature differentials trigger alerts before major performance losses or environmental risks occur.

3. **EER & COP Tracking**
   Performance degradation is quantified using a computed index based on deviations from baseline Energy Efficiency Ratio (EER) or Coefficient of Performance (COP). If the index drops below acceptable thresholds, the AI system isolates the root cause and suggests corrective actions. Such metrics are essential for facilities operating under Energy Performance Contracts (EPCs), where maintaining efficiency impacts compliance and financial results.

4. **System Upgrade Identification**
   AI insights guide decision-making around system retrofits. By analyzing runtime patterns, seasonal loads, and part-load efficiencies, facility managers can prioritize components offering the highest upgrade potential and quantify energy savings through simulations. This also supports decarbonization by identifying interventions that reduce emissions and improve operational sustainability.

5. **Incentives Compliance**
   In many European countries, financial incentives are available for energy-efficient HVAC upgrades. AI monitoring systems play a key role in quantifying and validating actual energy savings, ensuring compliance, and unlocking funding opportunities.

Examples of Digital Services

This article includes examples of various applications that show the potential of these systems in maintenance tasks and decision-making.

A. Condenser Health in Air-Cooled Chillers

Application*:* Hotel
Model*:* 30RBP550R / Scroll Compressors / Air-Cooled / 2 circuits
Evaporator*:* Direct expansion brazed-plate heat exchanger
Condenser*:* All-aluminium micro-channel coils (MCHE)
Refrigerant*:* R-32
Observations & findings*:*
The Condenser Refrigerant - Air Temperature Difference (also known as Approach Temperature) in air-cooled chillers typically ranges between 18°F to 27°F. This is the temperature difference between the saturated condensing temperature (refrigerant temperature in the condenser) and the ambient air temperature entering the condenser. A higher approach means the chiller is working harder (less efficient).

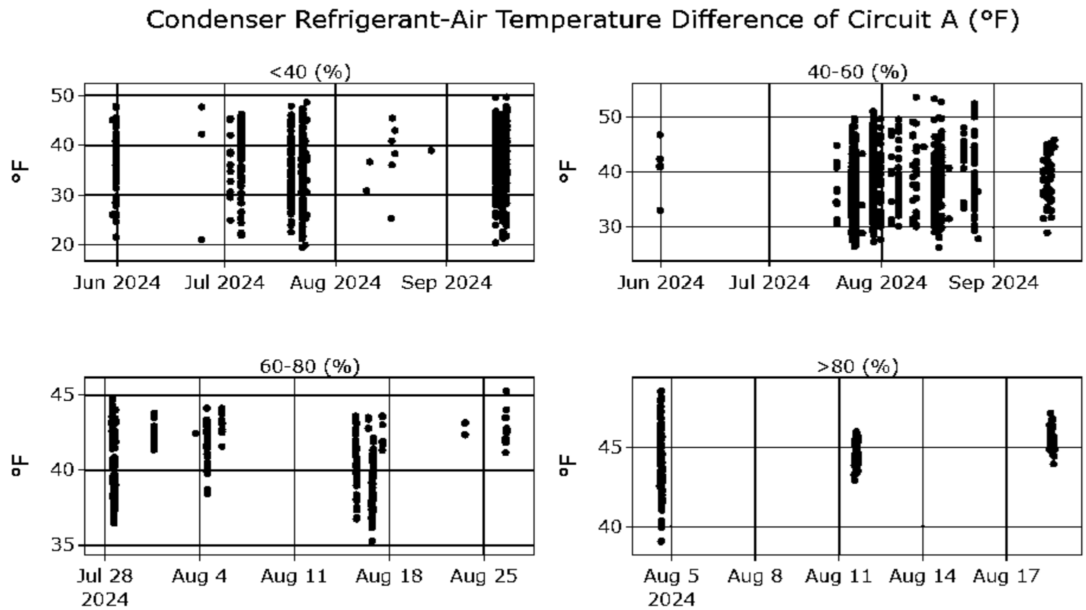

Figure 1: Approach Temperature for Air-Cooled Chiller

The condenser refrigerant-air temperature difference is higher than normal; this indicates condenser fouling that will impact the efficiency of the unit, but also minimize the life expectancy.

The AI model includes all the data libraries needed to calculate the level of energy waste that the unit is having, which will help to quantify the ROI (Return On Investment) of the possible actions to be taken. In this case, the unit is having 27% higher energy consumption than expected.

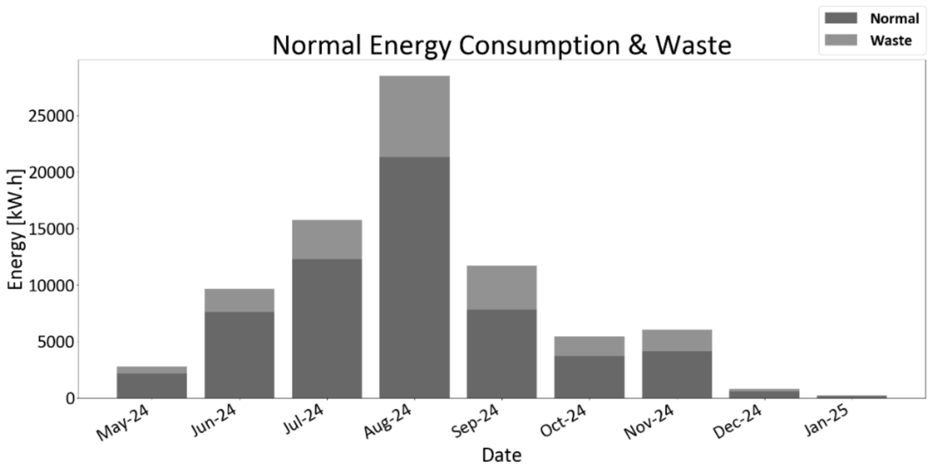

Figure 2: Monthly Energy Waste

***Recommendations**:*

Based on the insights provided by the monitoring system, the recommendations in this case include planning the coil cleaning as soon as possible and analyzing the possibility of making a coil treatment due to the exceptionally dusty environment.

B. Refrigerant Leak

***Application**:* Hospital
Model: 30KAV-1100 / Variable Speed Screw Compressors / Air-Cooled / 2 circuits
***Evaporator**:* Flooded shell and tube heat exchanger
***Condenser**:* Micro Channel Heat Exchanger
Refrigerant: R-1234ze
***Observations & findings**:*

AI monitors the main parameters on refrigerant circuits to detect deviations from normal operating ranges based on load and ambient conditions. The expansion valve regulates refrigerant flow into the evaporator. If refrigerant levels are low, the valve may remain more open or show erratic movement to maintain proper superheat.

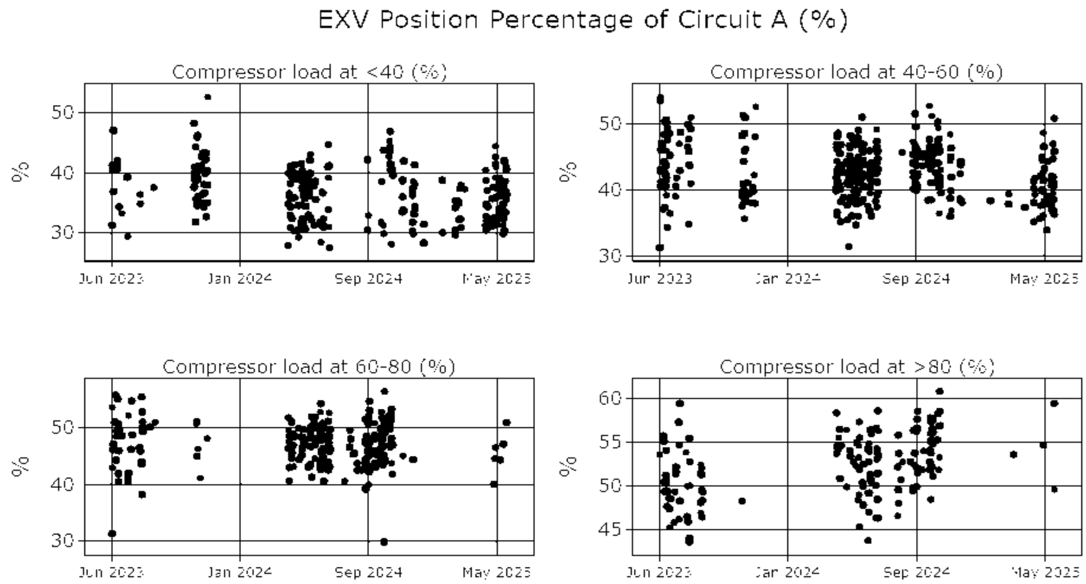

Figure 3: Expansion valve position

Other key parameters include the suction and discharge pressures, which represent the pressures on the low- and high-pressure sides of the refrigeration circuit. A drop in suction pressure is often one of the first signs of a refrigerant leak, indicating a reduced refrigerant charge. Discharge pressure may also fluctuate abnormally as the system tries to compensate. Also, the temperature difference across the evaporator (between inlet and outlet water or air) may decrease if less refrigerant is available to absorb heat.

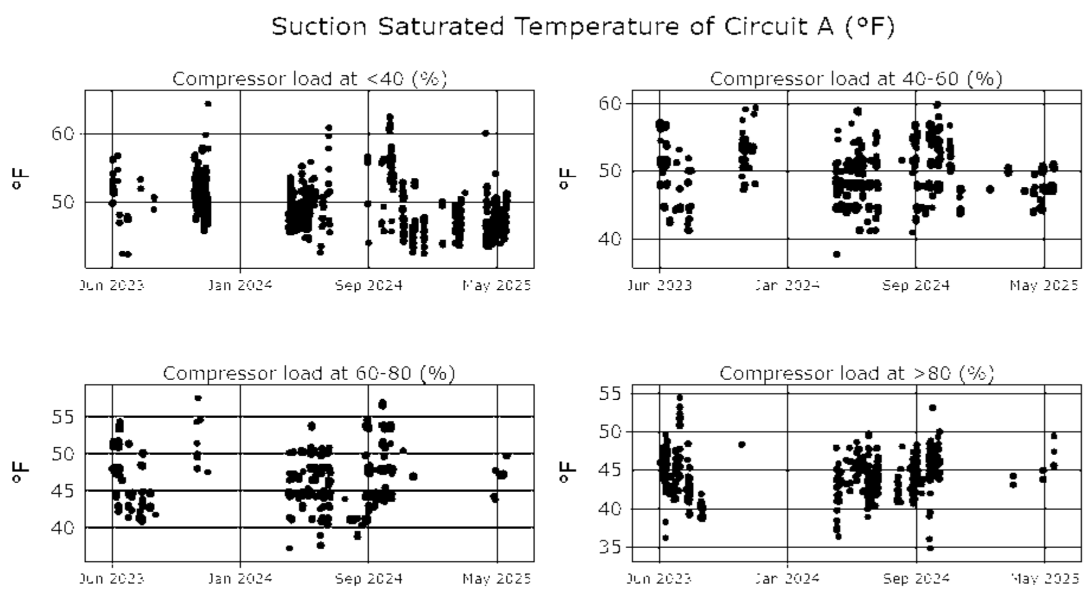

Figure 4: Suction Saturated Temperature

Other variables that are analyzed are the evaporator pressure and approach, discharge superheat, condenser approach, or the evaporator water temperature difference. All together will help the user to determine if there is a real refrigerant leak in the unit.

The suction saturated temperature of circuit B is lower than normal; the evaporator approach and the discharge superheat of circuit B is higher than normal. The condenser air-refrigeration temperature difference of circuit B is decreasing. All these conditions indicate that circuit B of this unit has a refrigerant leakage issue with a high severity index.

Recommendations:
Refrigerant leaks may cause the system to cycle more frequently or run for longer periods to maintain the desired temperature setpoints. In this case, the fact that the unit serves a hospital makes it especially important that the leak is repaired in the shortest possible time.

C. VFD Fan Upgrade

Application: Industry
Model: 30XA802 / Screw Compressors / Air-Cooled / 2 circuits
Evaporator: Flooded Multi-pipe Type
Condenser: Micro Channel Heat Exchanger
Refrigerant: R-134a
Observations & findings:
AI monitoring detected that condenser fans on the air-cooled chiller were running at 100% speed even when ambient temperatures were below 20°C. By modeling energy consumption with VFD modulation, the AI system estimated an 18% reduction in chiller power use, with a projected payback of 18 months for the retrofit.

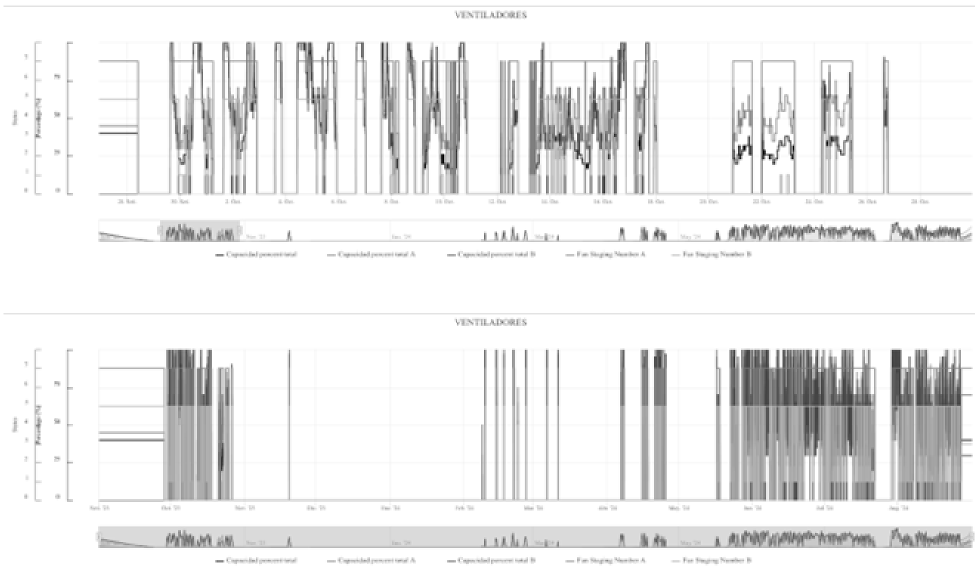

Figure 5: Fan Staging

Recommendations:
The insight provided by the monitoring system helped the facility manager prioritize the VFD upgrade in the next capital plan, reducing the operating cost and the CO_2 emission of the HVAC system.

Implementation Considerations

Although these monitoring systems are becoming easier to integrate, being installed as standard during unit manufacturing and connected during the start-up, some considerations must be taken when implementing them:

- Data Accuracy and Resolution: Reliable performance requires high-quality sensor data and standardized data formats.
- Workforce Readiness: Staff must be trained to understand diagnostics and execute prescribed actions.
- Cost-Benefit Analysis: Deployment should be guided by clear ROI metrics and KPIs (Key Performance Indicators). It is necessary to quantify the energy and maintenance cost savings that the system has generated.

Quantifiable Benefits

- Downtime Reduction: Unplanned outages reduced by up to 50%.
- Energy Optimization: HVAC energy use decreased by 10–25% through dynamic control.

- Maintenance ROI: Improved labor efficiency and material usage from task prioritization.
- Equipment Longevity: Component life extended by up to 25% via early-stage detection.
- Compliance Enhancement: Improved refrigerant tracking for F-Gas and ESG (Environmental Sustainability Goals) reporting.

Conclusions

AI-driven prescriptive maintenance is transforming the way HVAC systems are managed. By integrating real-time monitoring, predictive analytics, and automated decision-making, this approach delivers measurable gains in performance, sustainability, and reliability.

No longer experimental, AI is becoming a trusted ally in the pursuit of decarbonization and operational excellence. For facilities aiming to meet energy, environmental, and financial goals, prescriptive maintenance offers a strategic pathway that aligns smart technology with long-term success.

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Topical Article

Smart Controllers Enable Innovative and Sustainable Residential Thermal Network Design and Operation

DOI: 10.23697/vw8x-0v65

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Smart controlled thermal networks offer a promising pathway to sustainable residential heating and cooling. This article shows how model predictive control is used to optimise performance across cost, emissions, and efficiency in four collective thermal energy systems. The results reveal that a smart controlled two-pipe network with variable temperature operation achieves optimal performance, reducing network heat losses and investment costs. Simulation-based sizing using smart control demonstrates a remarkable 69% reduction in required heat pump capacity compared to conventional methods. These findings show that smart control is an important technology for developers implementing collective thermal energy systems in residential developments.

