GreenHeat

The next generation of AI-based services for heat pumps.

Programm / Ausschreibung	Digitale Technologien, Digitale Technologien, AI for Green Ausschreibung 2022	**Status**	abgeschlossen
Projektstart	01.10.2023	**Projektende**	31.03.2026
Zeitraum	2023 - 2026	**Projektlaufzeit**	30 Monate
Keywords	1		

Projektbeschreibung

Schätzungen zufolge verbrauchen Gebäude in der Europäischen Union etwa 40 % der gesamten Energie. Studien zeigen, dass Wärmepumpen das Rückgrat eines zukünftigen nachhaltigen Heiz- und Kühlsystems sein werden. Heutige Wärmepumpen haben jedoch große Schwächen, wenn es darum geht, die Energieeffizienz zu gewährleisten und gleichzeitig die Komfortanforderungen zu erfüllen. Das Projekt GreenHeat entwickelt interpretierbare AI-Methoden zur Fehlererkennung und -diagnose sowie zur optimalen Regelung. Das interdisziplinäre Projekt GreenHeat strebt einerseits wissenschaftliche Entwicklungen an, die über den internationalen Stand der Technik hinausgehen. Gleichzeitig streben die Industriepartner eine weltweite Technologieführerschaft für die innnovativen Energy Services an.

Abstract

Within the European Union, it has been estimated that buildings consume about 40% of energy. Studies show that heat pumps will be the backbone of a future sustainable heating and cooling system. However, current heat pumps have severe weaknesses in providing energy efficiency guarantees and simultaneously satisfying comfort requirements. The project GreenHeat develops interpretable AI methods for Fault Detection & Diagnosis and for Optimal Control. On the one hand, the interdisciplinary project GreenHeat strives for scientific developments beyond the international state of the art. Yet, simultaneously, the industrial partners aim for global technology leadership.

Endberichtkurzfassung

The GreenHeat project set out to make heat pumps more efficient and more reliable. Over the course of the project, the team successfully achieved all major goals and delivered methods that support a more sustainable and affordable heating future.

Understanding Needs and Real-World Challenges

At the beginning of the project, the team worked closely with experts from industry and research to understand what is needed to improve heat-pump technology. Through interviews with 11 experts, the project team identified key challenges such as the lack of automated fault detection, limited monitoring of entire heating systems, and the difficulty of using flexible electricity prices for cost-efficient operation. These insights helped shape the direction of the research.

Developing New Ways to Detect Problems Early

The project created a method to automatically detect soft faults in heat pumps, i.e. problems that are often overlooked until they become serious, for example: Compressor efficiency loss , which can lead to higher energy use and eventual failure and Condenser silting , where deposits reduce heat transfer and lower system performance.

To identify subtle performance issues in heat pumps, the project team developed a regression-based residual method. This approach uses machine-learning models to learn how a healthy heat pump normally behaves. The model predicts key operating values, such as temperatures or power consumption, based on other measurements in the system.

During operation, the predicted values are compared with the actual measurements. The difference between the two is called a residual . Under normal conditions, these residuals remain small and stable. When a soft fault begins to develop, the residuals start to deviate. By monitoring these deviations, the system can detect problems long before they become visible to users or technicians.

The advantages of this method are the following: (1) It can detect gradual performance degradation that traditional rule-based systems often miss. (2) It requires only standard sensor data, making it suitable for real-world deployment. (3) By identifying faults early, the approach helps reduce energy waste, avoid costly breakdowns, and extend the lifetime of heat-pump systems.

Exploring Large Language Models for Detecting Heat-Pump Faults

In addition to developing traditional machine-learning methods, the project explored a new and innovative idea: using large language models (LLMs) to detect faults in heat-pump systems. Although these models are usually designed to understand text, they can also be adapted to analyze technical data.

To test this idea, the team used a publicly available simulation dataset that models how heat pumps behave when their efficiency drops. The dataset includes several weeks of operating data and indicates exactly when a fault occurs. The team compared standard machine-learning methods, e.g., multi-layer perceptron neural networks with an LLM-based technique. The LLM-enhanced approach performed best and was able to extract more meaningful patterns from the complex heat-pump data, leading to much higher accuracy in detecting faults. This suggests that LLMs may be especially useful for analyzing complicated systems where traditional methods struggle.

To take this further, the team investigated whether a model trained on large simulated datasets could be applied to real-world building data. Using data from an office building equipped with a heat pump, the researchers tested a fine-tuned LLM on real sensor readings. Even though the real-world data lacked complete fault labels, the model still showed clear signs of successfully transferring its knowledge from simulation to reality. Statistical tests confirmed that its predictions were significantly better than random guessing, indicating that the model had learned meaningful fault-related patterns.

Smarter Control for Lower Energy Costs

Many households combine heat pumps with photovoltaic panels. While this is an efficient and climate-friendly setup, it also creates a practical challenge: solar power is often available at times when the home does not immediately need heating or hot water. One way to use the surplus energy is to temporarily “overheat” the home’s thermal storage tanks. However, overheating too much wastes energy and reduces the heat pump’s efficiency. Finding the right balance is therefore essential.

To address this, the project team used the models of two single-family homes which simulate how the buildings, heat pumps, storage tanks, and photovoltaic systems behave throughout the year to train a reinforcement-learning (RL) agent. The RL agent hourly receives information such as storage temperatures, solar forecasts, heating demand, electricity prices, and temperature forecasts. Based on this data, it decides how much to overheat the thermal energy storage tanks when the photovoltaic system yields a surplus and sends this information back to the simulation. The goal is simple: reduce the household’s net electricity costs while maintaining comfort. The results of the experiments show that RL agents can achieve electricity costs close to the theoretical optimum. This demonstrates that reinforcement learning can help households save money while supporting the transition to a cleaner energy system.

Projektkoordinator

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Projektpartner

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