TALLINN UNIVERSITY OF TECHNOLOGY
SCHOOL OF ENGINEERING
Department of Electrical Power Engineering and Mechatronics

OPTIMIZING RESIDENTIAL HEATING: IMPLEMENTING PREDICTIVE CONTROL ALGORITHM WITH WEATHER AND ELECTRICITY SPOT PRICE INTEGRATION

ELAMUTE KÜTMISE OPTIMEERIMINE: ENNUSTAVA KONTROLLI ALGORITMI RAKENDAMINE KOOS ILMASTIKU JA HETKEHINNA INTEGREERIMISEGA

MASTER THESIS

Student: Gokul Raveendran Thekkoot

Student code: MAHM214173

Supervisor: Hadi Ashraf Raja (Researcher)

Supervisor: Aleksander Liin (Baltic sales manager Ouman OY)

Tallinn 2024

(*On the reverse side of title page*)

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Department of Electrical Power Engineering and Mechatronics

THESIS TASK

Student: Gokul Raveendran Thekkoot, MAHM 214173

Study programme, MAHM, Mechatronics

main speciality:Department of Electrical Power Engineering and Mechatronics

Supervisor(s): Hadi Ashraf Raja (Researcher), Alexander Liin (Baltic sales manager Ouman OY)

Thesis topic:(in English) OPTIMIZING RESIDENTIAL HEATING: IMPLEMENTING PREDICTIVE CONTROL ALGORITHM WITH WEATHER AND ELECTRICITY SPOT PRICE INTEGRATION

(in Estonian) ELAMUTE KÜTMISE OPTIMEERIMINE: ENNUSTAVA KONTROLLI ALGORITMI RAKENDAMINE KOOS ILMASTIKU JA HETKEHINNA INTEGREERIMISEGA

Thesis main objectives:

1. Objective is to enhance the system redundancy by designing a control algorithm for supply water set point, taking account of real-time outdoor temperature sensor data and weather forecasts.

2. Focuses on utilizing Nord pool electricity price data to manage electricity consumption by the heat pump efficiently.

3. Design and implement optimal control algorithm in an existing building with a heating system to access and compare heating system performance.

Thesis tasks and time schedule:

No.	Task description	Deadline
1	Detailed study of heating system, compilation of background research and assessment of all possible challenges.	20.11.2023 – 3.12.2023
2	Determining a practical approach for comparing real-time outdoor temperature sensor data with forecasting methods.	5.12.2023-11.12.2023
3	Formulating control algorithm incorporating Nord pool electricity price data and weather data.	13.12.2023 - 20.12.2023
4	Development and implementation of predictive control algorithm in system model using MATLAB Simulink.	13.09.2024 - 20.09.2024
5	Working on with controller application by using Ouflex BA tool, including validation and testing of algorithm.	20.12.2023 - 29.12.2023

No.	Task description	Deadline
7	Thesis report compilation.	25.09.2024 - 10.11.2024

Language: ………… **Deadline for submission of thesis:** "……."………20….a

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PREFACE

This thesis explores the application of an optimal control algorithm to improve comfort levels in residential buildings. The proposed work focuses on enhancing comfort while also considering the cost factor. The objective is to strike the right balance between providing comfort and managing costs effectively. Achieving a comfortable living environment while being mindful of costs is crucial in residential buildings. This equilibrium ensures that people feel comfortable in their homes without spending too much. For this purpose, developed a control algorithm which was later compared with previous algorithm based on system performance in terms of two parameters 1) cost and 2) indoor temperature.

The thesis structure is based on the requirements and data sets provided by Ouman OY, a Finnish manufacturer of controllers for the building automation industry, as part of their new project. The newly developed control algorithm was implemented on target building Tihaase 19, Harju County ESTONIA, and was renovated in August 2017 by Profener OÜ. The simulations were carried out using a software tool called Ouflex BA Tool. It is essential to mention that the automation controller and data acquisition software utilized in the study are sourced directly by the company.

I am writing to thank Mr.Kari Heikkila, the Export Manager at Ouman OY, for allowing me to undertake this project. I am sincerely thankful to Jilson Jose (Technical Support Specialist) and Aleksander Liin (Baltic Sales Manager) at Ouman OY. Additionally, I appreciate Mr. Alfred Liin, the owner of the target building, for supporting me throughout the project by providing all the necessary building data and allowing the installation of controllers for the study.

I am highly grateful to Prof. Hadi Ashraf Raja for his immense guidance and support throughout the research period at Tallinn University. Finally, I want to thank my parents for their constant support and encouragement throughout my studies and career.

List of abbreviations and symbols

COP	(Coefficient Of Performance)	This represents heat pump efficiency.
DH	(District Heating)	This system distributes heat generated in a centralized location for residential and commercial heating requirements.
DHW	(Domestic Hot Water)	This refers to domestic hot water used usually for bathing, cooking, and cleaning purposes.
GSHP	(Ground Source Heat Pump)	Heat pump variant that uses ground as a heat source or sink.
HMI	(Human Machine Interface)	A user interface that connects a human to a machine.
ERR	(Energy Efficiency Ratio)	Measure of a heating or cooling system's efficiency in converting energy into heating or cooling output.
CI	(Comfort Index)	Measure of effectiveness of a heating or cooling system in maintaining indoor temperatures within a comfortable range.
nZEB	(Nearly Zero Energy Building)	Refers to buildings with exceptionally high energy efficiency and minimal energy usage.
RES	(Renewable Energy Sources)	This encompasses naturally replenished energy sources like solar, wind, and hydro power.

RH	(Radiator Heating)	This heating system utilizes radiators to evenly distribute heat within a structure.
SCOP	(Seasonal Coefficient Performance)	This quantifies the efficiency of a heat pump across an entire heating season.
EER	(Energy Efficiency Ratio)	a metric used to measure the efficiency of cooling or heating devices such as air conditioners.
CI	(Comfort Index)	metric used to evaluate the perceived comfort of an environment based on various factors such as temperature, humidity, air quality, and sometimes even noise levels or lighting.

1 . BACKGROUND AND CONTEXT FOR RESIDENTIAL HEATING SYSTEM CONTROL

There have been radical changes in energy generation and theories in the last few years. Conventional energy generation and non-replenished energy sources pose challenges due to the extreme emission of carbon-contained pollutants that lead to global warming [2]. The carbon neutrality concepts face a huge backdrop due to the expanded usage of fossil fuels and heavy dependence on non-renewable energy sources. In the current scenario, Baltic countries are increasingly focusing on RES (Renewable energy source) in DH systems (Biomass, geothermal, and solar thermal energy) because of environmental impacts caused by the over-exploitation of traditional fossil fuels[1].

The heat curve method is widely used in water-bound radiator systems for indoor climate regulation. This method effectively maintains a comfortable indoor environment regardless of outdoor temperatures. However, it does not consider crucial factors such as electricity prices or forecasted weather data. HP uses a temperature sensor to monitor outdoor temperatures and adjusts the heat curve accordingly. Although there are control techniques that could incorporate this information, they often require simulating the system over a specified horizon, incorporating future electricity prices and weather forecasts. This limitation underscores the need for a more advanced control algorithm, which is the focus of this paper.

The heat curve method is widely used in water-bound radiator systems for indoor climate regulation. This method effectively maintains a comfortable indoor environment regardless of outdoor temperatures. However, it does not consider crucial factors such as electricity prices or forecasted weather data. HP uses a temperature sensor to monitor outdoor temperatures and adjusts the heat curve accordingly. Although there are control techniques that could incorporate this information, they often require simulating the system over a specified horizon, incorporating future electricity prices and weather forecasts. This limitation underscores the need for a more advanced control algorithm, which is the focus of this paper.

Many factors, including climate and resident behavior, influence the heating requirements in residential buildings. In addition, the architecture of a heating system is determined by various factors such as the characteristics and location of the building, the climate, the heat source used, the user’s preference, scalability, and resilience to

[1] https://www.stat.ee/en/find-statistics/statistics-theme/energy-and-transport/energy

fluctuations. A typical heating system for a private house comprises an HP as the primary heat source that caters to two different requirements: Radiator heating and Domestic hot water heating. The heating requirements of the building dictate the choice of heat source. To achieve effective energy management in a residential building, it is crucial to synchronize the operation of the system. This necessitates the use of an automation controller and an optimal control algorithm. This paper presents a novel control algorithm that regulates energy consumption and ensure energy management by dynamically adjusting set point temperatures for space heating. The primary objective is to maintain thermal comfort for the occupants at acceptable levels, considering the complex trade-off between comfort and cost.

Keywords: Renewable energy sources, Domestic hot water, radiator heating, Solar panels, Greenhouse gas, Global warming, gas chambers, fossil fuels.

1.1 Motivation

There is a growing effort to reduce greenhouse gas emissions, with the EU committing to a 55% reduction compared to 1990.Achieving this target involves narrowing the gap between energy consumption and generation, and one way is to reduce overall energy consumption. Estonia heavily depends on non-renewable energy sources such as oil shale, with renewable energy contributing less to the total electricity production. Space heating constitutes a substantial portion, approximately 59% of total household energy needs, and in 2018, nearly half of space heating and DHW in Estonia were powered by electricity. In 2021, 60% of Estonia’s one- and two-residential buildings utilized heat pumps for heating purposes [4]. Residential buildings account for over 40% of the world’s energy consumption. Numerous studies over the years have aimed to enhance the performance of building energy systems [3], [4], conducted an analysis exploring various factors influencing thermal comfort and energy conservation. These factors encompassed cultural studies, climate conditions, socio-economic aspects, and more. It would be economically and environmentally beneficial to use low electricity prices. Given these factors, there is significant interest in developing a control algorithm for efficient household energy management. Rather than relying solely on the current outdoor temperature to determine the RH circuit’s supply water temperature set value, this thesis seeks to enhance system redundancy by integrating weather forecasting and spot price to identify a modulated room temperature for comfort. The potential economic benefits of this approach are promising, offering a significant change in user comfort for residential buildings.

1.2 Purpose

The thesis provides an optimal solution for improving comfort in residential buildings by using modern control methods to maintain indoor temperature through heat pumps. Contemporary consumers can now monitor forecasted weather data and hourly electricity prices, allowing them to mitigate the impact of significant cost variations. The focus is on managing the timing and magnitude of energy usage to ensure advanced user comfort through space heating and to reduce energy costs, rather than stressing on minimizing overall energy consumption. The approach involves preparing a household for additional heating hours by anticipating high heating demands in the upcoming hours, relying on outdoor temperature and weather forecast data. Beyond merely reducing energy costs, the primary focus is sustaining a comfortable indoor climate.