Introduction

The newer generation district heating networks are designed to operate at lower temperatures, with some systems even approaching ambient temperatures. These lower temperatures facilitate the integration of a broader range of distributed renewable energy sources and the integration of prosumers. At the same time, the relative share of energy demand for domestic hot water is expected to rise due to increased levels of renovation and insulation. Consequently, the importance of domestic hot water production grows, necessitating a careful balance: network temperatures must remain sufficiently high to enable effective temperature boosting for domestic hot water supply, while also being low enough to maximise overall system efficiency and minimise heat losses.

Designing integrated residential energy systems is complex and challenging, particularly when selecting the optimal system configuration. Modern district heating concepts span a wide spectrum: from ambient-temperature networks relying on decentralised heat pumps, to higher-temperature systems capable of directly supplying domestic hot water, and multiple-pipe networks separating space heating, space cooling, and domestic hot water. Additionally, controlling these complex systems is very challenging. Fortunately, smart (heat pump) controllers enable the coordination of multiple heat sources and the anticipation of demand patterns, weather predictions, and energy costs, significantly enhancing system performance.

Four System Configurations are Investigated

Although numerous system configurations could be considered, four main concepts are investigated. Concept 1, illustrated in Figure 1, features a network with one supply and one return pipe operated at ambient temperature. This network serves as a heat source for the decentralised heat pumps that create domestic hot water and space heating in the dwellings. The central heat pump maintains the network temperature within its boundaries. The main advantage of this configuration is its ability to directly provide space cooling through the network, while simultaneously repurposing the heat extracted during cooling to support domestic hot water production.

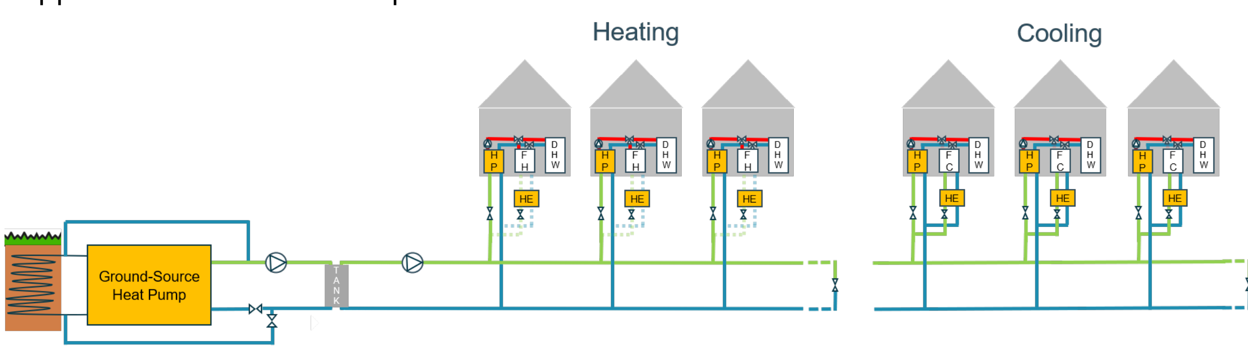

Figure 1: Concept 1 - Ambient-temperature network

Concept 2, represented in Figure 2, features an intermittent-temperature network consisting of one supply and one return pipe with varying temperature levels. For most of the day, the network operates at a temperature suitable for space heating. However, at specific times, the smart controller increases the temperature to optimally charge the domestic hot water tanks in the dwellings. In this configuration, the central air-source heat pump and ground-source heat pump are installed in parallel before the central tank. This setup allows each heat pump to operate during its most efficient period to provide higher supply temperatures: the ground-source heat pump primarily operates in winter thanks to higher ground temperatures, and the air-source heat pump mainly operates in summer thanks to higher air temperatures. A major drawback of this concept is its inability to provide space cooling through the network, necessitating individual air-conditioning units in each dwelling.

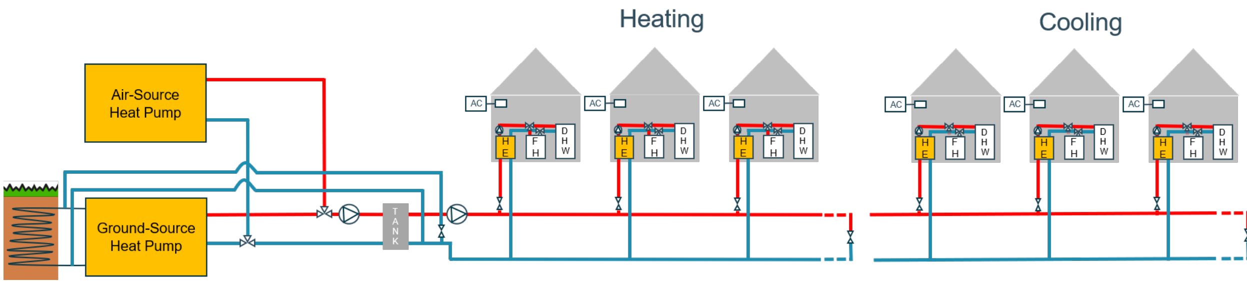

Figure 2: Concept 2 - Intermittent-temperature network

Concept 3, illustrated in Figure 3, features a three-pipe network consisting of one supply pipe for space heating, one supply pipe for space cooling, and one return pipe. The network is connected to two central tanks: one tank is maintained at a temperature suitable for space heating, and the other tank at a temperature level appropriate for space cooling. The space heating supply also serves as the heat source for the decentral heat pumps in the dwellings to produce domestic hot water.

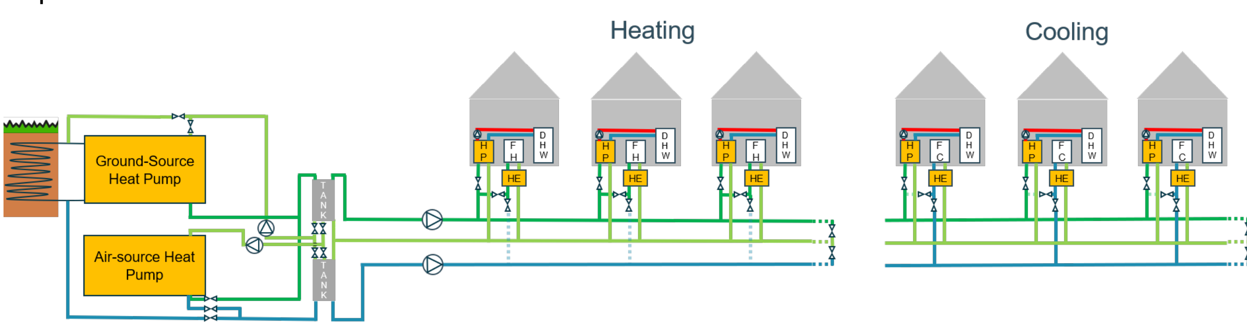

Figure 3: Concept 3 - Three-pipe network

Concept 4, represented in Figure 4, features a four-pipe network consisting of one supply pipe for space heating, one supply pipe for space cooling, one supply pipe for domestic hot water, and one return pipe. In this configuration, all energy services are supplied via the network using three central tanks, each maintained at a temperature suitable for space heating, space cooling, or domestic hot water, respectively. Consequently, no individual production units are required within the dwellings, limiting the investment costs at the building level. The combination of a central air-source and ground-source heat pump is also possible in this case; however, it is not shown to limit the complexity of the drawing.

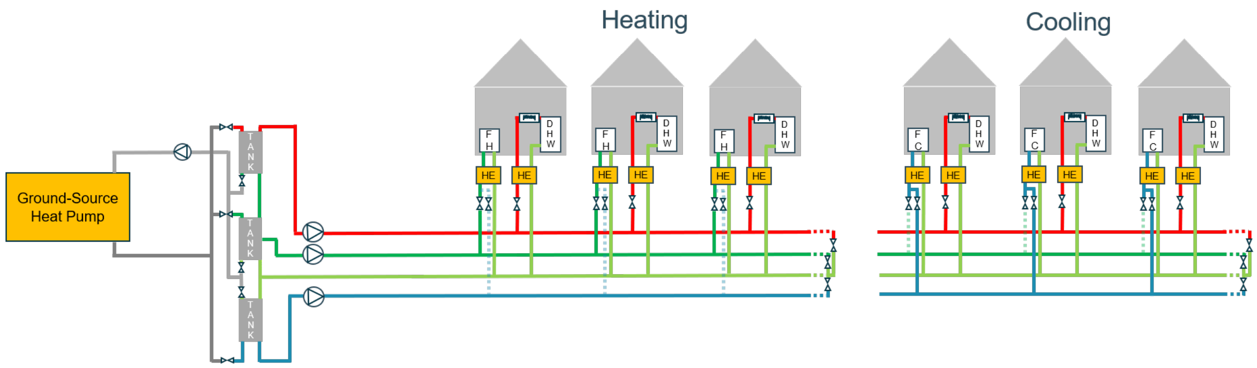

Figure 4: Concept 4 - Four-pipe network

MPC as a Smart Controller

The collective thermal energy systems are controlled using Model Predictive Control (MPC), a smart control strategy that leverages the dynamic behaviour of system components to optimise performance. Unlike traditional rule-based control approaches that *react* to current conditions, MPC *anticipates* future events and optimises control decisions accordingly.

MPC offers several key advantages for controlling complex thermal systems. It can handle non-linear, physics-based models that accurately represent the dynamic behaviour of heat pumps, thermal storage tanks, and building envelopes. Additionally, MPC incorporates predictions of future disturbances and demands, enabling proactive system adjustments rather than reactive responses.

Traditional MPC uses a feedback loop to correct for prediction and model uncertainties. However, this study implements a specific variant of MPC that assumes perfect predictions and a perfect system model, eliminating the need for this feedback loop. This leads to a best-case scenario, allowing focus on fundamental performance differences between system configurations under optimal control conditions without uncertainties.

The MPC controller minimises a multi-criteria objective function that simultaneously maximises energy efficiency, minimises operational costs, and minimises CO_2 emissions, while maintaining thermal comfort. The controller thereby shifts operation to periods of higher heat pump COPs, lower electricity prices, and cleaner grid electricity. The controller incorporates real-time predictions of user demand profiles, weather conditions, electricity prices from the Belgian day-ahead market, and grid CO_2 intensity. By anticipating periods of optimal conditions, the system can preheat thermal storage and the thermal mass of buildings and the network during periods of low-cost or clean energy availability, thereby reducing both costs and emissions while maintaining user comfort.

The control strategy is implemented in *Modelica* using component models from the *IDEAS* and *Buildings* libraries, with the *Toolchain for Automated Control and Optimisation* providing the optimisation framework. A schematic representation of this smart control is shown in Figure 5.

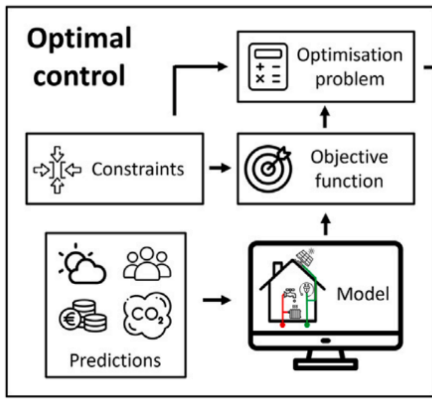

Figure 5: Schematic representation of optimal control used in the smart controller

Operation of the Smart Controller

The smart controller analysis reveals strong correlations between cost minimisation and CO_2 emissions reduction. For this purpose, three different objective functions were tested: one aimed at only minimising cost, another at only minimising CO_2 emissions, and a third at only maximising efficiency, all while maintaining thermal comfort. Figure 6 illustrates that the variations in key performance indicators remained minimal, typically within 1-2% of each

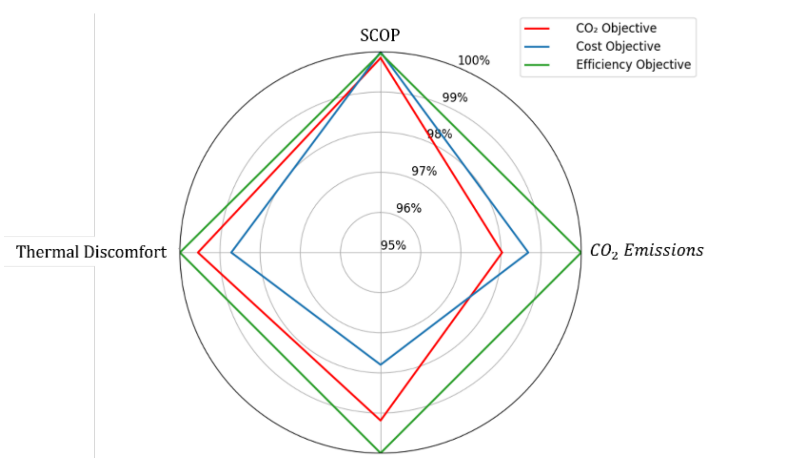

Figure 6: Impact on key performance indicators under varying objective functions

other. Consequently, the smart controller aligns the cost minimisation of developers with the emission reduction goals.

This strong correlation in the results stems from two reasons. First, the operational costs and CO_2 emissions are inherently linked to the electricity generation mix. During periods of high renewable energy generation, both electricity prices and the grid's CO_2 intensity are low. Second, the smart controller exploits the system dynamics to shift energy demand in time. Figure 7 demonstrates the controller’s ability to shift the heat pumps' operation to low-price periods when optimising for costs.

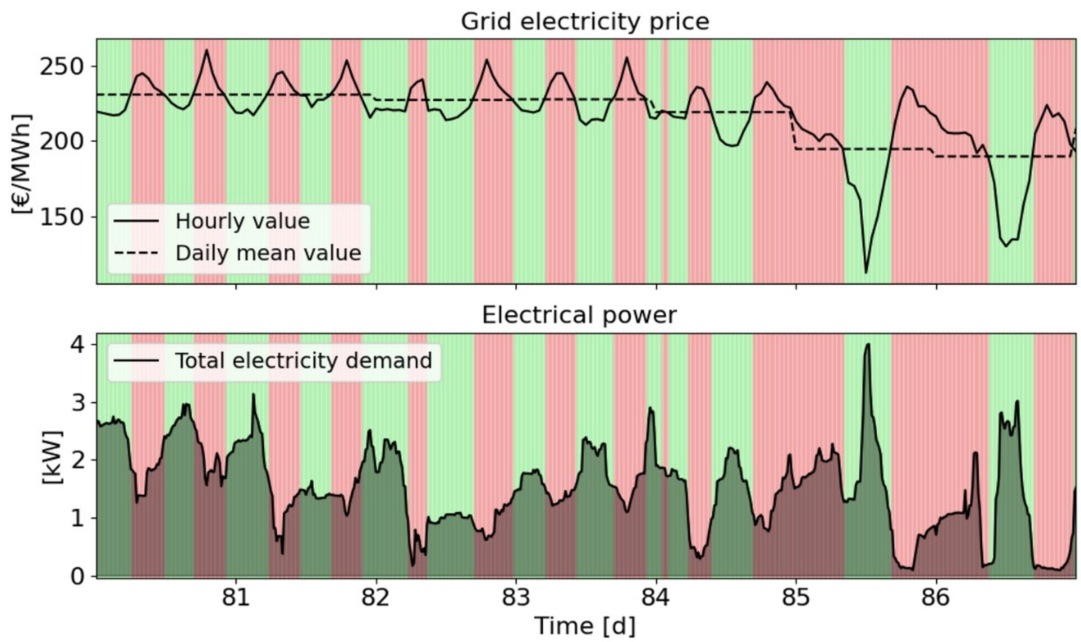

Figure 7: Behaviour of the smart controller when minimising operational costs

Smart Controller Operates a Three-Pipe Network as a Two-Pipe Network
The analysis of the smart controller behaviour showed that the three-pipe network (concept 3) could be effectively simplified to a two-pipe configuration. In the residential use case studied, space heating and space cooling demands rarely occurred simultaneously, making the separate space cooling pipe redundant. Furthermore, the space heating pipeline naturally operated at lower temperatures suitable for cooling during summer, since the recovered heat from space cooling could be reused for domestic hot water production, while increasing energy efficiency.

These findings led to concept 3*, illustrated in Figure 8, which is an improved version of concept 3. Concept 3* features a network with a single supply pipe that switches supply temperatures between a temperature adequate for heating in winter and cooling in summer.

This configuration reduced network losses by approximately 25%, while also reducing investment costs by 20%. The smart controller's ability to anticipate weather, demand patterns, electricity prices, and emissions enabled this simplification without compromising thermal comfort or system performance.

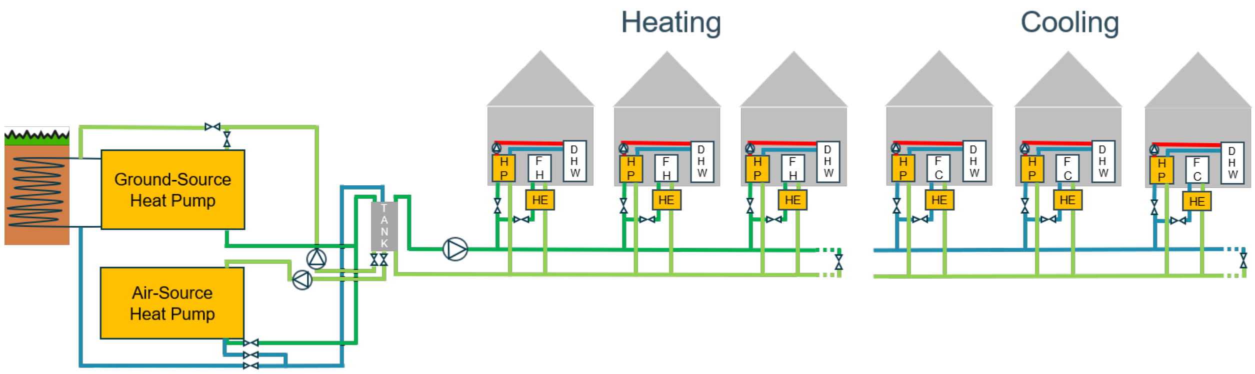

Figure 8: Concept 3 - Improved configuration of concept 3*

Simulation-Based Sizing of the Central Heat Pumps Reduces Installed Capacity by 69%

In collective energy systems, investment costs constitute a significant portion of total system costs, making appropriate component sizing crucial for economic viability. The central heat pumps were sized through a simulation-based approach that systematically evaluated different sizes through full-year simulations, including the smart controller, offering substantial advantages over conventional rule-based methods described by standards.

For the improved configuration (concept 3*), conventional sizing would require approximately 65 kW of thermal production capacity for three dwellings, while simulation-based sizing demonstrated that only 20 kW was sufficient to maintain thermal discomfort, leading to a 69% reduction in heat pump capacity and significant cost savings. As mentioned before, perfect predictions and a perfect system model were assumed. For real-world implementations, safety factors or stress testing under extreme conditions should be included to account for uncertainties.

In hybrid heat pump setups, the sizing method also identifies how the capacity is divided between the air-source and ground-source heat pumps. When both space heating and domestic hot water are provided centrally (concepts 2 & 4), an air-source and ground-source heat pump with the same capacity perform best, as each heat pump can operate at its most optimal time. However, when only space heating is produced centrally and domestic hot water decentrally (concepts 1, 3 & 3*), a system with only a ground-source heat pump performs best. In this configuration, the air-source heat pump remains underutilised during the summer months when no central heat demand is required, leading to a significant cost increase.

Two-Pipe Network Shows the Best Techno-Economic Performance

The techno-economic comparison revealed significant performance differences across the various network configurations investigated. Figure 9 demonstrates the relationship between annual total costs and system efficiency, represented by the overall SCOP (calculated as the total heat supplied by the heat pumps divided by their total electricity demand), with the improved two-pipe network (concept 3*) achieving the best balance of lower total costs and favourable SCOP values.

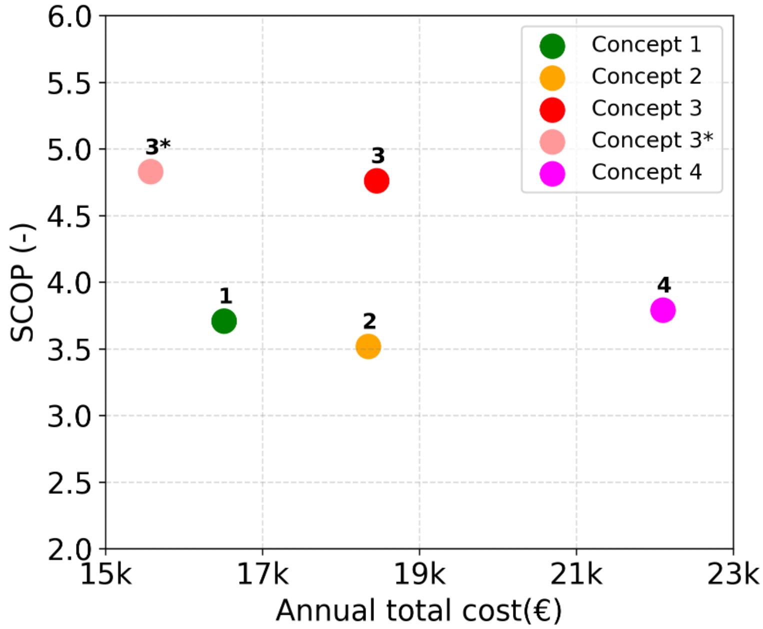

Figure 9: SCOP vs. annual total costs across the different concepts

Network Heat Losses in the Different System Configurations

Network heat losses varied substantially across configurations based on operating temperatures, as shown in Figure 10. The ambient-temperature networks (concept 1) and improved two-pipe systems (concept 3*) achieved the lowest heat losses at approximately 9% of the centrally produced heat, thanks to their lower operating temperatures and simplified piping configurations. In contrast, the intermittent-temperature networks (concept 2) and four-pipe systems (concept 4) exhibited the highest losses at 18-24% due to elevated operating temperatures and multiple supply lines.

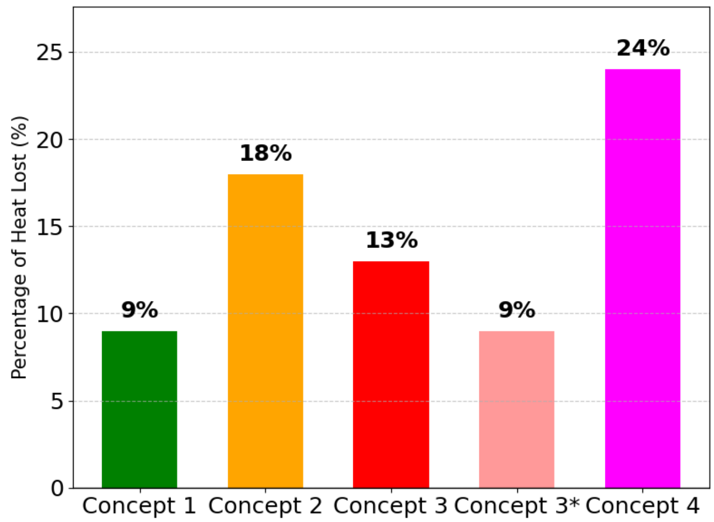

Figure 10: Network heat losses in the different system configurations

Conclusions

The use of model predictive control as a smart controller in thermal networks offers many advantages. This article focuses on two key benefits. First, MPC enables the development of innovative concepts when included in the design process. In this way, a three-pipe network (concept 3) was reduced into an improved two-pipe network (concept 3*), emerging as the most promising solution with the best balance of technical performance and economic viability. Additionally, including optimal control in a simulation-based sizing approach leads to a reduction of the central heat pump capacity by up to 69% and significant cost savings compared to conventional methods. Second, the MPC controller minimises a multi-criteria objective function that simultaneously maximises energy efficiency, minimises operational costs, and minimises CO_2 emissions, while maintaining thermal comfort. However, the smart controller aligns the cost minimisation of developers with the emission reduction goals. These findings provide valuable guidance for evaluating collective thermal energy systems and demonstrate that, fortunately, economically driven decisions align with environmental objectives, supporting the decision-making of policymakers, developers, and practitioners.

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Topical Article

Applying Artificial Neural Networks for Predicting the COP of a Stirling-Based High-Temperature Heat Pump

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This study employs a Multilayer Perceptron Feedforward Artificial Neural Network (MLP FFANN) trained with the Levenberg–Marquardt Backpropagation algorithm to predict the coefficient of performance (COP) of a Stirling cycle High-Temperature Heat Pump (HTHP). The ANN model, tested with various neuron numbers, used sigmoid and Purelin activation functions. Inputs included temperature ratios, sink/source temperatures, and hot water inlet temperatures. The 4-6-1 topology showed strong predictive performance, with correlation coefficients up to 0.995 and low MSE. Results confirm the ANN's accuracy and reliability in predicting COP for HTHP systems.

Introduction

The industrial sector is a leading source of global greenhouse gas (GHG) emissions [1] and presents a major challenge in the transition to a low-carbon society [2]. Heating accounts for roughly 50% of global energy consumption, with the industrial sector responsible for approximately 44% of that demand [3]. Heat pumps (HPs), a renewable energy source, can upgrade low-quality waste heat into high-temperature heat, offering significantly higher energy efficiency than conventional methods, such as fossil fuel boilers. The advancement of High-Temperature Heat Pumps (HTHPs) capable of achieving sink temperatures above 150°C has become a prominent area of research and development. Due to the high cost and time demands of experimental studies, artificial intelligence offers an efficient alternative for predicting values from existing data. Among these methods, Artificial Neural Networks (ANNs) are widely used across various fields, including manufacturing, optimization, signal processing, and energy systems [4]. A literature review shows no prior development of an ANN model for estimating the COP of a Stirling Cycle-based HTHP. This study fills that gap by applying an ANN to predict the COP of a Stirling Cycle HTHP using helium as the working fluid in a heating system.

HoegTemp HTHP system

This study applies ANN to predict the performance of the 400 kW HoegTemp High-Temperature Heat Pump, developed by Enerin (see Figure 1). Using helium (R-704) and operating on the Stirling cycle, the unit is installed at IVAR's biogas plant in Stavanger, Norway, for steam supply and waste heat recovery in a CO_2 capture process [5]. The HoegTemp heat pump is engineered to deliver a thermal capacity of 400 kW. Heat output is measured via a pressurized water circuit linked to a steam generator. Data covers sink temperatures of 139–199°C and source temperatures of 21–22°C. Water temperature is measured via in-flow Pt-100 sensors. Flow rates are recorded using an in-line vortex meter (sink side) and an in-line electromagnetic meter (source side). The heat pump operated for 30–90 minutes per test. Mean temperature and flow values over a stable 30-minute period were used for calculations and reporting [5]. The COP of the Stirling cycle HTHP is calculated using the following equation:

$$COP = \frac{Q_h}{W_E} \qquad \textbf{Eq. (1)}$$

Where COP denotes the performance coefficient, Q_h is the thermal energy delivered, and W_E represents the electrical energy consumption.

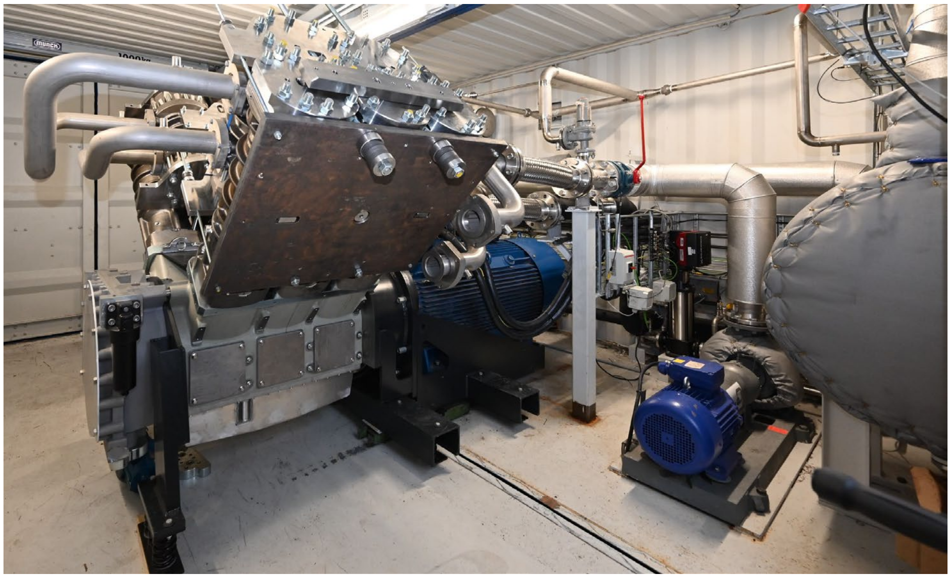

Figure 1: HoegTemp HTHP at IVAR biogas facility [5]

ANN Approach

This study used MATLAB R2023a Neural Network Toolbox to develop an MLP Feed-Forward Back-Propagation (FFBP) ANN. Various single hidden-layer configurations with different neuron counts were tested. The network was trained using the Levenberg-Marquardt (LM) algorithm [6]. Figure 2 shows the FFANN structure used to predict COP, including input, output, and hidden layer neurons. The ANN model's input layer included the temperature ratio (1.4–1.6 K/K), average sink temperature (139–199°C), average source temperature (21–22°C), and hot water inlet temperature (137–197°C). The output layer predicted the COP, ranging from 1.4 to 1.7. The input and output dataset used in the developed BPFF ANN model is randomly divided into 60%, 20%, and 20% for training, validation, and testing, respectively. the Tansig transfer function was applied to the hidden layer, while the Purelin transfer function was used for the output layer of the ANN, to determine the most suitable transfer functions for predicting the COP of the HTHP. To evaluate performance, error analysis was performed. In this study, the Mean Squared Error (MSE) and Correlation Coefficient (R) were used to assess the accuracy of the ANN. Training of the Neural Network (NN) was stopped when the target error dropped below 0.01. It is important to note that the sampling iteration for the trained ANN was set to 1000 by default.

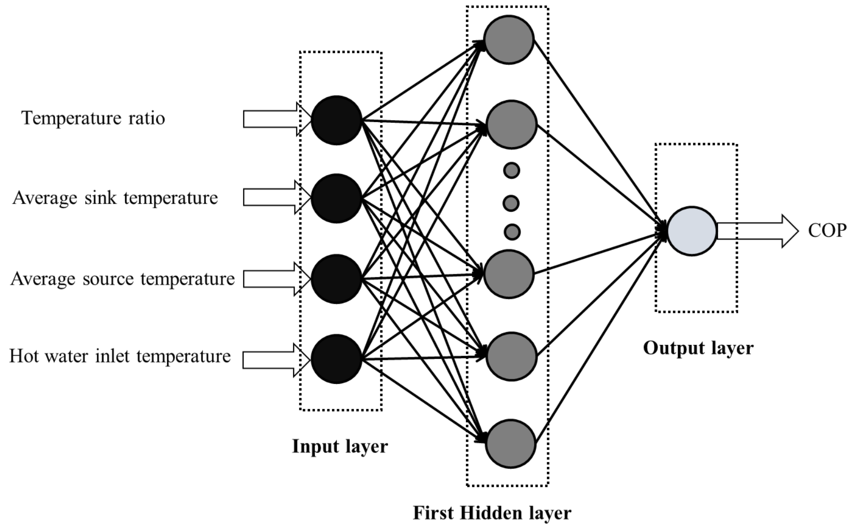

Figure 2: Schematic diagram of an MLP-FFNN with one hidden layer

ANN Results

Experimental data and related parameters were used to train the ANN, testing various neuron counts in a single hidden layer. Based on Table 1, the optimal configuration was a 4-6-1 FFBP network with Tansig-Purelin functions and LM training (1 epoch), yielding the lowest MSE and highest R-value for accurate COP prediction.