1.3 Problem evaluation

Presently, residential buildings heavily rely on water-based heating systems for space heating. These systems determine the flow line temperature, regulating the water entering the system based on outdoor temperature. However, they do not account for forecasted weather conditions. It presents an opportunity to highlight the advantages of integrating forecasted weather data into the system for optimal energy management in residential buildings. Using modern automation controllers and control strategies enables the incorporation of such data; thus, the following questions arise.

The research questions guiding this thesis are: Can we reduce the electricity cost for a heat pump while still ensuring comfort by employing optimal control strategies that consider Nord pool hourly electricity price data and weather predictions?

1.4 Aim and scope

The thesis aims to develop an optimal control algorithm for a heating system with a single heat source using an Ouman automation controller for residential building applications. This innovative approach focuses on three key areas:

1. The thesis aims to enhance the system redundancy by designing a control algorithm for supply water setpoint for RH, taking account of real-time outdoor temperature sensor data and weather forecasts.

2. The thesis focuses on utilizing Nord pool electricity price data to manage electricity consumption by the heat pump efficiently.

3. Design and implement an optimal control algorithm in an existing building with a heating system to access and compare the performance of the heating system.

The newly developed algorithm will be applied in a real-world setting, a target building with a heating system, using actual data sets to assess and compare the performance of the system. This practical implementation and validation of control algorithms on automation controllers will demonstrate their effectiveness in energy management. The system’s operation and the controller’s performance are assessed using key parameters: energy consumption by the heat pump and the cost of purchased electricity, COP of heat pump and user comfort level in the building. This evaluation will measure the system’s efficiency and the controller’s effectiveness in managing energy usage and costs.

1.5 Delimitations

1.5.1 Simplified house model

The target residential model, the Simplified House model, is a simplified representation of a residential building. It does not consider the number of occupants, their user behaviours and preferences, the furniture arrangement, the frequency of opening and closing windows and doors, and the usage of lights or other electrical appliances, which could moderately affect a building’s energy consumption and thermal comfort.

1.5.2 Heat pump type

The residential building selected for this study is equipped with a ground-source heat pump. A ground-source heat pump, also known as a geothermal heat pump, uses the earth's natural heat to warm or cool a building by transferring heat to or from the ground, depending on the season.

1.5.3 Heat pump model

The effectiveness of heat pumps in real-world settings relies heavily on monitoring the temperatures of the inlet and outlet flows, as these directly impact the efficiency and performance of the system. At the same time, complexities related to sensors, valves, and pumps are overlooked. Maintaining optimal temperature differentials is essential for achieving the desired heating or cooling outcomes.

1.5.4 Other

Burning wood in a household can influence heat optimization. Although wood is renewable and cost-effective, it can affect air quality, present challenges in efficiency and control, and require additional maintenance.

1.6 Summary

In summary, the advent of predictive control for optimize building heating systems signifies a revolution in energy management technology. By integrating weather forecasts and spot pricing data, the system promises to enhance heating efficiency and reduce energy costs while ensuring occupant comfort, thereby piquing the interest of professionals in building automation. This chapter provides a foundation by explaining the rationale for using predictive control strategies, highlighting the limitations of traditional heating control methods, and showcasing the advantages of this approach. As we delve deeper into the upcoming chapters of this thesis, I explore the theoretical framework, strategies for implementation, and evaluation of the performance of the predictive control system. The primary goal of this research is to enrich the existing knowledge in building automation and provide valuable, practical insights for development and deployment of heating control systems, thereby offering a significant contribution to the field.

This paper presents an advanced control algorithm designed to improve the comfort levels in buildings. It prioritizes RH over DHW, ensuring they are maintained at acceptable levels. The study underscores the importance of achieving comfort through improved controller techniques rather than altering building practices or user preferences.

1.7 Structure of thesis

The introductory chapter of this thesis has provided a clear explanation of the reasons behind our research, what motivates me, and the specific goals I aim to accomplish. The author also defined the scope of our study, outlining what aspects we will be focusing on. These initial discussions pave the way for us to explore and apply control methodologies to enhance the efficiency of residential heating systems in the upcoming sections.

Chapter 2 explores the heating system of a residential building, explaining how RH and DHW work and detailing the HP model and type (GSHP). It also introduces the important efficiency measure, the Coefficient of Performance (COP).

In Chapter 3, focus is on the replication of a predictive controller using MATLAB Simulink. The goal of this chapter is to demonstrate the predictive behavior of the controller, highlighting how it optimizes heating control by adjusting setpoints based on future weather conditions and fluctuating energy prices. The simulation results provide insights into the controller’s ability to ensure user comfort while minimizing energy costs, showcasing its effectiveness in dynamic and variable environments.

Chapter 4 consists of a summary of the previous algorithm before thoroughly examining the proposed algorithm. Provides a detailed explanation of the algorithmic conditions, their rationale, and the implementation process using the Ouflex automation tool. The goal of this chapter is to show how the newly developed algorithm optimizes residential heating systems.

Chapter 5 of the thesis presents the benchmarking results, which involve acquiring data and analyzing the heating system’s performance by implementing a control algorithm. This chapter provides insights into how well the heating system works under the influence of the newly implemented control algorithm, exploring its effectiveness and efficiency in managing indoor temperatures at acceptable levels.

2 . MAIN BODY

This chapter covers the theory behind heating systems, including a background analysis of existing systems, the basics of residential heating setups, an overview of heat pump types, models, and their coefficient of performance, and finally a brief overview of the model predictive methodology used in this research to optimize system, setting a foundation for the practical work in this thesis.

2.1 Background analysis and related work

The significance of maintaining indoor temperature in residential buildings has always been paramount. In recent years, significant innovations have emerged, particularly in automation, predictive controls, and energy recovery systems, transforming how indoor climates are managed. Modern systems now incorporate adaptive controls, machine learning for predictive maintenance, and more efficient thermal energy reuse.

Over the past few years, building climate control has witnessed a surge in research. It includes studies on modelling and designing energy-efficient buildings (nZEB) and constructing control systems for dependent building models. However, many of these systems primarily rely on outdoor temperature to determine the set value for supply water temperature in RH. However, several studies have investigated the potential benefits of incorporating future weather predictions and hourly energy prices. These innovations can enhance resident comfort and reduce energy costs significantly. In a study [5] a control algorithm was developed that leverages the correlation between the maximum energy consumption during specific hours and the signals of price volume. Similarly, study [6] proposed a model for a heating system incorporating a heat pump and storage tank, capitalizing on the flexibility of heat pump operation to exploit lower electricity prices.

2.2 Residential heating system

As mentioned in the introduction, the proposed study was conducted on residential buildings with RH as the primary heat source. This section will provide further insight into how the RH and DHW work. RH uses radiation and convection to warm the surrounding space. The heated air rises to head level and tends to gather near the ceiling. Over time, the initially hot air cools predominantly and descends. For RH, an optimal hot water temperature of approximately 35-45 °C is required for effective indoor heating. Figure 2.1 demonstrate a typical residential heating system where the radiator releases heat into the surrounding air, causing it to warm up, become less dense, and rise. This rising warm air is replaced by cooler air, creating a convective current that efficiently distributes heat throughout the room.

- Heating system (Figure 2.1) utilizes devices known as radiators, which play a crucial role in maintaining the room temperature through hydronic heating. A heat pump heats water, and radiators act as heat exchange devices, extracting heat from this hot water.
- Notably, the heat exchangers' design ensures that the circuits for RH and DHW never mix.
- The hot water medium receives heat energy from heat source through the radiators installed inside the room. The heating demand of the heat pump fluctuates according to the outdoor temperature, consequently affecting the temperature of the water entering the radiators.

DHW operation

- A heating system combines a storage tank with a heat pump to meet Domestic Hot Water (DHW) needs (Figure A5.8). The temperature of the DHW supply can vary from 50 °C to 60° C based on outdoor temperatures, adapting to seasonal changes.
- In traditional setups, DHW flows directly to heat exchangers, where thermal energy from hot water transfers to cold mains water for distribution throughout the building. Unused hot water used circulates back to the storage tank through a dedicated circulation line, managed by a DHW circulation pump, ensuring efficient regulation and reuse within the heating system.
- To maintain an adequate supply, the system reheats water as needed, depends on the initial mains inlet temperature and the returning DHW circulation temperature.

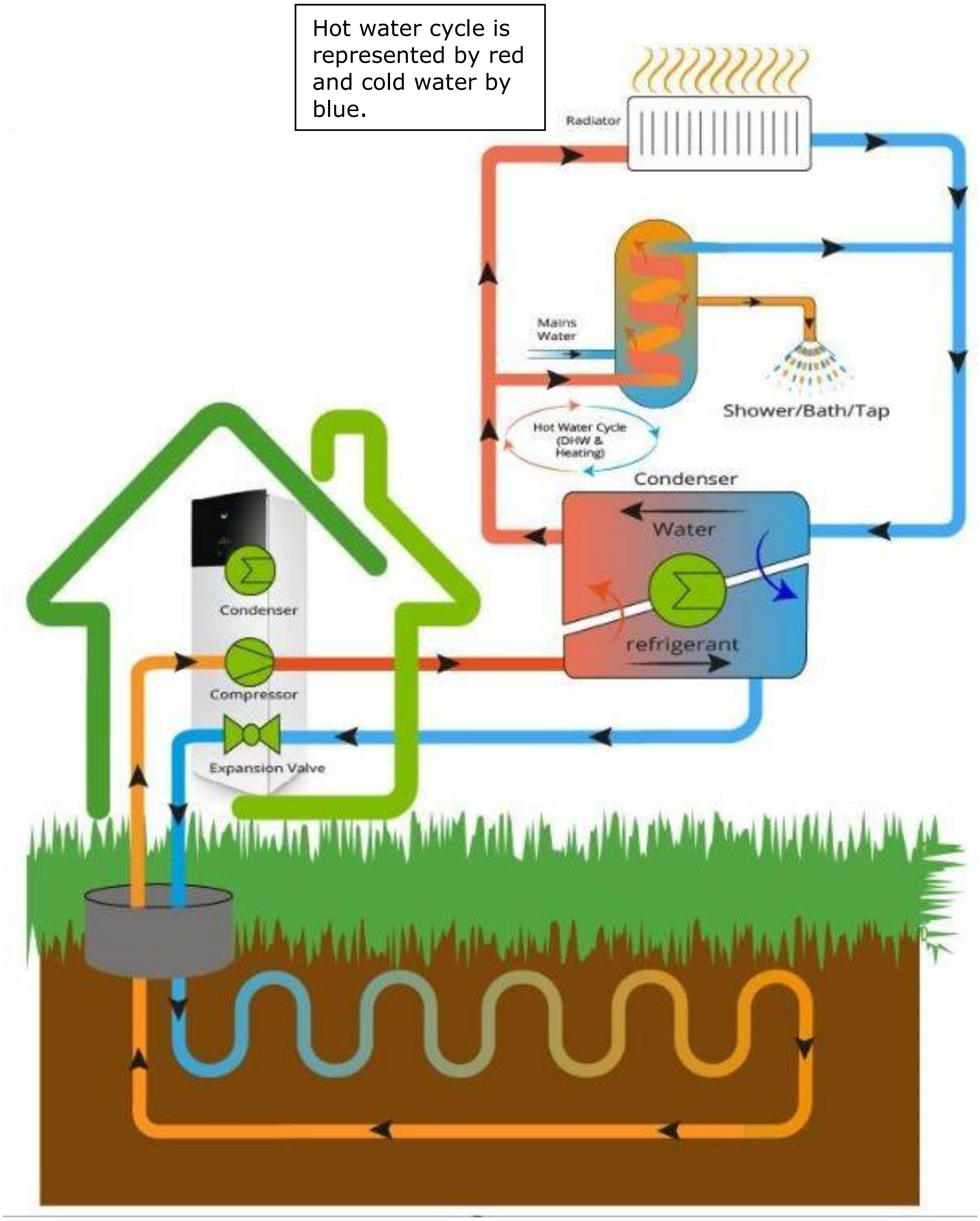


Figure 2.1 Residential heating system with GSHP[14]