Table 1: R and MSE of the trained ANN

	Observation	R	MSE
Training	7	0.9799	0.0016
Validation	3	0.9942	0.0002
Test	3	0.9951	0.0004

Table 2 presents the MSE and R for the training, validation, and testing datasets from the trained neural network. The low MSE values, approaching 0, and the high R values, nearing 1, confirm the high accuracy of the model's prediction (COP) across all dataset partitions. The MSE values for Training, Validation, and Test are 0.0016, 0.0002, and 0.0004, respectively (see Table 2).

Table 2: The optimal topology for COP prediction

Network	Training algorithm	Transfer function	Topology	Epoch
FFBP	LM	Tansig-Purelin	4-6-1	1

The performance of the initial prediction model is assessed using the coefficient of correlation and mean square error. The regression R values quantify the strength of the correlation between the model's outputs and the target values. As shown in Figure 3, the x-axis represents the empirical data, serving as the reference, while the y-axis displays the approximations generated by the ANN. Upon analysis, it is clear that the data points are almost aligned with the zero-error line. Training samples were used to train the network, with adjustments made based on the error during the process. Validation samples were used to assess the network's generalization ability and to determine when training should be stopped, as generalization ceased to improve. Testing samples, on the other hand, remained independent of the training process and provided an unbiased evaluation of the network's performance both during and after training. Figure 3 shows the ANN regression plot using the LM algorithm for COP prediction. The model achieved R-values of 0.97989 (training), 0.99421 (validation), 0.99509 (testing), and 0.96592 overall, indicating strong accuracy (R > 0.965). Compared to Thango et al. [7], who reported 96.38% accuracy, the proposed ANN model demonstrates high reliability for COP prediction.

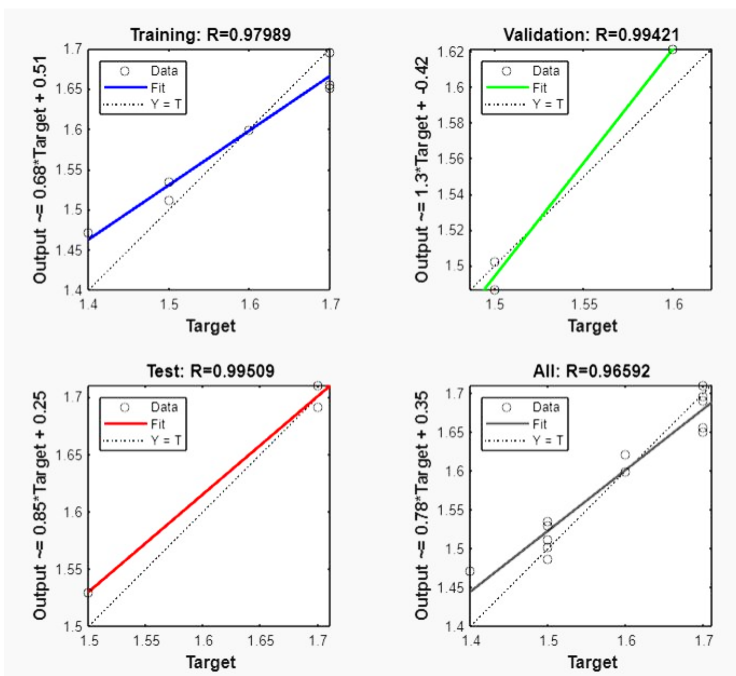

Figure 3: Correlation coefficient for predicting COP: training, validation, and testing

The first step in assessing the predictive capability of the ANN architecture is to confirm the successful completion of its training and learning phases. During the training phase of the MLP networks, information flows from the input layer to the output layer and is then fed back to the input layer to reduce errors. This iterative cycle is referred to as an "epoch." By the end of each epoch, the gap between the target and predicted data is expected to narrow, resulting in a reduction in MSEs. Figure 4 shows MSE variation during training. Initially, MSE was high but gradually decreased, reaching an optimal value of 0.00022234 at epoch one after five iterations. Further training reduced accuracy, triggering early stopping. Figure 5 displays the state transition outcomes of ANN, which describe gradient values, epoch numbers, and mu and validation checks. In an ANN, the gradient is used to assess how much the output of a function changes when there are modifications to the inputs. The gradient represents the backpropagation gradient for each epoch, displayed on a logarithmic scale. During the neural network training, the parameter “mu” was used to regulate the weights of neurons during training of the backpropagation process, specifically the weights. If training stops, it indicates that the maximum value of mu has been reached. According to the obtained results, the network achieved high validation accuracy, with training halted at the point of maximum failure to prevent overfitting.

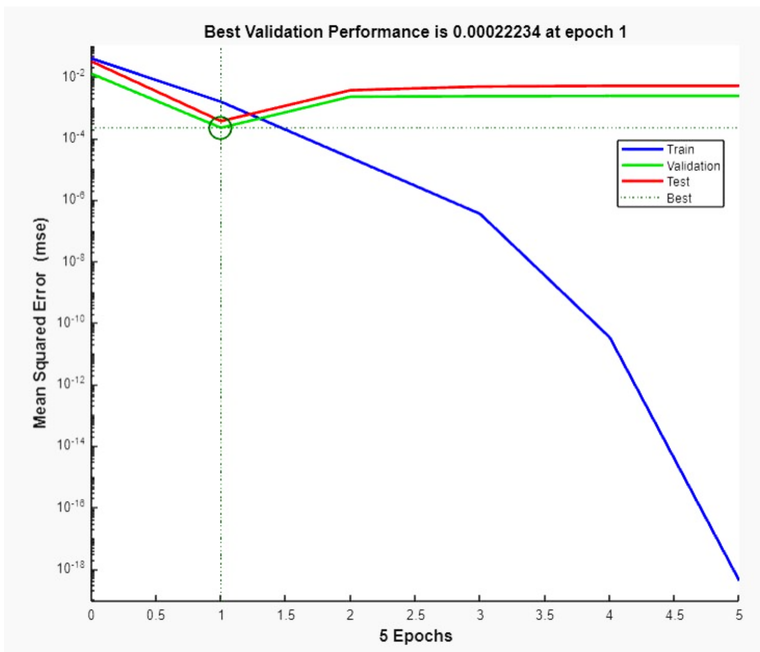

Figure 4: MSE variation for the trained ANN for the prediction of COP

Figure 5 shows the training gradient (3.83e-11) and maximum mu value (1e-8), both at epoch 5. The low gradient and near-zero mu reflect the LM algorithm’s efficiency in COP prediction. Training stopped at epoch five due to four consecutive validation failures, indicating the onset of overfitting as validation MSE began to rise.

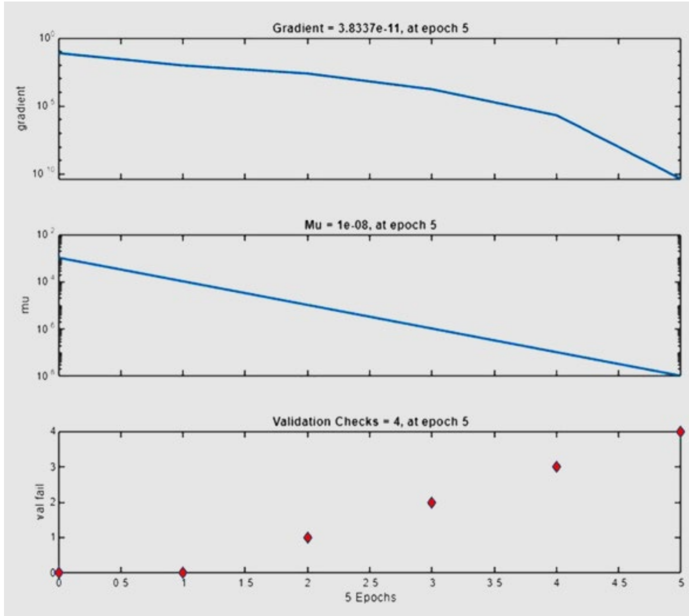

Figure 5: Gradient curve, momentum coefficient (mu), and best validation performance of the used ANN

Conclusions

This study used an MLP BPFF with the LM algorithm to predict the COP of a Stirling cycle high-temperature heat pump. Inputs included temperature ratio, sink/source temperatures, and hot water inlet temperature. Model performance was evaluated using the correlation coefficient and MSE during training, testing, and validation, achieving an overall R of 0.96592. The optimal 4-6-1 network used Tansig (hidden) and Purelin (output) functions with one epoch. The high R-value confirms the model's accurate prediction capability. COP predictions using FFNN are highly promising. The study demonstrates that neural networks are effective tools for identifying and optimizing HTHP performance. Trained models can be integrated into control systems for continuous prediction and adjustment.

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Topical Article

Outperforming the Heating Curve with Data-Driven Model Predictive Control

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Digital twins enable highly efficient control strategies such as model predictive control (MPC) and are therefore a promising technology to decrease energy consumption and reduce operating costs. A Hardware-in-the-Loop test bench combines a real heat pump with a simulated building to investigate the setup under realistic and dynamic operating conditions. This research compares an MPC using a digital twin within a cloud infrastructure against a conventional heating curve controller on a typical winter day. The MPC dynamically adjusts the compressor speed to maintain comfort while minimizing energy use. Results demonstrate that the MPC reduces electrical consumption by 11 % compared to the standard controller.

Introduction

Maximizing the environmental and economic benefits of heat pump systems while minimizing the impact on the electrical grid requires minimizing energy consumption. One way to minimize energy consumption is to increase the operating efficiency of the heat pump. The instantaneous efficiency of a heat pump largely depends on the given process temperatures and the heating capacity, which can be changed by the controller by adjusting the compressor speed. When heating buildings, the optimal operating point depends on the ambient air temperature, sink temperature, thermal demand, and user occupancy patterns. In practice, conventional control strategies typically use a heating curve with a PI controller that considers the ambient air temperature as the only input variable while neglecting further disturbance variables such as solar irradiation. This control setup leads to robust operation at the expense of suboptimal performance and, therefore, not maximum operating efficiency. A second way to minimize energy consumption is to only provide heat when it is actually needed, which is also possible by implementing further disturbances into the controller and knowledge about the building.

To achieve minimum energy consumption while maintaining robust operation at all times, advanced control methods are suggested in the literature.

Model Predictive Control (MPC) is a promising control strategy enabling maximization of energy efficiency and minimization of energy consumption using mathematical optimization based on process models of the entire system. To achieve optimal control, MPC uses these models to manage multiple disturbances. By incorporating weather forecasts, it predicts future system behaviour and proactively adapts the heat pump's next control step accordingly. Overall, the use of process models and mathematical optimization leads to optimal operation of the heat pump. Previous studies have demonstrated the effectiveness of MPCs in building energy management [1], [2], [3]), but experimental validation is still needed. Bringing MPC into practice, digital twins are proposed as a promising way of implementation in the literature.

In this work, we conduct experiments on a Hardware-in-the-Loop (HiL) test bench, combining a real heat pump with a simulated building environment. This approach allows us to implement MPC into a digital twin framework to evaluate the system performance under realistic conditions. The heat pump process model is provided with a data-driven approach. The paper is structured in the following way:

- **Section 2** introduces the HiL methodology and describes MPC fundamentals.
- **Section 3** presents the experimental results.
- **Section 4** summarizes the findings and discusses implications and limitations.

By demonstrating the advantages of MPCs in real-world applications, this work contributes to the development of smarter and more efficient heat pump systems for a sustainable energy future.

Methods

The HiL approach for building energy systems involves real-time coupling of actual hardware with dynamic simulation models; please refer to Figure 1 for a schematic view [4]. The entire setup is connected using an internal, fully digitalized Internet of Things approach, enabling bi-directional communication between the experiment and simulation environments. The setup fulfills the requirements of implementing digital twins at a technology readiness level of 7, which enables bringing highly-efficient control strategies into practice.

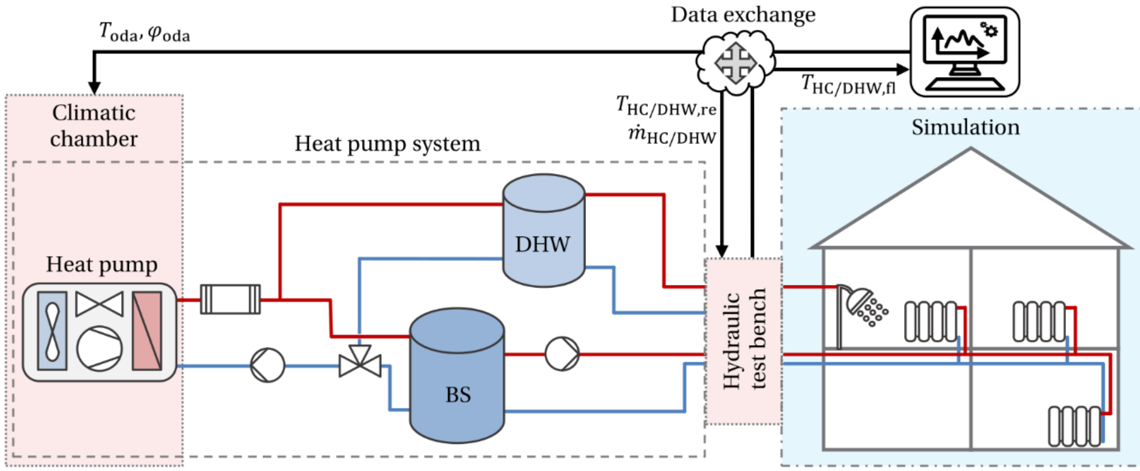

Figure 1: Schematic view of a Hardware-in-the-Loop test facility [7].

In the experimental environment, the climate chamber is designed to emulate realistic environmental conditions, e.g., for an air-source heat pump, by using weather data from a simulation, which are transmitted to the chamber's control system in real-time. The hydraulic test rig consists of multiple hydraulic circuits that can be used, e.g., to simulate hydronic heating systems as heat sinks. In the simulation environment, a building performance simulation model computes the heating demand in real-time and communicates the supply temperature and flow rates back to the test rig. In this way, the test rig emulates realistic operating conditions for the heat pump's sink side. The heat pump test bench features a commercially available heat pump modified with additional sensors and actuators, including an electronic expansion valve, a compressor with variable speed control, a four-way valve, and an evaporator fan. In this setup, the electronic expansion valve controls the superheat, while the fan operates at a constant speed. The basic controller implementation is set up with a conventional heating curve and PI controllers.

To allow for more sophisticated control strategies than conventional heating curves, the data-driven (DD) MPC framework is utilized in this work in a digital twin setup. DDMPC is a Python-based tool that enables the implementation of model predictive control [2], allowing for (1) the definition of the system's state space, (2) formulation of the optimization problem using CasADi [5] syntax, (3) integration of data-driven models, and (4) solution of the optimization problem using the Ipopt solver [6].

By solving the optimization problem, the MPC aims to achieve minimum energy consumption while maintaining the desired room temperature. The objective function is formulated to minimize the deviation of the room temperature from the setpoint and penalize high compressor speeds, as described by Equation 1.

$$\min_{u_{\text{Comp}}} \sum_{k=0}^{N} \underbrace{w_{T_{\text{Room}}} \cdot \left(T_{\text{Room}} - T_{\text{Room,set}}\right)^2}_{\text{Deviation of room set temperature}} + \underbrace{w_{u_{\text{Comp}}} \cdot {u_{\text{Comp}}}^2}_{\text{High compressor speeds}} \qquad \textbf{Eq. (1)}$$

The penalization of compressor speeds incentivizes the MPC to operate at low compressor speeds. Hence, the compressor speed is only set as high as needed, which leads to low energy consumption.

The MPC solves the optimal control problem every 10 minutes, applying the resulting compressor speed to the heat pump. A prediction horizon of 6 hours is used, with an artificial neural network predicting the future state of the system by estimating changes in room temperature based on weather forecast, future demand, and the heat pumps' operation over the prediction horizon. A more detailed description of the optimal control problem can be found in [3]. The results of the model predictive controller are compared to the reference controller in the next section.

Results

Figure 2 compares two different ways to control residential heat pumps: the MPC and a conventional heating curve controller. Weather data of a typical winter day of a test reference year [4] in Potsdam, 2015, is used. We filtered out startup procedures and included only periods when the compressor operates, to ensure a meaningful comparison.

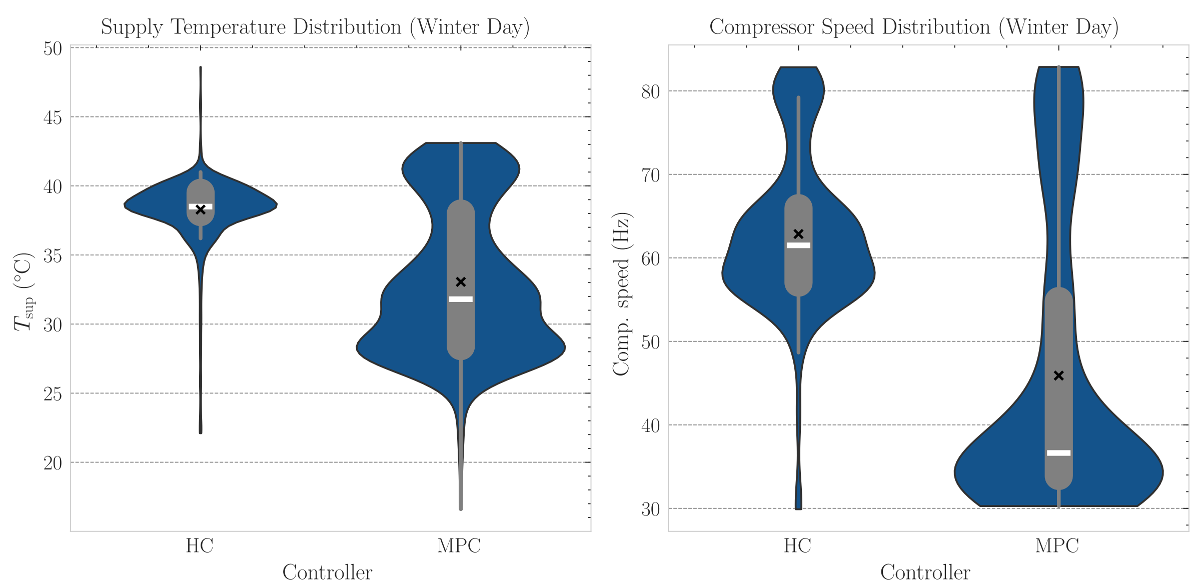

Figure 2: Distributions for the values of compressor speed and supply temperature (T_{sup}) for a typical winter. The heating curve controller (HC) is on the left, and the model predictive controller (MPC) is on the right for each value. In the center of each violin, we display a boxplot with the first to third quartiles being in the box. The median is marked with a white line, the mean is marked with an x.

The supply temperature shows differences between the two control methods. The heating curve controller runs at higher supply temperatures, as seen in the left subplot. The mean supply temperature (indicated through the black x) is 5 K higher with the heating curve compared to the MPC. This happens because the heating curve sets the supply temperature purely based on outdoor air temperature. In contrast, the MPC varies the supply temperature according to the solution of the optimization to maintain comfort while using less energy.

The MPC runs the compressor at lower speeds (about 30-40 Hz) compared to the reference controller (50-70 Hz). The mean compressor speed is 63 Hz for the heating curve and 46 Hz for the MPC. This is directly related to the higher supply temperatures required by the heating curve controller.

We also see that the compressor speed as well as the supply temperature spans over a greater area with the MPC compared to the HC. That highlights the variability of the MPC.
By running the system at lower compressor speeds and lower average supply temperatures, the MPC decreases energy consumption by 11 % compared to the heating curve. The SCOP is increased by 3 % using the MPC.

Conclusions
This study demonstrates the potential of model predictive control (MPC) for building energy systems:

- The study shows a successful experimental comparison between two heat pump controllers paving the way towards rapid control prototyping.
- The digital twin framework with MPC has a high overall potential and outperforms the heating curve due to the integration of disturbance variables and forecasts.
- The limitations of the study include the assumption of perfect forecasts for weather conditions and user behavior, which may not be realistic in practice. This could result in lower savings in reality, as the MPC may not be able to adapt to unexpected changes in the system or user behavior.

Overall, these findings show in an experimental study why advanced controllers like MPC perform better than basic heating curve controllers. While the heating curve only reacts on changes in the outdoor temperature, the MPC can adapt to various conditions, including solar radiation and occupancy patterns. By adjusting the compressor speed based on actual needs, the MPC maintains comfort while using less energy. This leads to an 11 % reduced energy consumption with MPC compared to a heating curve on a typical winter day while increasing the SCOP by 3 %. Overall, we presented how advanced controllers can reduce the energy consumption of heat pumps to minimize their impact on the electrical grid. In the next steps, the methodology should be demonstrated in a field test to further show its technological readiness and reduce hurdles for practical implementation.

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Topical Article

Future-Proofing Buildings for heat pump-integrated 5th Generation District Heating and Cooling: How Building Renovation and Optimal Control Shape Network Performance

DOI: 10.23697/1phb-m028

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5th Generation District Heating and Cooling (5GDHC) networks offer a promising solution to increase the share of residual and renewable energy sources (R^2ES). However, their efficiency depends on both building renovation levels and smart control strategies. This article presents insights from a scenario-based simulation study that examines how varying renovation levels affect system performance. The study demonstrates how Optimal Control (OC) can enhance heat pump operation, reduce peak demand, and support the viability of low-temperature networks for future-proof building clusters.

Introduction

The transition to climate neutrality by 2050 requires a fundamental rethinking of how we heat and cool our urban environments, considering both buildings and entire neighbourhoods. 5th Generation District Heating and Cooling (5GDHC) networks are gaining increased interest for their ability to provide simultaneous heating and cooling through a bidirectional network. By operating near ambient temperatures (T_s < 30°C), these systems can integrate large shares of renewable and residual energy sources (R^2ES), reducing primary energy use and carbon dioxide emissions.

However, the move to low supply temperatures and 5GDHC networks requires the connected buildings to be either highly energy-efficient or supported by advanced, integrated control strategies that can compensate for varying building performance. Renovation of existing buildings with poor energy performance is essential, though deep renovation is expensive and time-consuming, and perhaps not always needed. Meanwhile, managing and controlling multiple distributed heat and cold sources in a 5GDHC network presents significant challenges, with pumping power becoming a critical factor at low temperatures.

Given the importance of lowering building heat supply temperatures, the need for integrated optimal control strategies, and the cost barrier of large-scale renovation, this article presents insights from a simulation study showing how Optimal Control (OC) can act as a system integrator for a small virtual 5GDHC network with varying building renovation scenarios. The content of this article is based on the research work presented in [1].

Thermal Network and Buildings Description

A small virtual 5GDHC system serves as a use case with a Bidirectional energy – Directional medium flow (BiD) configuration, schematically shown in Figure 1. The system consists of three terraced houses and three office buildings, as representative of a mixed small Belgian district, and a central balancing unit. A centralized pump controls the direction of the flow in the network, while a three-way valve at the primary side of the substation modulates the medium flow rate in the substations towards a modulating water-source heat pump (WSHP) or a heat exchanger (HEx) for direct cooling, depending on whether the heating or cooling mode is selected. To allow heating/cooling in each zone of the building, an embedded floor emission system, controlled by valves, is used. A central balancing unit manages the heat imbalances within the network and keeps the network temperature within a specified range (5-16°C) by employing a large modulating air-source heat pump (ASHP) and a large modulating air-source chiller (ASCH). A water buffer tank is added to dampen the peaks in the network.

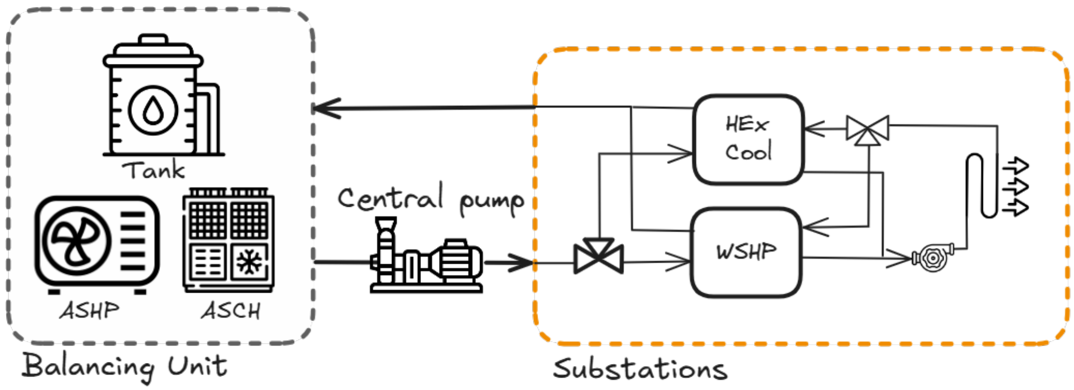

Figure 1: Simplified scheme of a bidirectional energy-directional medium flow 5GDHC network configuration

Ten renovation scenarios, from highly insulated buildings with mechanical ventilation with heat recovery (MVHR) to poorly insulated buildings with simple mechanical exhaust ventilation (MEV), and mixed-renovation scenarios, are analysed. Three different insulation levels (labels A, B, and C) are considered, according to the Belgian classification (Table 1). A summary of the considered renovation scenarios is presented in Table 2, highlighting the main parameters varying among the buildings connected to the district.

Table 1: U-values and air tightness values for insulation label A, B, C

	A	**B**	**C**	**Unit**
Windows	1.5	2.5	3	W/m²/K
Roofs and Ceilings	0.24	0.4	0.8	W/m²/K
Walls	0.24	0.6	0.6	W/m²/K
Floors	0.24	0.4	1.5	W/m²/K
Doors and Gates	2	2.9	3.5	W/m²/K
Air tightness	3.2	4	6	m³/h/m²

Table 2: Summary of considered renovation scenarios (Label, Ventilation, $\dot{Q}_{design}$ for Houses and Offices)

Scenario	**Houses** (Label / Ventilation / $\dot{Q}_{design}$ [W/m$^2_{floor}$])	**Offices** (Label / Ventilation / $\dot{Q}_{design}$ [W/m$^2_{floor}$])
1	All A / MVHR / 27.23	A / MVHR / 38.3
1_2	1 B / MEV / 52.67, 2 A / MVHR / 27.23	A / MVHR / 38.3
1_3	1 C / MEV / 62.04, 2 A / MVHR / 27.23	A / MVHR / 38.3
2	All B / MEV / 52.67	A / MVHR / 38.3

2_1	2 B / MEV / 52.67, 1 A / MVHR / 27.23	A / MVHR / 38.3
2_3	2 B / MEV / 52.67, 1 C / MEV / 62.04	A / MVHR / 38.3
3	All C / MEV / 62.04	A / MVHR / 38.3
3_1	2 C / MEV / 62.04, 1 A / MVHR / 27.23	A / MVHR / 38.3
3_2	2 C / MEV / 62.04, 1 B / MEV / 52.67	A / MVHR / 38.3
4	All C / MEV / 62.04	C / MEV / 87.53

Optimal Control

Optimal Control (OC) is used as a system integrator to minimise energy use, while providing thermal comfort. The employed optimal controller is an idealised model predictive controller that uses a detailed white-box system model (without model mismatch) and perfect knowledge of the weather conditions. Physics-based models of two-zones buildings, thermal systems (e.g., heat pumps, chillers), and hydraulic components are developed in Modelica and integrated into a single nonlinear programming (NLP) optimal control problem (OCP) in TACO (Toolchain for Automated Control and Optimisation), an in-house developed Modelica-based toolchain for nonlinear white-box Model Predictive Control (MPC) [2].

The main objective of the optimisation problem is to minimise (1) the total primary energy use, including all heat pumps, chillers, circulation pumps, and centralized pumps, (2) thermal discomfort inside the buildings, under specific constraints (e.g., minimum and maximum indoor temperature, floor surface temperature, network temperature). A more extensive description of the approach used to solve the NLP optimal control problem for a BiD configuration is presented by Dell'Isola et al. [3].

Optimal control problems are carried out for three representative months in winter, mid-season, and summer (January, April, and July).

To assess the renovation level impact, the different scenarios are compared, focusing on the electrical energy use, peak power, and seasonal performance factor (SPF), evaluated as the total useful heat provided in heating regime or extracted in cooling regime in all buildings, versus the total heat pump electric energy use over the simulation period.

5GDHC Network Performance Influenced by Renovation Levels

Figures 2 - 3 - 4 present the main results for different renovation scenarios for the three representative months. In all monthly simulations, the thermal discomfort remains very low, i.e., below 2.5 Kh/zone. Therefore, the different renovation scenarios are compared under equal thermal comfort conditions.

The study confirms that the renovation level strongly affects the network performance, especially in winter. Well-renovated buildings, with a higher insulation level and a better-performing ventilation system, require a lower heat demand, leading to lower primary energy use as expected (Figure 2). However, it is interesting to notice that even with medium or mixed renovation levels, the optimal control strategy helps maximising system efficiency, offsetting the higher demand with higher condenser heat pump power and comparable coefficient of performance (COP). This results in a relative SPF variation among the different scenarios of only 1.7%, except Scenario 4, with all label C buildings, which results in higher energy use, higher supply temperatures, and limited thermal interaction between the buildings.

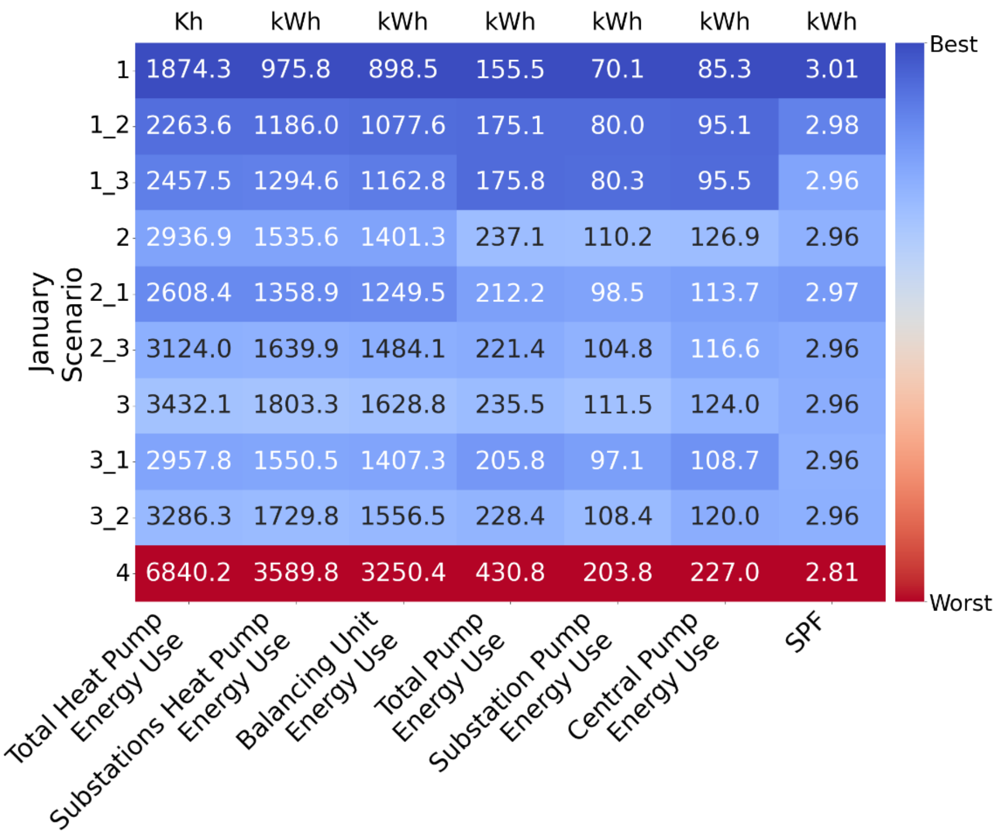

Figure 2: Performance indicators heat map for January OC simulation

Similar observations can be made for the transitional season in April in Figure 3, showing a similar ranking for the impact of the renovation levels.