2.2.1 Building heating system chart

The building heating system employs a GSHP as a primary heat source for RH and DHW. The heat pump efficiently channels heat into the radiators to warm the living spaces. Simultaneously, it dedicates its energy to providing hot water for domestic use, offering a comprehensive and energy-efficient solution for household comfort. Explore the symbiotic relationship in this integrated heating system between the heat pump, radiators, and DHW supply. The heating system schematic is shown in Figure 2.2. The system includes a ground source heat pump (GSHP), a hot water tank, radiators, and a domestic hot water (DHW) supply. The GSHP extracts thermal energy from the ground and transfers it to the hot water tank, where cold water is heated.

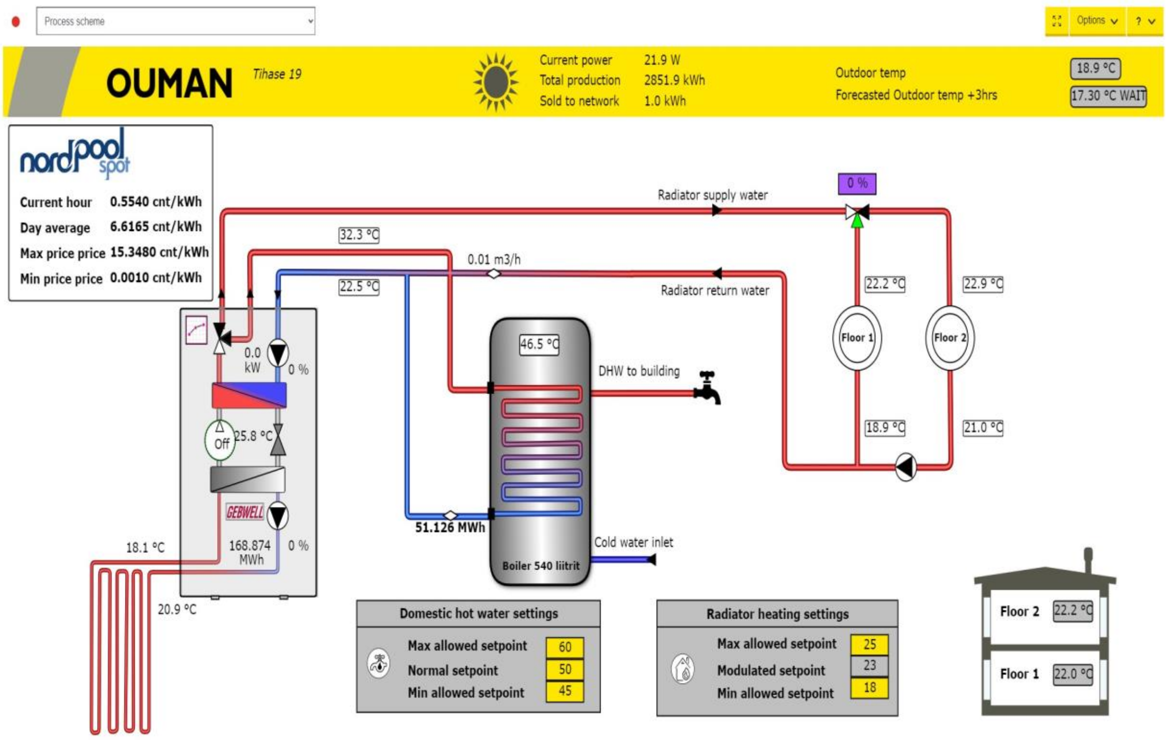


Figure 2.2 Heating system chart

2.3 Heat pump overview

The heat pump transfers thermal energy from one location to another within a closed loop, achieved through a compressor cycle. A heat pump moves heat energy from a heat source to a recipient, known as a heat sink. It absorbs heat from a colder area and moves it to a warmer space. A heat pump shifts thermal energy in the opposite direction of natural heat transfer. This method of heat generation does not involve converting energy from one form to another, thus eliminating associated conversion losses. Instead, it focuses on moving heat energy from an area of abundance to where it is most needed.

HP comprises four components: evaporator, compressor, condenser, and expansion device. The refrigerant acts as a working fluid that passes through all the components. The refrigerant is the working fluid that goes through all the components. The accompanying figure illustrates the operational principle of the compressor cycle. The system incorporates hot water carrying thermal energy directed to the compressor. The compressor elevates the pressure, subsequently increasing the temperature under constant entropy. The heated fluid then proceeds to the condenser, releasing heat into the indoor environment. Following this, the fluid moves to the expansion valve, causing a drop in both temperature and pressure. Finally, thermal energy can be transferred back to the water source as it passes through the evaporator, this process flow is demonstrated in Figure 2.3 [7].

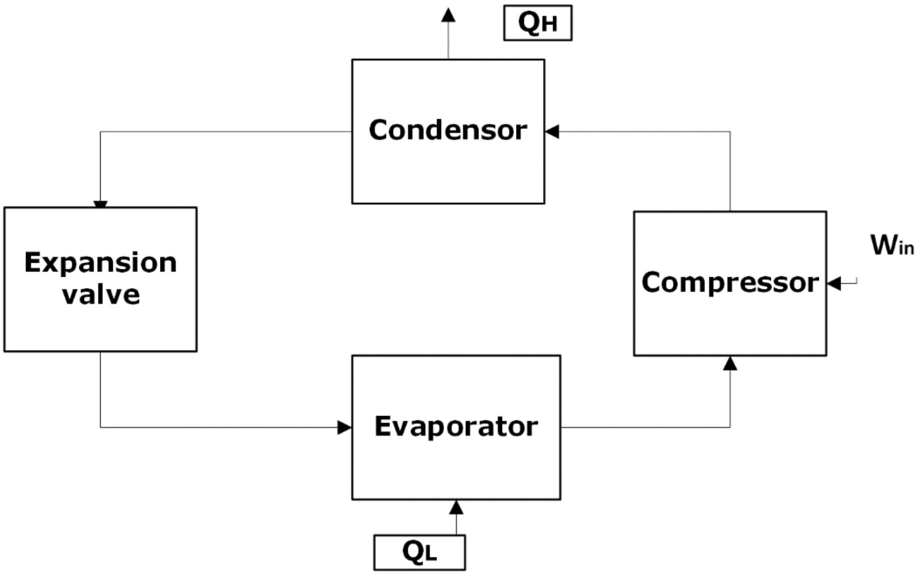


Figure 2.3 Heat pump process flow

Where Q_L: Heat absorbed(J/kJ), Q_H:Heat output/useful heat(J/kJ), W_{in}:Work input(J/kJ).

2.4 Coefficient of performance

The efficiency of heat performance is assessed using the COP, which represents the ratio between the heat output (Q_H) and the work input (W_{pin}) [7]. COP is expressed mathematically in Equation 2.1.

$$COP = \frac{Useful\ heat(cooling)output}{Electrical\ power\ input} \qquad (2.1)$$

A higher COP means greater efficiency, as it produces more heating or cooling output per unit of input energy. Heat pumps do not share a uniform COP, fluctuating depending on the operating conditions. For instance, a GSHP is expected to have a COP value within the range of 4-5[1]. HPs typically exhibit higher COP values during summer when outdoor temperatures are higher. This is because it is easier for HP to extract heat from warmer air or water sources, resulting in higher efficiency.

The efficiency of a heat pump, measured by its COP, is significantly influenced by both indoor and outdoor temperature conditions controlled by the HVAC system. As the indoor heating demand increases, the COP decreases because the heat pump must expend more energy and time to transfer heat into a warmer indoor space. Likewise, lower outdoor temperatures contribute to higher heat loss due to the larger temperature difference between indoors and outdoors, further reducing the COP. Since heat pumps extract heat from the outdoor air or ground, colder temperatures restrict the amount of available heat, thus lowering the heat pump's efficiency.

2.5 Overview of existing and proposed control approaches

The previous control algorithm adjusts indoor temperatures according to hourly energy prices, following a proportional method that reduces the temperature by 1°C for every 100 Euro increase once prices exceed a 100 Euro threshold. While this approach helps reduce energy expenses, it can lag during sudden price surges and does not accommodate individual comfort preferences. As a result, prolonged high-price periods may reduce indoor comfort due to the system's limited flexibility.

[1] NIBE Energy Systems. Ground source heat pump NIBE S1255 Product leaflet. Technical report, 2022. https://www.nibe.eu/assets/documents/27179/639862-2.pdf

In contrast, the proposed algorithm employs a predictive control strategy that uses weather forecasts and real-time Nordpool energy prices, enabling more precise and responsive temperature adjustments. By balancing comfort and energy costs and implementing limits for both, the new system adapts more effectively to changing conditions. This approach allows for a quicker response to price variations while maintaining comfortable indoor temperatures, achieving a better balance between cost efficiency and occupant comfort.

2.6 Optimal control

In optimal control, the objective is to govern a system efficiently to attain a specific performance goal. It involves identifying a control strategy that maximizes a defined performance criterion while considering various associated constraints. The thesis aims to ensure user comfort while keeping electricity costs in check by developing a control strategy for heat pumps. Thus, it can be described as an optimal control problem.

2.6.1 Predictive control

Predictive controller is an optimal feedback controller with a finite prediction horizon, enabling it to optimize control inputs over a limited period. It employs a dynamic system model to assess how the system behaves over this finite horizon, considering existing inputs and model dynamics. The predictions are combined with an objective function, which is then optimized. The objective function seeks to minimize or maximize a specific value or efficiency while adhering to predefined constraints. The resulting optimization solution generates the control signal. The controller uses current state feedback obtained through measurement and estimation to predict future states. The series of control signals derived from a sequence of predictions over the finite horizon contributes to the final state. The sequence optimizing the objective function is selected, and the initial control signal is applied for a specified period. This process is iteratively repeated [8]. Integrating PC within household energy management provides a systematic and advanced methodology for optimizing the performance of critical systems like Heating, Ventilation, and Air Conditioning (HVAC). The organizational process involved in predictive controllers is the following:

Control horizon

The prediction control framework functions within a predetermined control horizon, which signifies the prospective timeframe over which control actions are optimized. In Predictive Control, the control horizon M represents the number of future time steps over which control actions are optimized. The control input sequence is optimized over the control horizon is represented as follows in in Equation 2.2.

$$U = u(t), u(t+1), \ldots, u(t+M-1) \qquad (2.2)$$

Where *M* is control horizon (number of future control steps optimized).

Dynamic model

When anticipating future states of a system, a dynamic model is employed, providing a mathematical representation of the system under control. This model depicts the relationships between variables and their transformations, reflecting the system's behavior and interactions. In discrete time, typically with a time step T_s, it is commonly expressed in state-space form. Consider the state of the system denoted by X; the things we can control are in U, and what we measure or observe is Y. The dynamic model, showing how the system changes over time, is usually written in a set of equations called state-space form. A simple and common way to express this is with a Linear Time-Invariant (LTI) state-space representation given in below Equation 2.3, 2.4.

$$X = A\vec{X} + BU \qquad 2.3)$$

$$Y = C\vec{X} + DU \qquad (2.4)$$

A, B, C, D are matrices of the state vector with respect to time, U is the input vector, Y is the output vector, X represents derivative of state vector.

Objective function

In a controller, the objective function quantifies the system's performance goals. It serves as the criterion for determining the optimization of a control signal. This function incorporates specific states of the system and the control signal in a defined manner. In the case of a prediction controller, a prediction horizon (N) is established. The objective function in predictive control can be represented in a simple form in below Equation 2.5.

$$J = \sum_{k=t}^{t+P} \left(\|x_k - x_{\text{ref}}\|_Q^2 + \|u_k\|_R^2 \right) \qquad (2.5)$$

Where J is the cost function to be minimized, x_k is the predicted state at time k, x_{ref} is the reference state, u_k is the control action at time k, Q is the weighting matrix for the state error, R is the weighting matrix for the control effort.

Constraints

An advantage of using a prediction controller is its ability to account for system constraints during optimization[1]. These constraints can be imposed on various signals, including control inputs, state variables, or other parameters, to ensure the system operates within acceptable limits or deviation from a reference. Constraints are categorized as either hard or soft. Hard constraints are strict and not allowed to be violated, while soft constraints introduce a penalty to the objective function if violated. The constraints are often slack variables typically equal to zero if soft ones are not violated and thus add anything to the objective function. Let us denote the state vector X, the control input U, and the output vector Y. The constraints are expressed as inequalities. It can be expressed in Equation 2.6, 2.7, 2.8.

$$Xmin \leq Xk \leq Xmax \tag{2.6}$$

$$Umin \leq Uk \leq Umax \tag{2.7}$$

$$Ymin \leq Ymax \leq Ymax \tag{2.8}$$

The above inequalities define the boundaries the state, control inputs, and outputs should remain. The subscript k denotes the time period/step in the prediction horizon.

In conclusion, integrating predictive control strategies that utilize weather forecasts and energy prices into household energy management through HVAC optimization represents a sophisticated and adaptable approach. The ability to predict and adapt future scenarios ensures efficient decision-making, improved comfort, and cost-effectiveness in changing and uncertain conditions. It involves identifying a control strategy that maximizes a defined performance criterion while considering various associated constraints. The thesis aims to ensure user comfort while reducing electricity costs by developing a control strategy for heat pumps. Therefore, it is fair to describe it as an optimal control problem.

Chapter has covered a thorough introduction to heating systems, emphasizing heat pumps and how predictive control is utilized for effective energy management in the heating system.

1 Magnus Thorstensson. Elmarknadsstatistik, February 2017. URL https://www.energiforetagen.se/statistik/statistik-i-bilder/Elmarknadsstatistik/. Accessed: 2023-05-05

3. MODELLING AND CONTROL

This chapter explains how the house is modeled for the simulations. The RC model is used to represent the house's thermal behavior, using a state-space approach to evaluate its thermal capacity. Both the RC model and the controller are implemented in MATLAB Simulink. This setup replicates the entire system and shows how it responds to changes in external factors like weather conditions and spot prices, based on the simulation results.

3.1 Data acquisition

The simulations use data from a 10-day period, April 19, 2024, to April 30, 2024, gathered from the Ouman database. This data helps assess the control strategy's effectiveness by showing how the system responds to external factors such as weather and spot prices. Additionally, historical electricity spot prices were obtained from Nord Pool [9], which provides this data free for academic purposes. The target building also uses hourly spot price variations as part of the analysis.

3.2 System overview

The system includes a controller, a heat pump, and a house. The controller takes several inputs: the spot price (p_e), the current indoor reference temperature (T_{inr}), the actual indoor temperature, and the forecasted outdoor temperature (T_{out}, $T_{forecast}$). Based on these inputs, it calculates the electrical power input (u) needed for the heat pump to maintain the desired indoor comfort level. The heat pump then converts this electrical power into heat flow Q_H, which is delivered to the house. The house model is represented using an RC model for state-space analysis, with the indoor temperature (T_{in}) as the measured output. The outdoor temperature (T_{out}) and D includes all disturbances that impact the house, including influences from walls, windows, and user preferences. The overall system is depicted in the block diagram shown below.

Data is delivered to the controllers in hourly intervals. The electricity spot price remains unchanged for each full hour, while the temperature data is interpolated at each time step. This approach closely mimics real-world scenarios where spot prices are consistently fixed hourly, and weather forecasts undergo continuous variations. The controller operation can be graphically represented below Figure 3.1.

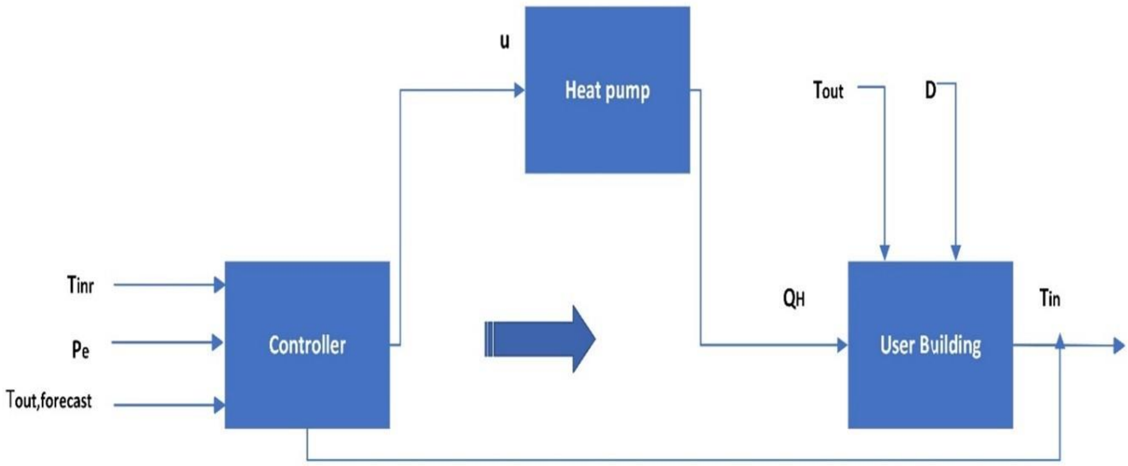


Figure 3.1 Predictive controller operation

3.3 Design of house model

RC thermal dynamics of house model

The RC (Resistance-Capacitance) thermal dynamics model is a fundamental method for simulating the thermal behavior of residential buildings. It represents the house's thermal system as an electrical circuit with resistors and capacitors, which helps to calculate how heat is distributed and stored over time. RC model of circuit is represented below Figure 3.2.

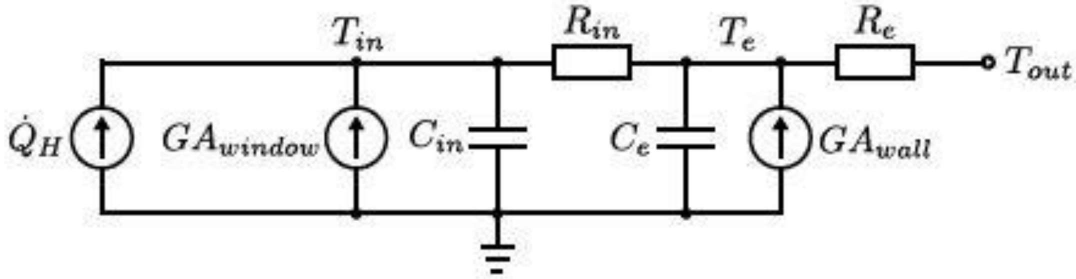


Figure 3.2 RC model[10]

The house is modeled using an RC approach, were Re represents the thermal resistance between the outside temperature and the house's envelope, which includes the walls and roof. Re accounts for heat transfer through convection between the outdoor air and the envelope, solar radiation on the outside walls, and conduction within the envelope. Ri represents the thermal resistance between the envelope and the indoor temperature, factoring in convection between the interior walls and air, solar radiation through windows and conduction in the wall. A capacitor, Ce, is placed between these thermal resistances, representing the thermal mass of the envelope, and allowing for the envelope temperature state, T_e. C_i represents the interior thermal capacitance, while Q_H denotes the heat flow provided by the heat pump to the interior. The second-order state-space model allows for the incorporation of solar radiation heat transfer through both the exterior walls $G_A wall$ and the windows $G_A window$.

To evaluate a house's thermal capability using a state-space model, we need to provide values for resistances and capacitances. These values vary for each house and should be determined either through analytical calculations based on the materials used or through experiments. The experiments should ideally be conducted with the house unoccupied, doors and windows closed, and environmental factors controlled, which is not feasible or in scope of this thesis. Instead, we use data from a Danish study [7], which estimated the resistance and capacitance of a typical Danish house using a first-order state-space model. The study found average values of R = 5.3×10−3°C/W and C = 24.5×106J/°C from five experiments. For our second-order model, we divide these values equally between the interior and the envelope, giving us R_i = R_e = 2.65×10−4°C/W and C_i = C_e = 12.25×106J/°C.