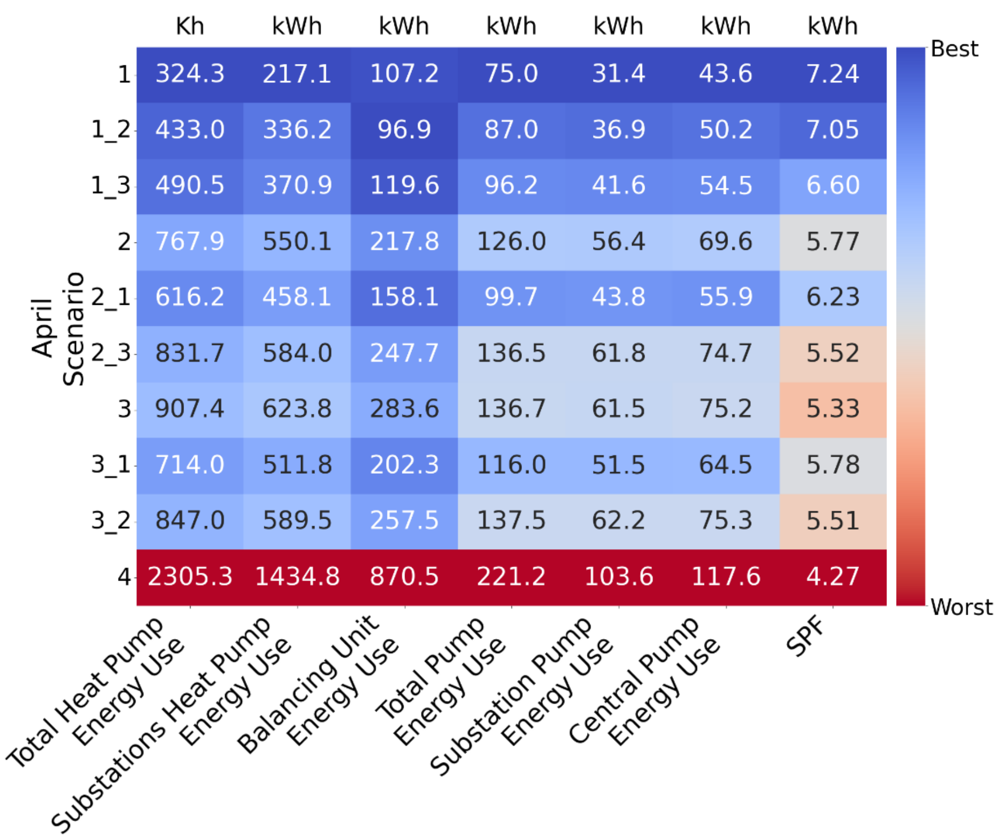

Figure 3: Performance indicators heat map for April OC simulation

Figure 4 shows interesting results for the summer period. The inclusion of buildings with a lower renovation level influences the system's optimal operation, leading to heat pump activation even in the cooling season. Optimal control exploits the buildings' thermal inertia and the diversity in thermal loads between houses and offices to optimise thermal interaction.

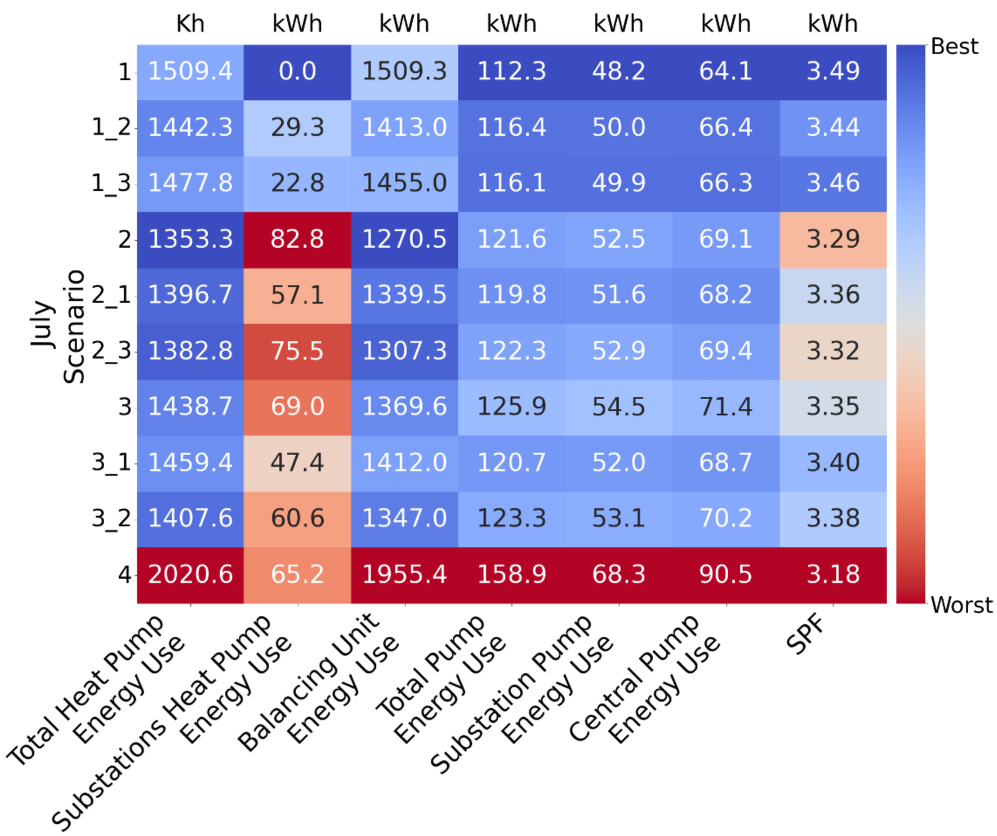

Figure 4: Performance indicators heat map for July OC simulation

Figure 5 shows how lower-performing residential buildings are used as heat sinks (still fulfilling thermal comfort constraints) during office cooling peaks, reaching the lowest total electric energy use for scenario 2. The decentralized heat pumps absorb heat from the network, limiting the need to operate the energy-intensive central chiller. On the other hand, the unnecessary activation of the heat pump for the building's owner is penalised in the SPF calculation.

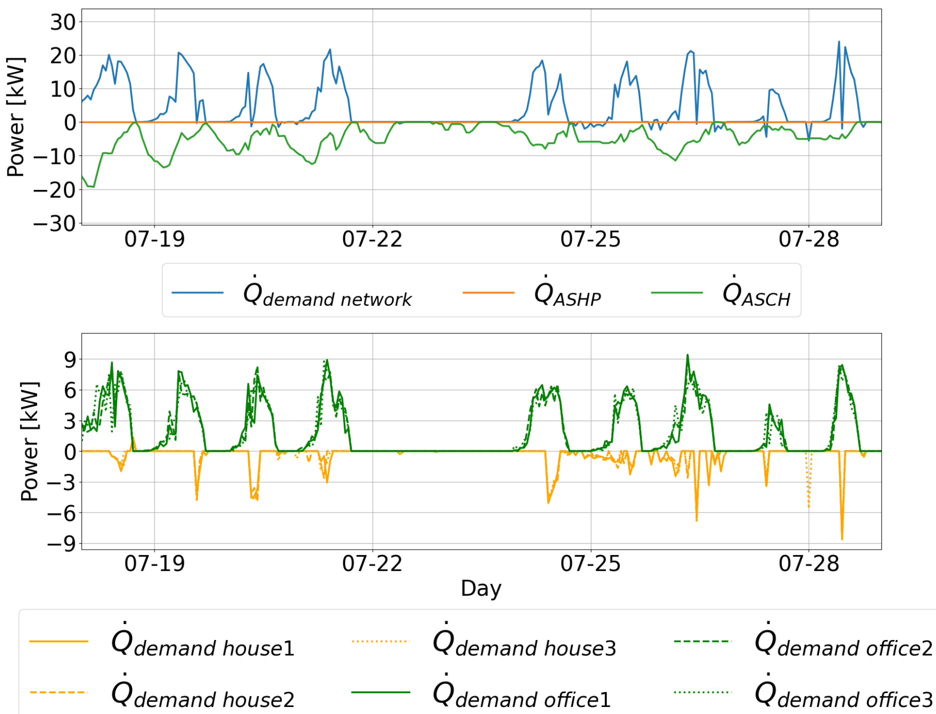

Figure 5: Scenario 2 thermal demand and supply in the period July 18-29

Heat pumps and chiller capacity

Figure 6 illustrates how central/decentralized heat pumps (HP) and central chiller (CH) capacities vary across different district renovation scenarios.[1] The results highlight how building performance shapes both peak demand and the optimal operation strategy for the district network by minimising total electrical energy use and thermal discomfort.

In worse-performing districts, buildings with lower insulation and thermal inertia require more continuous heating to ensure thermal comfort. This leads to larger decentralized HP capacities at the building level. The central HP capacities may either increase (e.g., scenario one vs. 1_2) or remain about the same (e.g., scenario two vs. 2_3), with the central HP operating more continuously but at a similar capacity. However, this comes at the cost of higher total energy use, as the heat pumps typically run for longer periods in worse-performing districts. On the other hand, the central chiller capacity always rises as district performance decreases (higher cooling demands), in order to provide direct cooling without an additional decentralized chiller.

[1] For Scenario 1, 2 and 2_1 the second highest peak power was considered. The highest peak power of the central HP has been filtered out, since it is a residual occurring just once at the end of the simulation period.

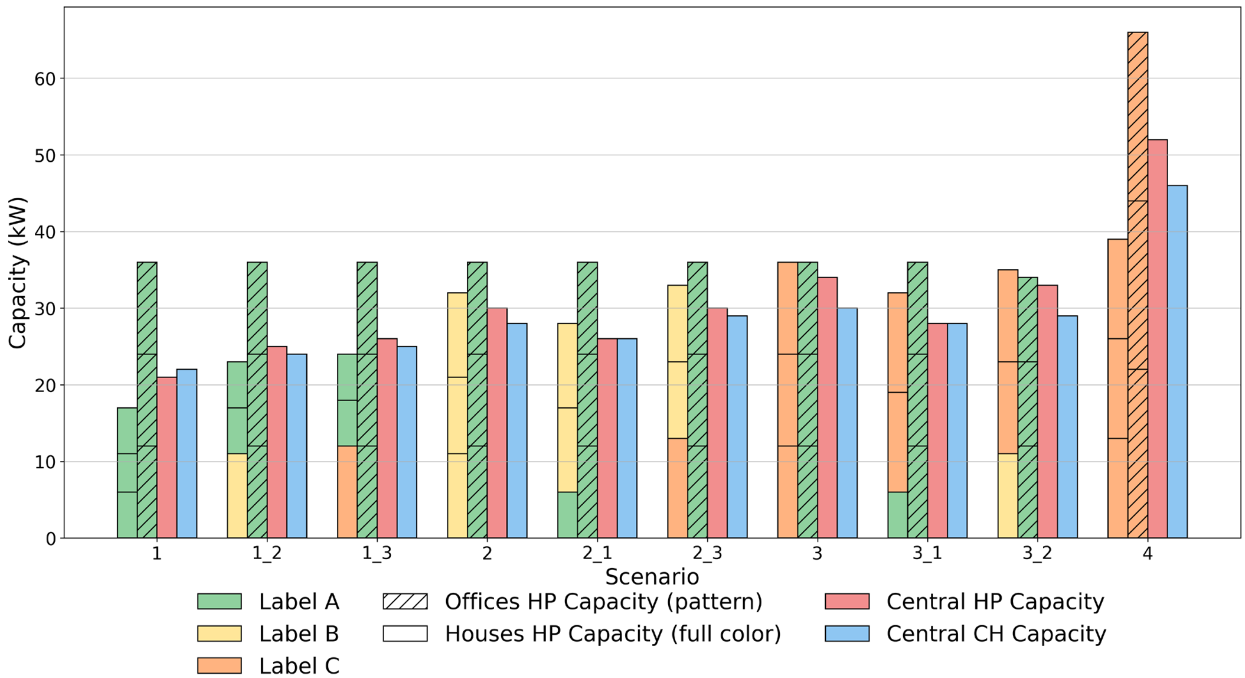

Figure 6: Heat Pumps and Chiller Capacity by Scenario

In better-performing districts, high insulation and good air tightness give buildings larger thermal inertia. Optimal control of these buildings results in less constant heating demand, with more distinct peaks occurring when heat pumps operate at their highest COP. The decentralized HP capacities are lower due to the lower demand (lower buildings heat losses), while the central HP capacity varies depending on the mix of building types (similarly to the considerations above). Regardless, total energy use is always lower in better-performing districts. Chiller capacity also consistently decreases with better renovation levels, thanks to reduced cooling needs.

The differences between scenarios with Label B and Label C are smaller than the jump to scenarios with Label A buildings. This is because both B and C use the same MEV system, while label A benefits from mechanical ventilation with heat recovery, significantly improving energy performance and reducing system loads.

In scenario 4, a lower renovation level for both the residential and office buildings makes the heat pumps and chiller sizes clearly higher compared to the other scenarios.

Conclusions

This study shows that 5GDHC networks can achieve strong performance even in districts with mixed building renovation levels, if equipped with an integrated optimal control strategy. The summer heat pump activation strategy illustrates how advanced control can transform what appears to be a disadvantage, such as poorly performing buildings, into a system-level asset, thereby helping to balance the network and to reduce overall energy use.

For the extreme renovation scenarios, the results align with existing literature: well-renovated buildings (Scenario 1) deliver high efficiency and good thermal comfort, while poorly-renovated districts (Scenario 4) are unsuitable for 5GDHC due to higher loads and reduced flexibility. In such cases, where the system is no longer self-balanced (as may also occur in offices-only or dwellings-only dominated districts), a 4th Generation District Heating (4GDH) network may be more appropriate. Overall, the findings demonstrate that optimal control is essential to unlock the full potential of low-temperature district heating and cooling systems.

Future work will include full-year simulations, a sensitivity analysis on geographical location using different weather datasets, and an investigation of smart ventilation control. In addition, the observed trends in peak power requirements for heat pumps and chillers across scenarios highlight the need for further research into integrated optimal sizing and control strategies in 5GDHC networks.

Acknowledgement

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Topical Article

Autodomos: Predicting Dwelling Heat Load Based on Internal Heat Pump Data

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A digital twin of an individual dwelling, including a heating system, can be used for predicting heat load. This is useful for determining when a heat pump should run based on forecasted ambient conditions (e.g., temperature, solar gain, wind), internal heat load, and electricity availability. In work conducted by TNO, the Autodomos algorithm has been developed, which generates a digital twin based on operational data from the heat pump. An Autodomos generated model is able to predict the dwellings' heat losses/gains and is able to calculate the required heating to be provided by the heat pump. This model can be used for self-configuring heat pump installations or to unlock the flexibility potential of a heat pump.

Introduction
Domestic heat pump installations face two important challenges:

1. The availability and price of electricity on the electrical grid.
2. The time and knowledge required by installers for installing and commissioning heat pumps, including after-sales service.

Both of these challenges can only be addressed if more information is known about the dwelling and its heating system. It needs to be known how much is the heat loss. How much will the dwelling heat up due to solar gain, and when? What happens if the heating is turned off/down for one or more hours, and what is the effect on efficiency when it is restarted at a later stage?

These questions can be answered with help from a digital twin of the installation, including the dwelling, heat emitter system, and the occupant. However, the time and knowledge required to make such a digital twin makes it unfeasible for mass deployment. In this work, TNO has developed an algorithm that can create a digital twin from the internal measurements of a heat pump without human interaction. The algorithm requires the following data points:

1. Supply water temperature; 2. Return water temperature; 3. Room temperature obtained from the thermostat; 4. Water flowrate or produced heat; 5. Weather conditions (can be obtained from weather station)

The digital twin uses a physics-informed neural network model of the dwelling with a heating system. Instead of putting all the data in a machine learning algorithm, it starts with physical relations of heat transfer. The unknown closure relations are then fitted using data-driven techniques. The result is that less data is required for training, and more realistic predictions can be made outside the bounds of the training data. Also, the found parameters have physical meaning.