State space model

The RC model depicted in Fig3.2 represents two states: indoor temperature (T_{in}) and envelope temperature (T_e), which corresponds to the temperature on the surface of the outside wall. While (T_{in}) is measured directly, (T_e) is not. The system is affected by the controlled input signal, heat output (Q_H), and disturbances such as outside temperature (T_{out}) and solar radiation (G). Cin is the amount of heat required to change the temperature of the interior by one degree and Ce typically represents a heat capacity of house. This gives differential equations. Energy balance equation for interior and exterior temperatures are:
Energy balance for the interior T_in in Equation 3.1.

$$C_{\text{in}} \frac{dT_{\text{in}}}{dt} = Q_H + G_{A_{\text{window}}}(T_{\text{out}} - T_{\text{in}}) - \frac{T_{\text{in}} - T_e}{R_{\text{in}}} \tag{3.1}$$

Energy balance for the exterior T_e in Equation 3.2.

$$C_e \frac{dT_e}{dt} = \frac{T_{\text{in}} - T_e}{R_{\text{in}}} - \frac{T_e - T_{\text{out}}}{R_e} + G_{A_{\text{wall}}}(T_{\text{out}} - T_e) \tag{3.2}$$

State space representation of state vector and input vector in matrix form as below:

The state vector is:

$$\mathrm{x(t)} = \begin{bmatrix} T_{\text{in}}(t) \\ T_e(t) \end{bmatrix}$$

The input vector is:

$$\mathrm{u(t)} = \begin{bmatrix} Q_H(t) \\ T_{\text{out}}(t) \end{bmatrix}$$

The state-space representation is generally given in Equation 3.3,3.4.

$$\frac{d\mathbf{x}(t)}{dt} = \mathbf{Ax}(t) + \mathbf{Bu}(t) \qquad (3.3)$$

$$\mathbf{y}(t) = \mathbf{Cx}(t) + \mathbf{Du}(t) \qquad (3.4)$$

Deriving state-space matrices from energy balance equation we get 3.5, 3.6.

For $\frac{dT_{\text{in}}}{dt}$

$$\dot{T}_{\text{in}} = \frac{1}{C_{\text{in}}}\left(Q_H - \frac{1}{R_{\text{in}}}T_{\text{in}} + \frac{1}{R_{\text{in}}}T_e + G_{A_{\text{window}}} \cdot T_{\text{out}}\right) \qquad (3.5)$$

For $\frac{dT_{\text{e}}}{dt}$

$$\dot{T}_{\text{e}} = \frac{1}{C_e}\left(\frac{T_{\text{in}}}{R_{\text{in}}} - \left(\frac{1}{R_{\text{in}}} + \frac{1}{R_e} + G_{A_{\text{wall}}}\right)T_{\text{e}} + \left(\frac{1}{R_e} + G_{A_{\text{wall}}}\right)T_{\text{out}}\right) \qquad (3.6)$$

Representing them in matrix form:

$$\mathrm{A} = \begin{bmatrix} -\frac{1}{C_{\text{in}}R_{\text{in}}} & \frac{1}{C_{\text{in}}R_{\text{in}}} \\ \frac{1}{C_e R_{\text{in}}} & -\frac{1}{C_e}\left(\frac{1}{R_{\text{in}}} + \frac{1}{R_e} + G_{A_{\text{wall}}}\right) \end{bmatrix}$$

$$\mathrm{B} = \begin{bmatrix} \frac{1}{C_{\text{in}}} & \frac{1}{C_{\text{in}}} \cdot G_{A_{\text{window}}} \\ 0 & \frac{1}{C_e}\left(\frac{1}{R_e} + G_{A_{\text{wall}}}\right) \end{bmatrix}$$

$$\mathrm{C} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$\mathrm{D} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

3.4 Heat pump model overview

The heat pump used in the house is modelled with a simple function $Q_H = f_{pin}$, leaving out internal dynamics. This simplification is to keep the model less complex and linear. The model establishes a relationship between electrical input and heat output power, considering that the heat pump's efficiency (COP) changes under different conditions. The source (temperature of thermal fluid from the ground source and flow temperature (fluid going into the radiator system) are measured directly after the heat pump is taken as a function for modeling. When the source temperature is assumed constant, the flow temperature is influenced by the input power and is treated as a factor of both the state and the input electrical power. The indoor temperature is maintained around $24^{\circ}C$, and the heating power in a system will be relatively constant for specific flow temperatures. In essence, it is possible to derive the function for each system $Q_H = f_{pin}$. Since $Q_H = f_{pin}$ is nonlinear, heat pump cannot be modelled as a linear model.

3.5 Ouman predictive controller

This section explains the implementation of Ouman predictive controllers, which use weather forecasts and future electricity price data to optimize both comfort and electricity costs based on a tuning parameter. Ouman's heating systems incorporate a PID controller that is tuned to adjust heating output in real-time, ensuring the system maintains the desired temperature setpoint despite changing environmental conditions. The control loop helps reduce temperature fluctuations and minimize energy consumption.

3.5.1 Controller implementation

Objective function

The objective function in a control system, especially for a predictive controller, typically represents the difference between the desired output (setpoint) and the actual output (measured process variable). The aim of the controller is to minimize this difference, also known as the error. In the final model mentioned below, the error signal generated is directly applied to the controller, which then automatically maintains the entire system. In our system, the objective function is to find the right balance between comfort (by keeping the indoor temperature close to the desired setpoint) and cost. The objective function combines two components:

1. Comfort (J_{comfort}): Minimizing the deviation of the indoor temperature from the setpoint.
2. Cost (J_{cost}): Minimizing the energy cost by integrating power consumption with real-time energy prices.

Comfort and cost objective represented in Equation 3.7,3.8.

$$J_{\text{comfort}} = \int_0^T \left(T_{\text{in}}(t) - T_{\text{setpoint}}\right)^2 \, dt \tag{3.7}$$

$$J_{\text{cost}} = \int_0^T p(t) \cdot p_{\text{heat}}(t) \, dt \tag{3.8}$$

Where $p(t)$ is the real-time energy price.

By adding above comfort equation, we get combined objective function as Equation 3.9.

$$J_{\text{total}} = \alpha \int_0^T \left(T_{\text{in}}(t) - T_{\text{setpoint}}\right)^2 \, dt + \beta \int_0^T p(t) \cdot p_{\text{heat}}(t) \, dt \tag{3.9}$$

J_{total} combines parameters α and β which are the weighting factors for cost and comfort, respectively, that determine the trade-off between comfort and cost. The parameter $p(t)$ is a state variable affecting cost, and p_{heat} represents the heating power or a cost-related quantity. The indoor temperature is denoted as T_{in}, while T_{setpoint} represents the desired set point. For balanced approach I took α and β = 5.

State space controller model

The indoor temperature T_{in} is derived and measured from the RC-model approach. The heating power Q_H serves as the controlled input signal, while the outdoor temperature T_{out} is an external disturbance that affects the system. The model is represented by a differential Equation below were Equation 3.10 represents interior temperature and 3.13 for exterior temperature. The laplace transformation of below interior and exterior temperature equation is represented in Equation 3.11, 3.12 and 3.14, 3.15 respectively;

For $T_in(s)$:

$$C_{\text{in}} \frac{dT_{\text{in}}}{dt} = Q_H - G_{A_{\text{window}}}(T_{\text{in}} - T_{\text{out}}) - \frac{T_{\text{in}} - T_e}{R_{\text{in}}} \tag{3.10}$$

In Laplace domain:

$$C_{\text{in}} s T_{\text{in}}(s) = Q_H(s) - G_{A_{\text{window}}}(T_{\text{in}}(s) - T_{\text{out}}(s)) - \frac{T_{\text{in}}(s) - T_e(s)}{R_{\text{in}}} \tag{3.11}$$

$$T_{\text{in}}(s) = \frac{Q_H + G_{A_{\text{window}}} T_{\text{out}}(s) + \frac{T_e(s)}{R_{\text{in}}}}{C_{\text{in}} s + G_{A_{\text{window}}} + \frac{1}{R_{\text{in}}}} \tag{3.12}$$

For $T_e(s)$:

$$C_e \frac{dT_e}{dt} = \frac{T_{\text{in}} - T_e}{R_{\text{in}}} - \frac{T_e - T_{\text{out}}}{R_e} = G_{A_{\text{wall}}}(T_e - T_{\text{out}}) \tag{3.13}$$

In Laplace domain:

$$C_e s T_e(s) = \frac{T_{\text{in}}(s) - T_e(s)}{R_{\text{in}}} - \frac{T_e(s) - T_{\text{out}}(s)}{R_e} + G_{A_{\text{wall}}}(T_e(s) - T_{\text{out}}(s)) \tag{3.14}$$

$$T_e(s) = \frac{\frac{T_{\text{in}}(s)}{R_{\text{in}}} + \left(\frac{1}{R_e} + G_{A_{\text{wall}}}\right) T_{\text{out}}(s)}{C_e s + \frac{1}{R_e} + G_{A_{\text{wall}}}} \tag{3.15}$$

By simplifying we aim to express $T_{\text{out}}(s)$ as a function of $Q_H(s)$

Substitute $T_in(s)$ into the equation for $T_e(s)$ we get 3.16.

$$C_e s T_e(s) = \frac{T_{\text{in}}(s) - T_e(s)}{R_{\text{in}}} - \frac{T_e(s) - T_{\text{out}}(s)}{R_e} + G_{A_{\text{wall}}}(T_e(s) - T_{\text{out}}(s)) \tag{3.16}$$

Above equation results in a system of equation solved out for $T_{\text{out}}(s)$ represented in Equation 3.17.

$$C_e s T_e(s) + T_e(s) \left(\frac{1}{R_{\text{in}}} + \frac{1}{R_e} - \frac{1}{R_{\text{in}} \left(C_{\text{in}} s + G_{A_{\text{window}}} + \frac{1}{R_{\text{in}}} \right)} \right) = \frac{Q_H + G_{A_{\text{window}}} T_{\text{out}}(s)}{R_{\text{in}} \left(C_{\text{in}} s + G_{A_{\text{window}}} + \frac{1}{R_{\text{in}}} \right)} + \frac{T_{\text{out}}(s)}{R_e} \quad (1) \tag{3.17}$$

After simplifications, the transfer $\frac{T_{\text{out}}(s)}{Q_H(s)}$ function will be in the form 3.18.

$$G_{\text{sys}}(s) = \frac{b_0}{a_2 s^2 + a_1 s + a_0} \tag{3.18}$$

Where b_0, a_2, a_1, a_0 are derived constants from system parameters. we get PID controller transfer function 3.19.

$$G_{\text{PID}}(s) = K_p + \frac{K_i}{s} + K_d s \tag{3.19}$$

Substituting $G_{cl}(s)$ and $G_{PID}(s)$ into the above equation gives the complete closed-loop transfer function. The closed-loop transfer function $G_{cl}(s)$ represented in 3.20.

$$G_{\mathrm{cl}}(s) = \frac{G_{\mathrm{sys}}(s)G_{\mathrm{PID}}(s)}{1 + G_{\mathrm{sys}}(s)G_{\mathrm{PID}}(s)} \tag{3.20}$$

State space equation can be expressed in Equation 3.21 and 3.22.

$$C_W \frac{dT_W(t)}{dt} = Q(t) - h_W\left(T_W(t) - T_{\mathrm{env}}\right) \tag{3.21}$$

$$\frac{dT_W(t)}{dt} = \frac{Q(t) - h_W\left(T_W(t) - T_{\mathrm{env}}\right)}{C_W} \tag{3.22}$$

the term C_W represents the thermal capacitance, $Q(t)$ represents the heat input, h_W is heat transfer coefficient, T_W is water temperature and T_{env} is outdoor temperature.

State space representation In state space form:
Where $x(t)$ is T_{in}, which represents the internal temperature, $u(t)$ represents the heat output Q_H, and $y(t)$ is T_{out}, which represents the heat output [11] [12].

System matrix $A : A = -\frac{h_W}{C_W}$

Input matrix $B : B = \frac{1}{C_W}$

Output matrix C :C = 1

Feedthrough matrix D : D = 0

3.6 Matlab Simulink representation of model

I have developed a first-order RC circuit state-space model to simulate and evaluate the thermal behavior of a house, replicating the dynamics of the real system. The state-space equations have been calculated, and the model was implemented in MATLAB Simulink. This Simulink model simulates the thermal dynamics using a two-state RC model. The inputs include G_A = 2000Wm^{-2}(heat gain through the window), Q= 500J (internal heat input), and $T_{out}(s)$ = 6$^{\circ}C$ (external temperature). The model has two integrators representing T_e (external temperature) and T_{in}(internal temperature). Resistors R_i and R_e are modeled using gain blocks $G1$ and $G2$, The gains are represented by $\frac{1}{R1}$.

The Summing blocks combine the effects of heat inputs and resistances. The model calculates the internal temperature Tin over time, showing the system's thermal response. The output is displayed using a scope. Matlab simulink visual representation is shown in Figure 3.3.

From the RC model output shown in Figure 3.4, temperature begins at a high value based on the system's initial conditions. After this initial period, the temperature usually decreases exponentially, which is typical for RC circuits. In these thermal circuits, a sudden change in temperature or heat input results in an exponential response as the system moves toward equilibrium. Once the transient effects have settled, the temperature stabilizes at a constant level, if heat inputs and external conditions remain unchanged.

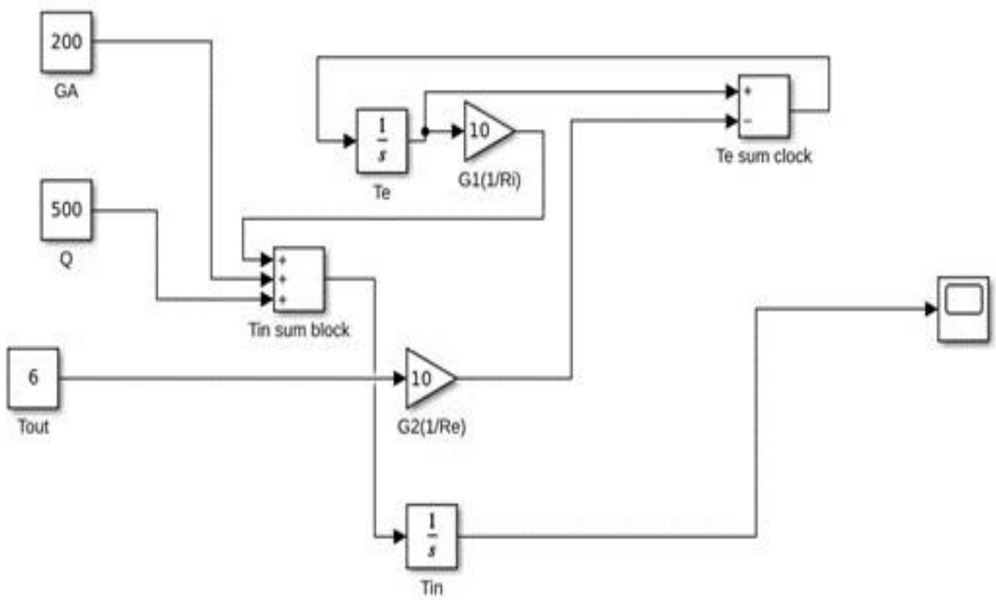


Figure 3.3 RC circuit simulink model

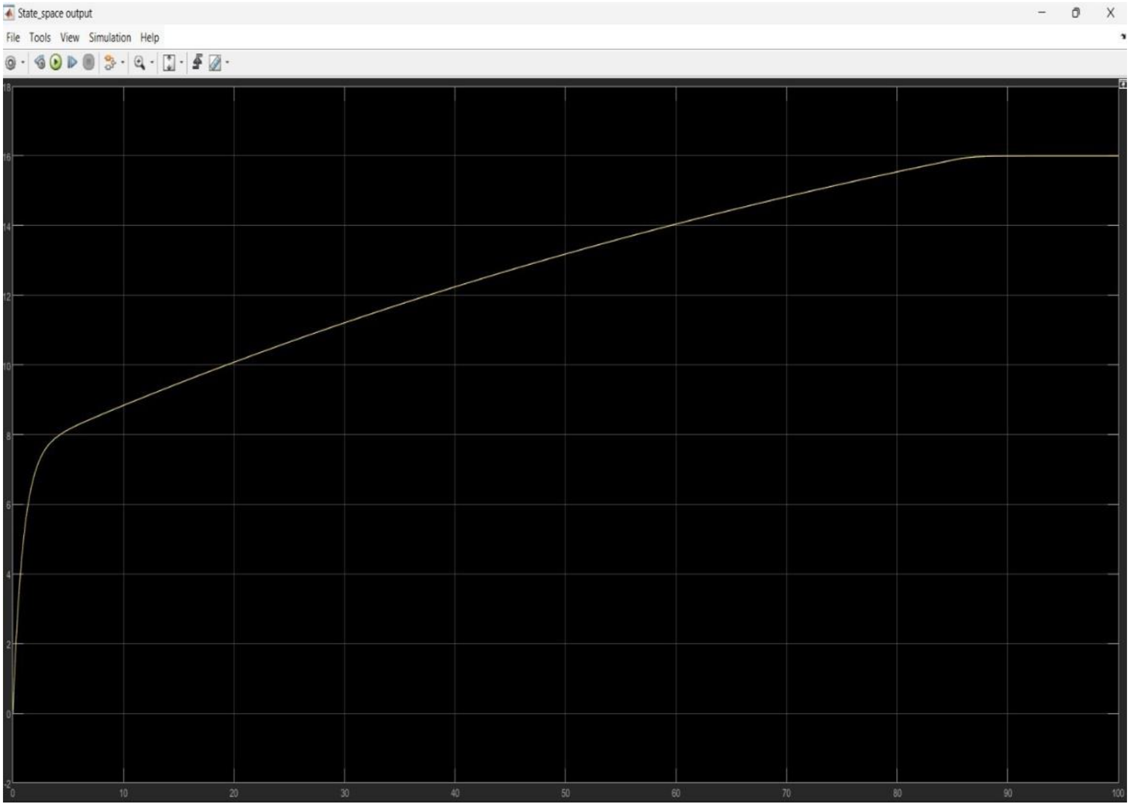


Figure 3.4 RC model output

The output from the RC model is input to a predictive controller, Simulink model representation is shown in below Figure 3.5. Where the controller uses the state-space output to determine the error between the desired temperature setpoint and the actual internal temperature T_{in}. The PID controller then processes this error using its proportional, integral, and derivative components to adjust control variables, such as heating elements, to minimize the error and ensure precise regulation of the internal temperature, achieving better control and stability of the thermal environment.

The output plot indicates that the system stabilizes with only a small steady-state error, exhibits a slight but manageable overshoot, avoids significant oscillations, and reaches the desired temperature within a reasonable amount of time. Predictive controller output can be seen in below Figure 3.6.