Heat balance of a dwelling
A typical dwelling has several heat flows, which can be sources or sinks. In a dynamic system, an imbalance leads to a change in its state parameters. The rate of change of the temperature of a mass is defined by the amount of imbalance and the thermal inertia of the mass.

$$\frac{dT}{dt} = \frac{\Sigma Heat\ flow}{Inertia}$$

For a dwelling, five heat flows are identified:

1. Transmission heat loss due to conduction via the façade of the dwelling. This is a function of the insulation value and the temperature difference between the indoor and outdoor environments.
2. Ventilation heat loss: The air exchange from indoor to outdoor and vice versa. This is a function of the amount of the temperature difference between indoor and outdoor, and the ventilation/air leakage rate. The latter can be a function of wind speed, wind direction, and occupant behaviour.
3. Internal gain: The amount of heat the occupants and appliances release in the dwelling. This is a function of mainly the user behaviour
4. Solar gain: This is the heat gained by the dwelling via the sun. This is a function of solar strength, sun azimuth and elevation, and occupant behaviour (shading).
5. Heating gain: This is the heat added to the dwelling by the heating system. This is the variable to be controlled to keep the indoor conditions within satisfactory boundaries.

Functional Description of the Autodomos Algorithm.
A digital twin of a dwelling created by the Autodomos algorithm is able to distinguish the five heat flows in a prediction.

The Autodomos algorithm works in three consecutive steps:

<u>Step 1:</u> Building energy signature. In this step, a three-day average of the heat load is fitted against the three-day average ambient temperature.
<u>Step 2:</u> Fitting of the dynamic system. For an accurate dynamic response on the short- and long timescale, the model should be redefined to a two-mass building model, which is shown visually as an RC-network in Figure 1. In this step, the building energy signature from step 1 is used as a starting point for fitting a dynamic system.

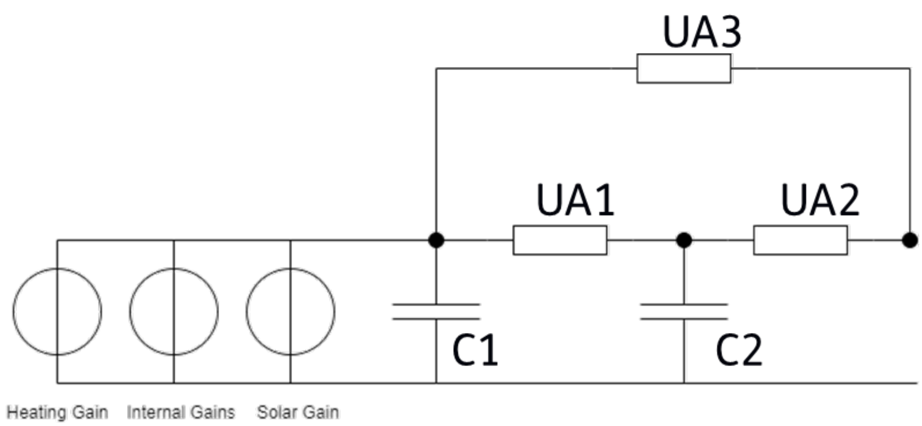

Figure 1: Alternative representation of a physical building model

Step 3: After completing step 2, the model is quite effective in determining the dynamic behavior of the dwelling and heating system. This model can be used to predict the effect of turning off the heating system for several hours. However, the model has some residual error because it lacks a few aspects:

-proper definition of solar gain, ventilation, and internal gain
-influence of user behaviour on the different heat gains and losses.

By using parallel shallow neural networks, this residual error can be linked to the missing aspects of the model:

-The effect of solar gain can be linked to the elevation and azimuth of the sun. The effect in this case is determined by how much the solar radiation contributes to the heat balance of the dwelling.
-The ventilation rate can be an effect of the time of day and day of week and is assumed to be determined by occupant behaviour.
-The internal gain can also be matched to time of day, day of week, and month of year to describe user patterns.

By fitting the residual error after step 2 to the three aspects above, the unknown gains (and losses) can be attributed to physical effects. In many AI/Machine learning applications, the outcome is a black box. Since Autodomos uses physics-informed neural networks, the outcome can be linked to physical phenomena, which also makes it explainable. Another benefit of physics-informed neural networks is that it requires less data to train since the main relations are already established before the learning procedure. This should also make it more robust in conditions that did not occur during the training period.

A typical prediction made by the model can be found in Figure 2.

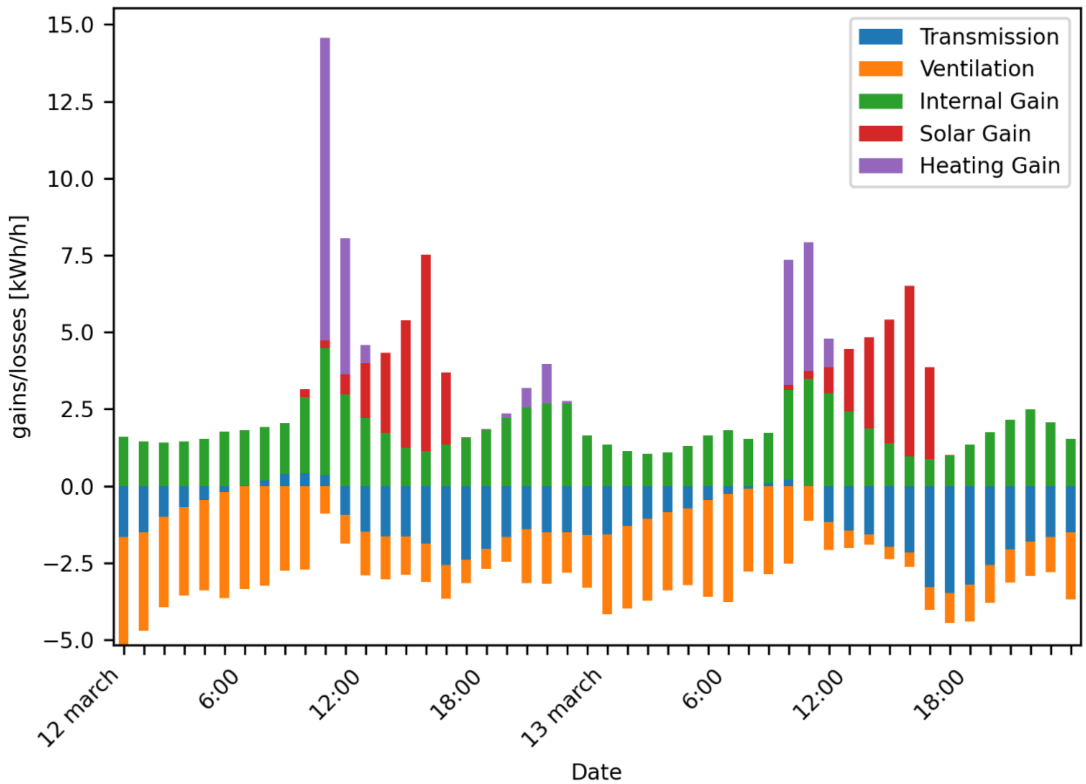

Figure 2: heat distribution prediction of a dwelling for two days in March in the Netherlands. For the heating gain prediction, a target room temperature setpoint is maintained. Note that the machine learning algorithm may encounter difficulties in determining the exact ventilation loss and internal gain, as increasing both will not result in a significant change in the overall heat balance. The transmission loss in this graph is defined as the heat loss from C1 to C2 and might thus give a phase shift with the total heat loss of the total building mass.

Physical Explanation of the Machine Learning Fitted Parameters.

Since the model acquired by the physics-informed neural network is not a pure black box, the outcome has physical meaning. For validation purposes, the outcome can be sanity checked against physical parameters. In Figure 3, this is done for the internal heat load. The graph shows a typical internal heat load by occupants and appliances during the course of 24 hours. A clear morning and (larger) evening peak can be distinguished, which likely corresponds with this occupant's daily habits.

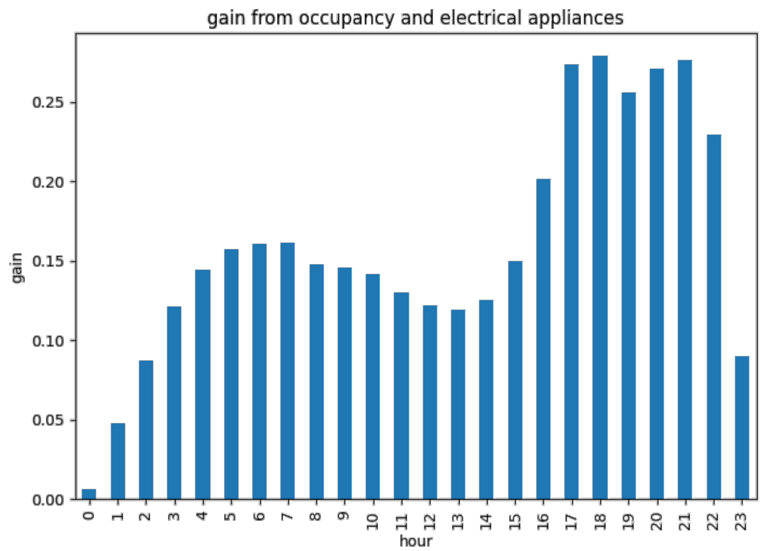

Figure 3: Time-dependent heat source, which is interpreted as internal gain

A second explainer is shown in Figure 4. On the left, the outcome of the model: the sensitivity of the dwelling to solar irradiation. Blue indicates that the solar irradiation will not cause the dwelling to heat up; red indicates high sensitivity of the dwelling to solar irradiation. It is noted that the solar sensitivity is high if the sun's azimuth is South-West between 210° and 250° and the sun's elevation is above ~16°.

Figure 4 (right side) shows an aerial view of the dwelling. In this case, it is a terraced house. By marking the directions 210° and 250° as found from the analysis of solar gain influence on the heat balance, it actually matches the orientation of the house façade (and thus windows)

On the bottom graph, it shows what the angle of the sun should be above to add influence the heat balance of the dwelling. This coincides very well with the data found from the learned relation between the position of the sun and the influence of the sun on the heat balance.

The same conclusion can be drawn for the elevation. If the sun sets below an elevation of 16°, it is hidden behind the roofs of the adjacent housing block. In Figure 4-right, this distance is shown in the aerial photograph. In Figure 4-bottom, this is graphically represented, and in Figure 4-left, the effect is clearly visible in the result.

It is worth noting that the model is trained solely on data from the heat pump, in conjunction with open-access meteorological data. The required heat pump data comprise supply temperature, return temperature, flow rate, and thermostat temperature.

Another advantage of the physics-informed neural network is that the fundamental physical relations are fixed. Since merely the closure relations are fitted, the model will not likely predict unphysical behaviour outside the domain of the training data, which is the case for black box models.

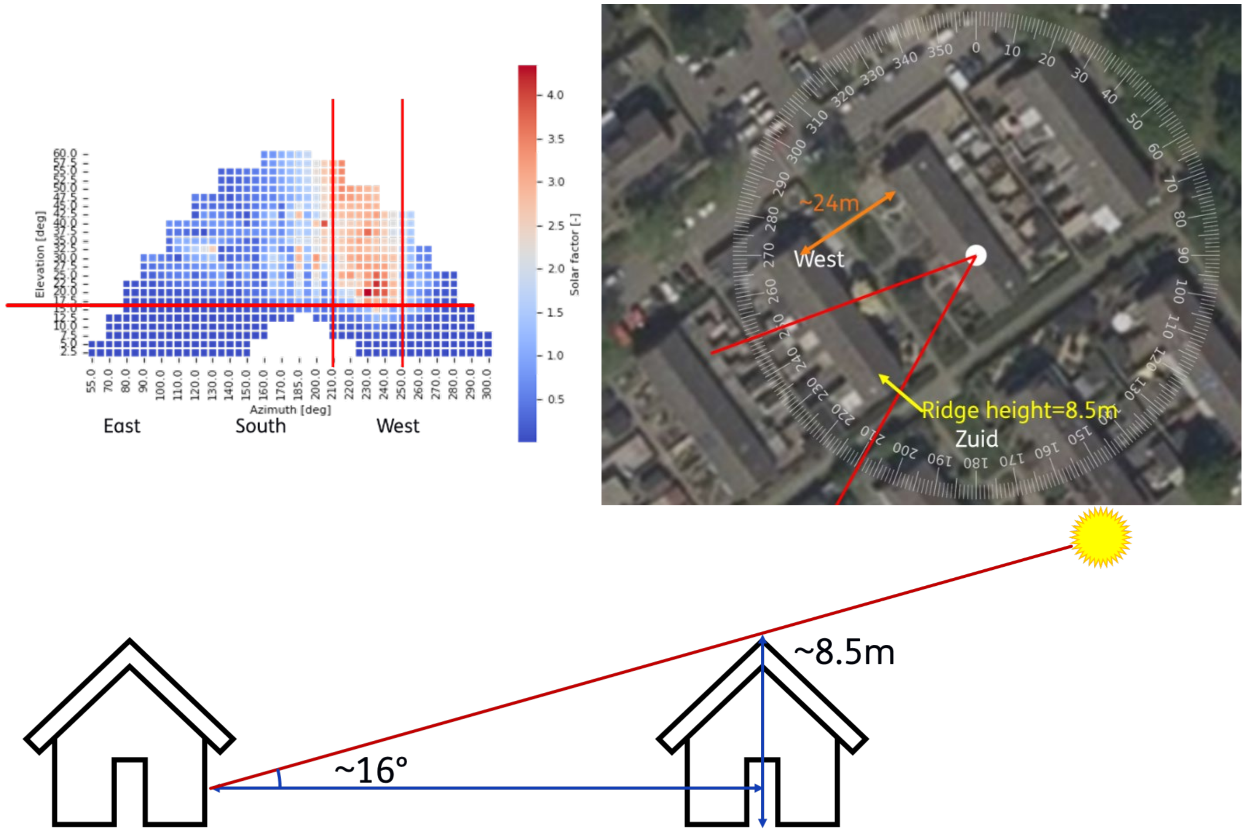

Figure 4 Left: Effect of solar radiation magnitude as a function of the sun's azimuth and elevation on the heat balance of a dwelling. Blue: no effect, Red: high effect. The physical relevance of this graph is related to window orientation and shading. Right: physical explainer 1: the same azimuth shown on an aerial photograph shows the orientation of the house façade with windows. Bottom: physical explainer 2: With the house spacing measured from the aerial photo, and the height of the ridge, the angle of the sun can be determined when it is behind the next row of houses.

Conclusions

In this work, it was shown that a comprehensive dwelling model can be trained using mainly heat pump operational data without user/installer intervention. It is Important that the physics-informed neural network techniques give physical meaning to fitted results and require less data when compared to deep learning techniques. Also, these models are more likely to predict well outside the training data range.

The working of the algorithm has been shown; however, it is still in the proof-of-concept phase. It is yet to be determined what the minimum data required is, and it should also be tested on a larger variety of dwellings and heating systems. Currently, two projects on the development of the application are being set up. In one project, the dwelling model will be used for deriving 'ideal' settings for space heating without intervention, thus creating the basics for a self-commissioning heat pump.

In the second project, the dwelling model will be used in combination with a moving horizon controller. The dwelling/heating system/heat pump model will be used to create heat pump control scenarios for the coming period, hence the name horizon. These scenarios will be evaluated in terms of energy costs, comfort, and electricity availability. The scenario with the highest rating will be executed by the heat pump.

TNO is looking for partners for further development. As the national research institute of the Netherlands, TNO is not a product developer. If parties are interested in developing the IT infrastructure or using this technology in their products, please contact the author of this article.

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National Market

Norway: Heat Pump Market Report

DOI: 10.23697/3mhv-aj39

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Norway, a global leader in heat pump adoption alongside Sweden and Finland, showcases a unique energy transition model. Driven by early electrification, historically low electricity prices, and minimal gas heating, the Nordic region boasts unparalleled widespread adoption of heat pumps. Despite a recent market correction after the sales records of 2022-2023, the long-term outlook remains strong. While Norway's district heating is less extensive than its neighbours', heat pumps contribute nearly 10 % of its production. The share of heat pumps in district heating and industrial processes is expected to grow.

Introduction

Norway stands as a global leader in heat pump adoption, consistently boasting one of the highest per capita penetrations of heat pumps in the world. This success story is shared with its Nordic neighbours, Sweden and Finland. This common ground stems from a combination of early and extensive electrification of society, historically low electricity prices (predominantly from hydropower in Norway and nuclear/hydro in Sweden/Finland), and a notably low reliance on natural gas for building heating. While all three excel in heat pump deployment, their approaches to complementary heating solutions like district heating vary.