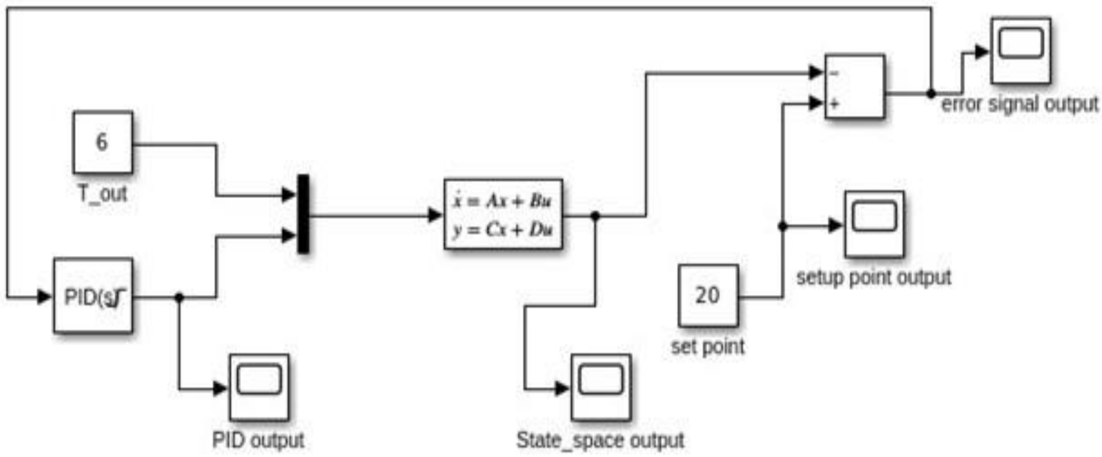


Figure 3.5 Predictive controller MATLAB Simulink model

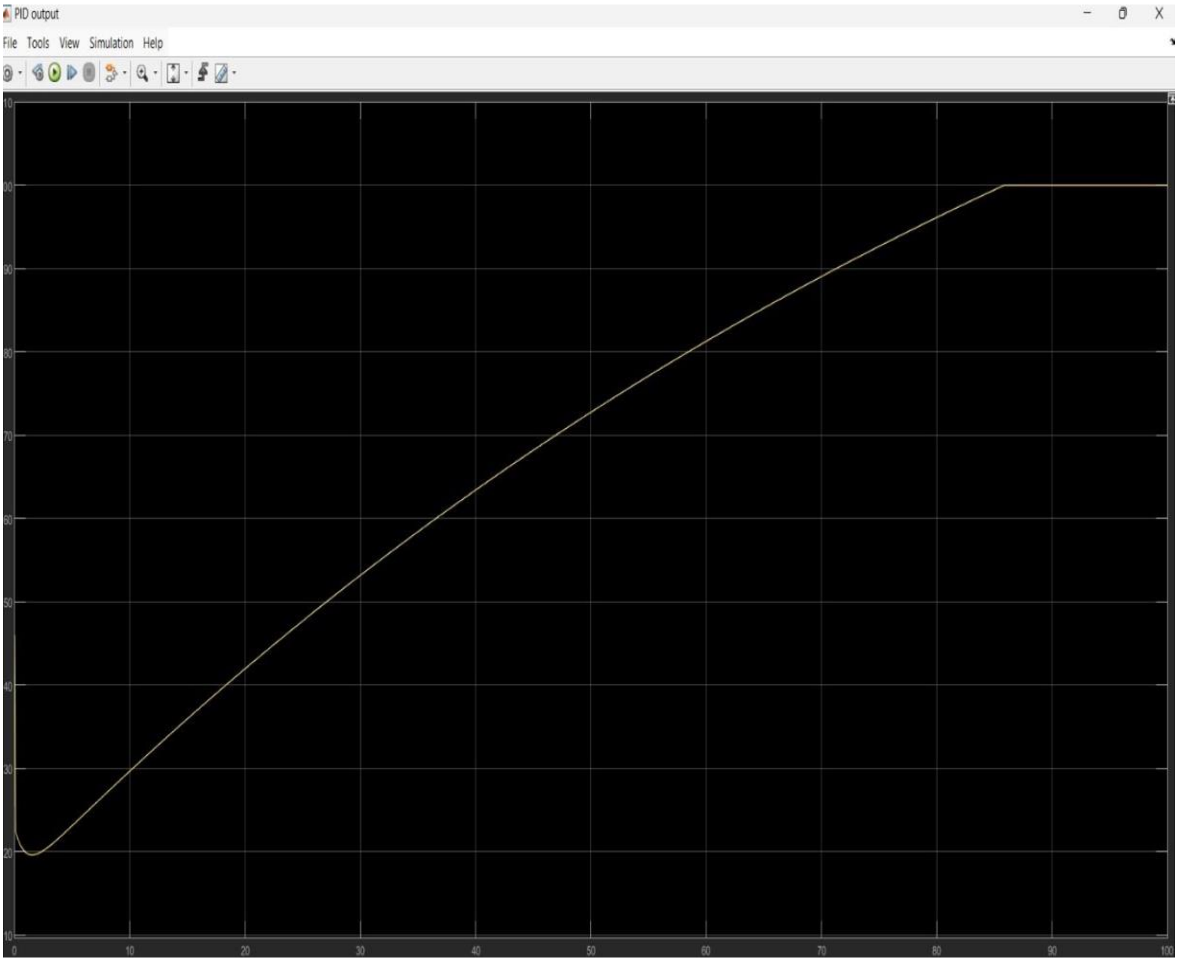


Figure 3.6 Controller output

3.7 Implementation of a predictive model using MATLAB function block in Simulink

The predictive control model developed in MATLAB Simulink effectively illustrates the system's ability to make dynamic and real-time adjustments to heating input, control signals, and power output in response to variations in spot prices and weather conditions. This model was designed to forecast future indoor temperature changes using weather and spot prices. Based on these forecasts, the predictive model provides optimal setpoints for the controller, enabling the system to proactively adjust to anticipated changes in weather conditions.

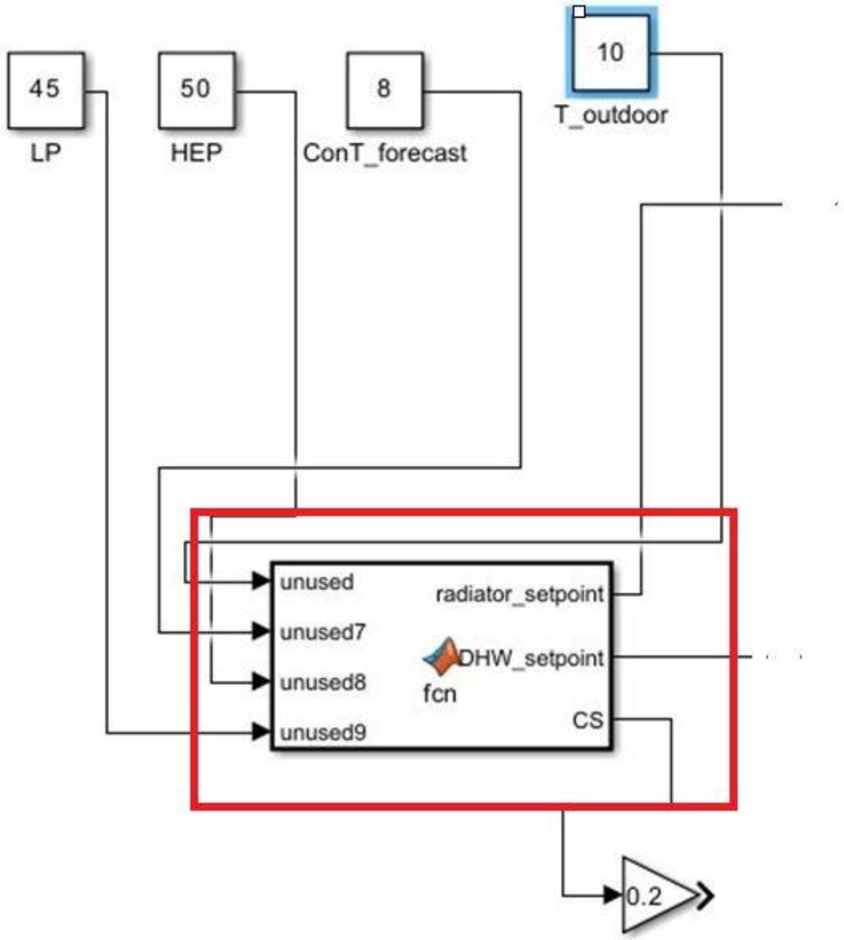


Figure 3.7 Predictive control block

By integrating predictive control, the system not only optimizes energy use but also ensures that occupant comfort requirements are met. Predictive controller block shown in below Figure 3.7. By running simulations over a two-week period with actual weather and spot price datasets, the model demonstrates its capacity for predictive control. The results highlight how the system anticipates and adapts to changing conditions, optimizing its performance in real-time. This adaptability ensures that the system can proactively adjust its outputs, thereby showcasing its robust predictive capabilities and responsiveness to real-world fluctuations.

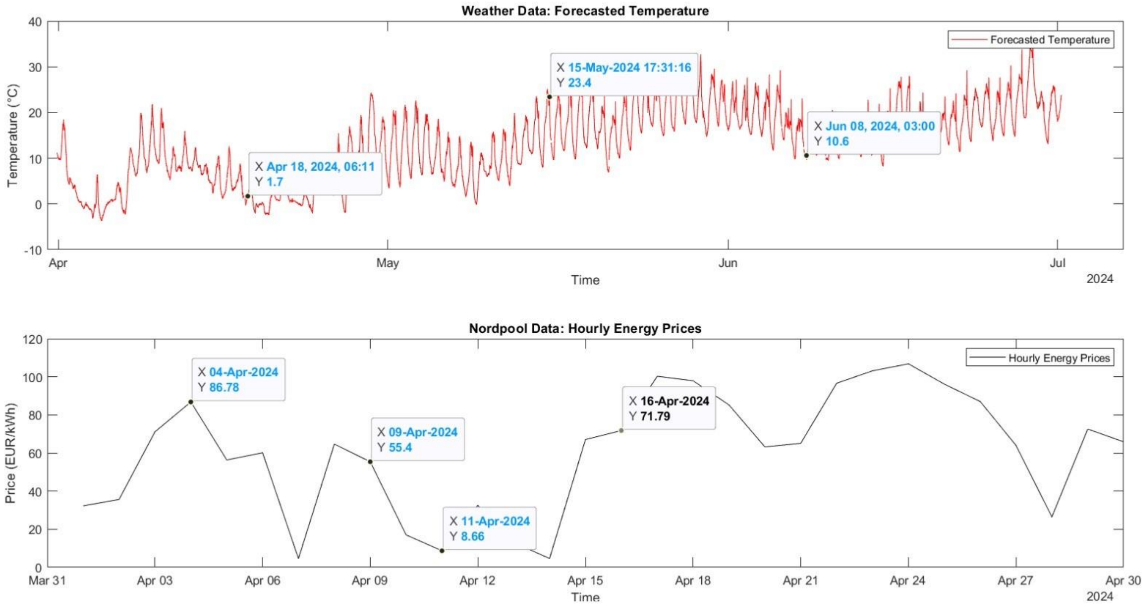


Figure 3.8 Weather and spot price variations

Then I integrated datasets into my MATLAB Simulink model and ran simulations to create a visual representation of weather conditions and spot electricity prices. The Figure 3.8 shows this graphical representation, highlighting the variations in weather and electricity prices over time for given data sets. This visual allows me to observe how fluctuations in weather, such as temperature changes, and variations in electricity prices influence the heating system. Analyzing this visual data helps in understanding the impact of external factors on system performance, which supports more informed decisions for optimizing energy efficiency and reducing costs.

The model generates plots that visually demonstrate how indoor temperature, domestic hot water (DHW), and radiator setpoints adjust dynamically over time in response to changes in weather conditions and spot electricity prices shown in Figure 3.9. These plots provide a clear depiction of the system’s real-time adjustments to external factors, illustrating how it optimizes both comfort and energy efficiency by adapting to variations in weather and electricity costs.

To assess the dynamic performance of the heating system, I conducted a simulation focusing on a brief period during the last week of April, (the red highlighted region in Figure 3.10 is to represent the simulation period from April 27-30). This timeframe presented an interesting test case, as the forecasted weather showed a significant drop in outdoor temperatures, while spot energy prices fell considerably. This combination created an ideal scenario for testing the effectiveness of our control strategy, which relies on predictive algorithms to optimize both energy efficiency and comfort.