Lower Electricity Prices Led to a Decline in Heat pump Sales in 2024

Electricity is the main source of heating in Norway, and there is a strong correlation between sales of heat pumps and electricity prices. In years with high electricity prices, heat pump sales increase since the main reason for purchasing heat pumps in Norway is to save money on electricity for heating. Cold winters and hot summers also drive the heat pump market, since increased comfort is also an important reason to buy heat pumps.

Around 95% of air-to-air heat pumps in Norway are used for heating, and high-quality "Nordic models" dominate the market. These are models tested for minus 25 °C or lower. Pure chillers and air conditioners for commercial buildings are not recorded in heat pump statistics in Norway.

In the fall of 2021, electricity prices skyrocketed, a trend further intensified by increasing gas prices in Europe, following the Russian invasion of Ukraine in February 2022. This followed 2020, which had the lowest electricity prices since 2002. In 2022 and 2023, Norway had abnormally high electricity prices, which contributed to two years of record sales of heat pumps. This surge was further propelled by the COVID-19 pandemic, where travel restrictions led to increased household spending on home renovations, including heat pump installations.

Supply chain disruptions experienced across Europe during the COVID-19 pandemic led to significant delivery delays. Consequently, many heat pump orders placed in late 2022 were not installed until spring 2023. This suggests that actual demand in 2022 was even higher than sales figures indicate, with a corresponding slight overstatement in 2023 sales.

With the introduction of a very favourable electricity price subsidy scheme in Norway, combined with rising housing interest rates, a decline in sales for 2024 was anticipated, and this proved to be the case. Air-to-air and air-to-water heat pumps experienced a moderate decline, while sales of brine-to-water heat pumps fell by over 40%.

Total market heat pumps 1995 – 2024

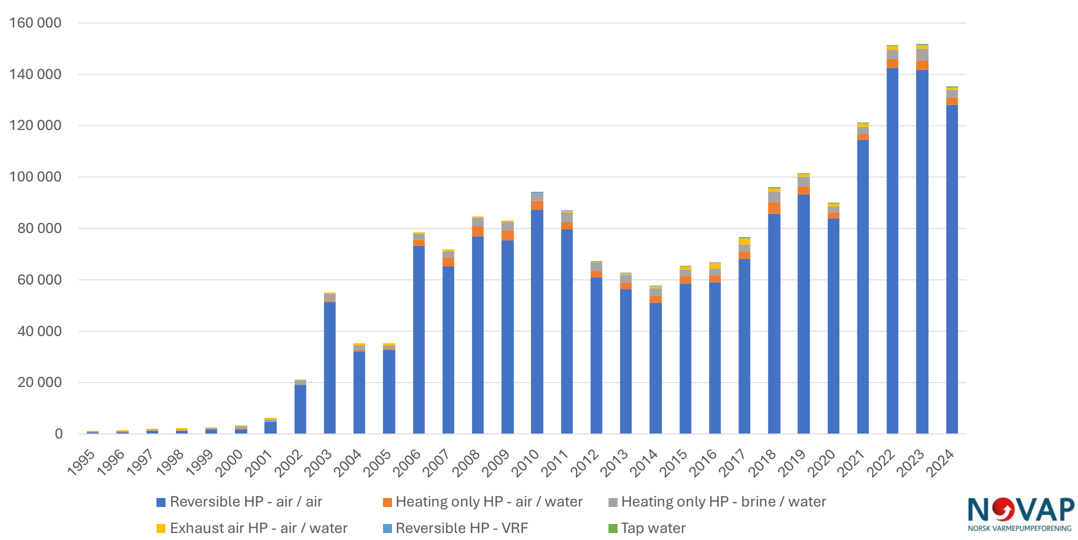

Figure 1: Annual sales of heat pumps in Norway 1995-2024 (Norwegian Heat Pump Association)

Air-to-water and brine-to-water heat pumps 1995 – 2024

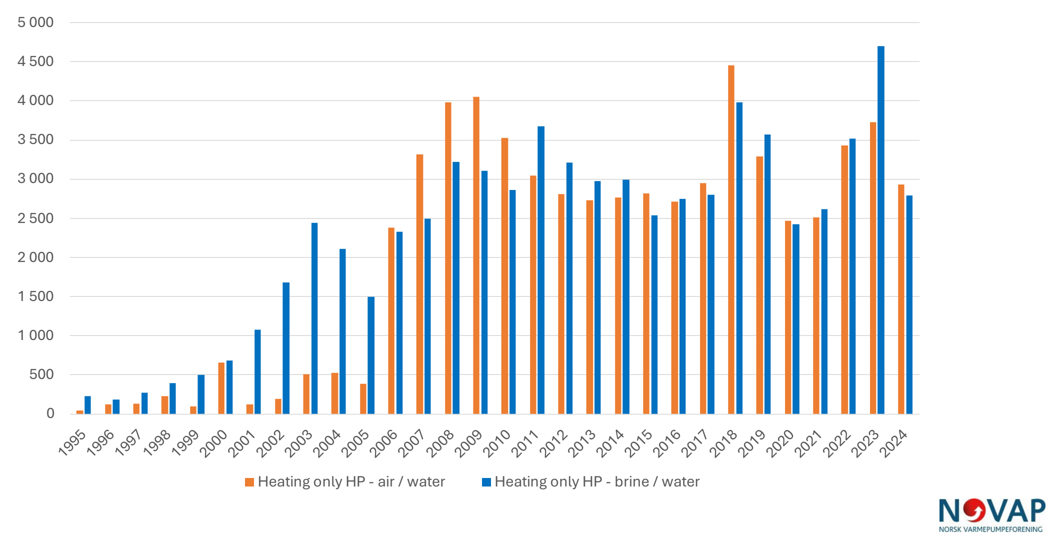

Figure 2: Annual sales of air-to-water and brine-to-water heat pumps 1995 – 2024 (Norwegian Heat Pump Association)

A Nordic Model: Early Electrification, Low Electricity prices, and no Gas Dependency
The high per capita penetration of heat pumps in Norway, Sweden, and Finland is deeply rooted in their historical energy landscapes. Unlike much of Central and Southern Europe, these countries underwent significant electrification of their societies early on, leveraging abundant domestic renewable energy sources – primarily hydropower in Norway and a mix of hydro and nuclear power in Sweden and Finland.

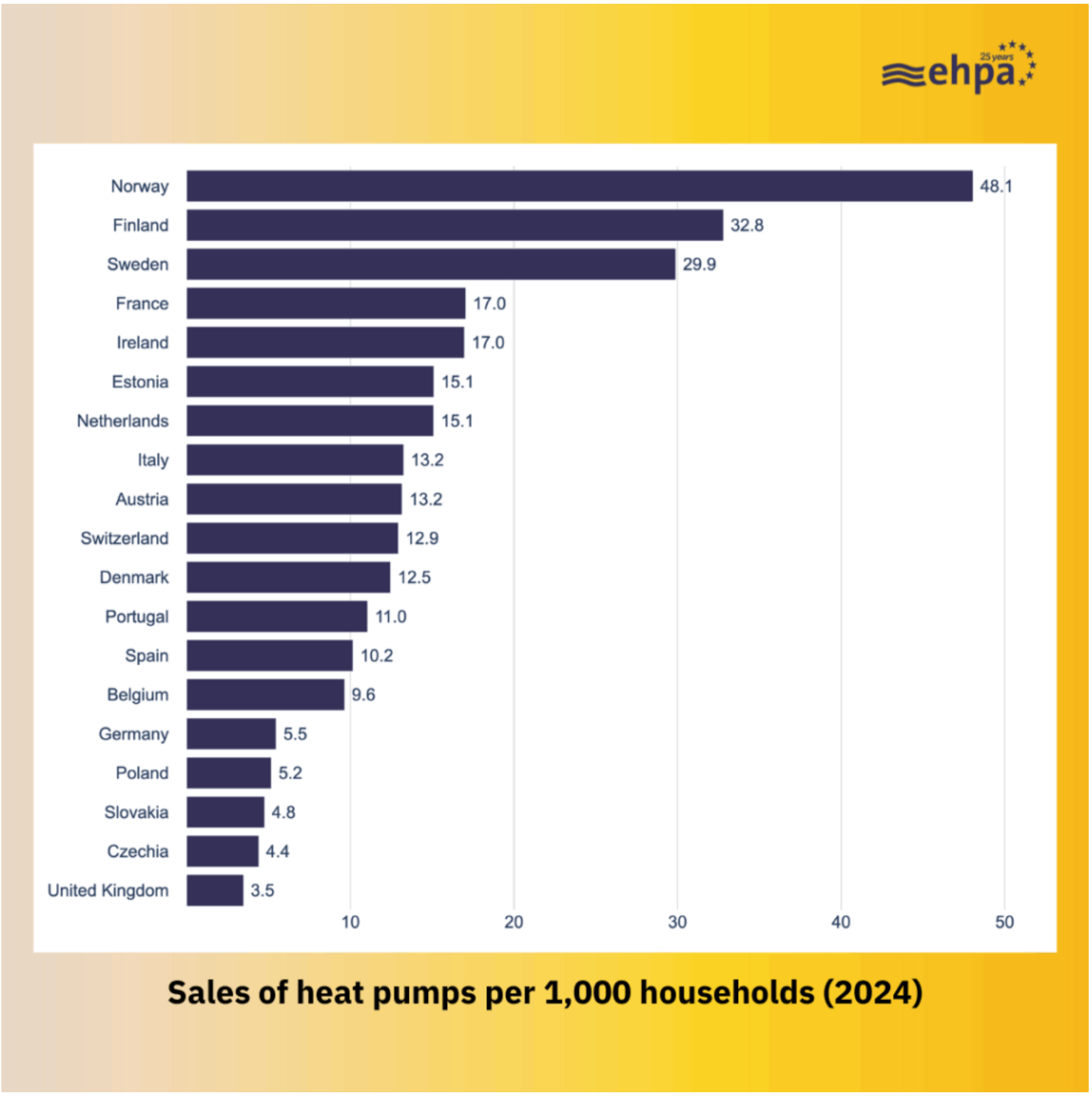

Figure 3: Sales of heat pumps per 1,000 households in Europe (European Heat Pump Association, EHPA) [1]

Norway boasts a nearly 100% renewable share in its electricity production, consistently exceeding 98% in a normal year, primarily driven by hydropower and wind power. In 2024, total electricity production in Norway amounted to 157.2 TWh, which was a record high production:

- Hydropower: Around 89.1% (140.0 TWh).
- Wind power: Around 9.3% (14.5 TWh).
- Solar power: Around 0.2% (0.25 TWh).

In 2024, the total renewable share of energy use in Norway increased to 55.4%. This means that almost half of the total energy use in Norway is still fossil (mainly transport and industry). In 2024, power consumption in buildings amounted to 64 TWh, while the total energy consumption in Norway was 215 TWh. Heat pumps deliver over 12 TWh of ambient heat annually.

Important Drivers for Heat Pump Sales:

- **Abundant, historically low-cost electricity:** For decades, electricity has been the dominant energy carrier for heating in Norway. This made electric heating a natural choice, and as heat pump technology matured, it offered a significantly more efficient alternative to direct electric resistance heating, leading to substantial economic savings for consumers.
- **Minimal natural gas infrastructure:** Unlike many other European nations, Norway, Sweden, and Finland have developed very little natural gas infrastructure for heating buildings. This meant that when fossil fuel heating began to be phased out, there was no large incumbent gas heating sector to displace, simplifying the transition to electric-based heating solutions, such as heat pumps. This absence of gas dependency meant a smoother pathway to decarbonization of the heating sector. Use of fossil oil for heating in buildings has been banned in Norway since 2020.

While all three Nordic countries share these fundamental drivers, their development of district heating networks differs. Sweden and Finland have a significantly higher penetration of district heating compared to Norway. In Sweden, district heating covers more than half of the total heat demand, and similarly high figures are seen in Finland, particularly in urban areas. In Norway, district heating is particularly widespread in larger cities and densely populated areas.

Market Overview and Key Trends

The Norwegian heat pump market, particularly for individual installations, has shown remarkable resilience and growth, driven by the factors mentioned above. Over 60% of

Norwegian households now utilize heat pumps for heating, showcasing widespread consumer acceptance.

Most heat pumps installed in Norway are air-to-air heat pumps, largely due to their cost-effectiveness, ease of installation, and suitability for single-family homes. Unlike most buildings in Europe, direct electric heating is common in Norway, making air-to-air heat pumps a natural choice. Air-to-air heat pumps can be the main heating source in small energy-efficient homes, but will only cover part of the heating needs in buildings with a large heating demand. It is becoming more common to purchasing two or more air-to-air heat pumps in larger houses or combining them with wood heating on cold days.

However, there are several buildings with hydronic heating systems where air-to-water and ground source heat pumps are used. These heat pumps are most common in larger houses and commercial buildings. Many older buildings that were heated with fossil oil converted to heat pumps during the period before the ban was introduced in 2020. The use of exhaust air heat pumps is less widespread than in Sweden and Finland, since all new buildings are delivered with balanced ventilation with heat recovery.

Distribution of Heat Pumps in Norway
In the period 1987 - 2024, over 1,9 million heat pumps have been sold in Norway:

- Air-to-air: almost 1,76 million
- Air-to-water: over 63,000
- Liquid-to-water (brine-to-water): over 71,000
- Exhaust air heat pumps: over 28,000
- More than 1,5 million heat pumps are in operation, accounting for more than 12 TWh of ambient heat.

Key Trends Shaping the Norwegian Market Include:
- **Increased focus on performance and quality:** As the market matures, consumers and installers alike are increasingly prioritizing high-quality, energy-efficient models that perform optimally in Norway's colder climate zones.
- **Digitalization and smart controls:** Integration of smart controls, remote monitoring, and connectivity features is becoming standard, allowing for optimized operation, energy management, and integration with smart home systems.
- **Role of Natural refrigerants:** The market is actively adapting to F-gas regulations, with a growing interest in natural refrigerants for higher efficiency and lower GWP

(Global Warming Potential) solutions. Norway has a CO_2-tax on refrigerants, which has contributed to increased demand for natural refrigerants in commercial buildings. The use of R290 in air-to-water heat pumps in residential buildings is already common, and the use of natural refrigerants for several types of heat pumps is expected to grow rapidly.

Expected Sales Outlook

Despite the recent dip, the long-term outlook for heat pump sales in Norway remains positive and robust. Electricity prices are expected to settle at a higher level than in previous years, which will contribute to increased demand for heat pumps. However, the government has introduced a new scheme where households can choose a state-subsidized low electricity price that can drive down demand somewhat.

Enova, a state-owned entity, has for many years promoted heat pump adoption through support schemes for residential, commercial, and industrial sectors. The design and funding levels of future support initiatives will remain crucial factors impacting heat pump sales.

In recent years, households have only received support for brine-to-water heat pumps, with a modest 855 euros. In 2023, new support programs were introduced for commercial buildings and housing cooperatives, as well as an improved support program for larger heat pump systems. There are separate programs for innovative large heat pump projects, as well as for heat pumps in industrial processes.

Enova is expected to introduce strengthened support programs for heat pumps in households for the period 2025-2029.

As the large number of heat pumps installed over the last 15-20 years reach their end-of-life, a significant replacement market will emerge, ensuring a steady baseline for sales. It is expected that new building regulations with increasingly stringent energy performance requirements for new buildings will favour heat pump installations.

Growth in the commercial, industrial, and district heating sectors for larger heat pump solutions will contribute significantly to overall installed capacity, even if individual household sales stabilize.

A huge potential lies in the extensive renovation market, where many older buildings still rely on less efficient heating systems. Targeted incentives or information campaigns could accelerate this transition.

The continued integration of large-scale heat pumps into district heating networks and their broader application in industrial processes for heating and cooling represent significant growth areas for decarbonization.

Heat pumps can play a crucial role in providing demand response services, shifting consumption to periods of lower prices or higher renewable energy availability, thereby supporting grid stability.

Conclusion and Future Outlook

Norway's heat pump market serves as a compelling success story, underpinned by its distinct energy history and proactive policy landscape. Alongside Sweden and Finland, it highlights a successful model for decarbonizing heating through early electrification and the avoidance of gas dependency. While the recent sales trends indicate a market normalization after an exceptional boom, the fundamental drivers for heat pump adoption remain strong.

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