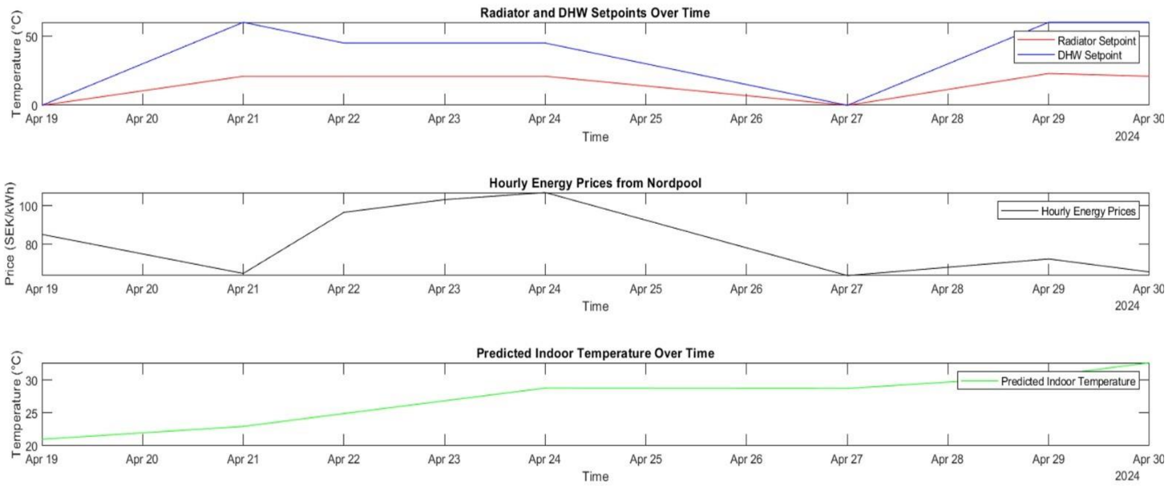


Figure 3.9 Predictive output

According to our control strategy, the system increases the radiator heating (RH) and domestic hot water (DHW) to their maximum set points in response to these conditions. This proactive adjustment helps the building prepare for upcoming periods of higher energy prices and colder weather, ensuring the household is ready for less favorable conditions when energy costs are higher, and temperatures drop.

As a result, the indoor temperature is maintained at a comfortably high level, not just for the immediate comfort of the occupants, but also to provide a thermal buffer for future high-price, low-temperature hours. This strategy offers two key benefits: it maximizes user comfort while lowering overall energy costs. By preheating the building during off-peak, lower-cost hours, the system reduces energy usage during expensive peak times. In this way, the control algorithm uses predictive technology to anticipate changes in weather and energy prices. The Figure 3.11, Figure 3.12 illustrates the control signal output generated by the Simulink model, which varies in response to changes in weather conditions and spot electricity prices. This dynamic variation highlights the predictive control capabilities of the system, as it adjusts the control signal proactively to optimize performance based on anticipated external factors. The plot would provide insight into the timing and intensity of system activations as it adjusts the heating to meet performance goals.

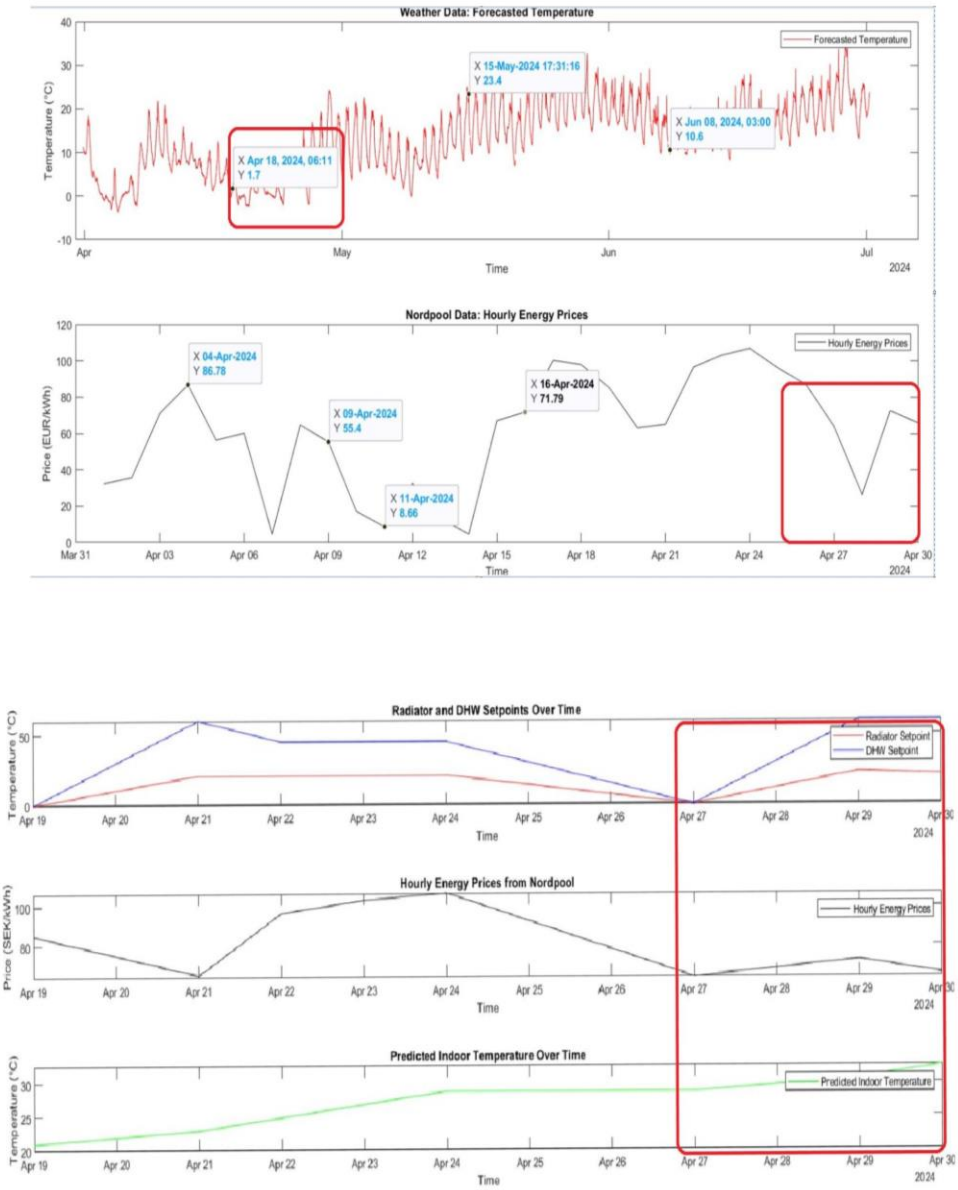


Figure 3.10 Comparison of prediction output with data sets

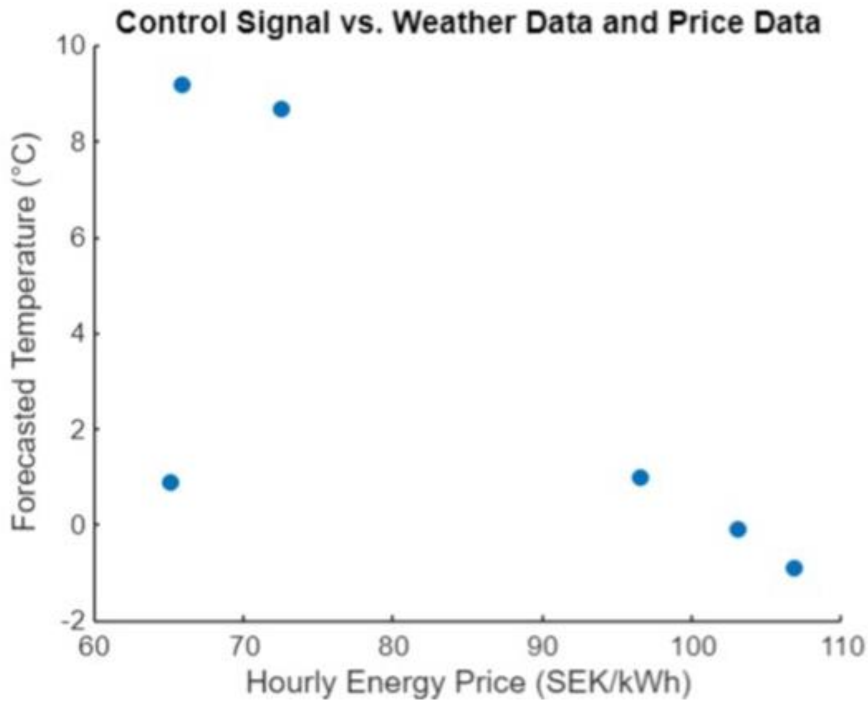


Figure 3.11 Control signal output

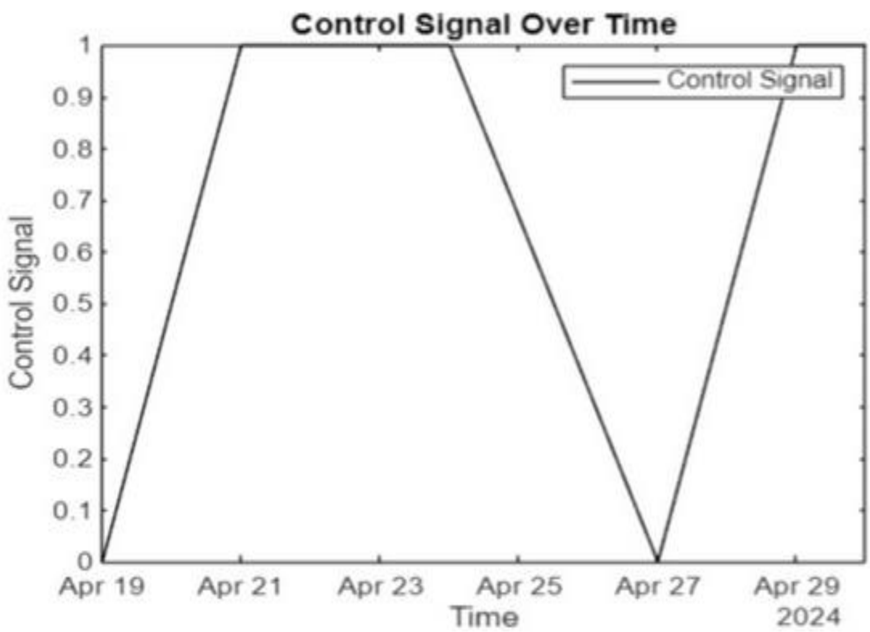


Figure 3.12 Control signal over time vs weather and spot price

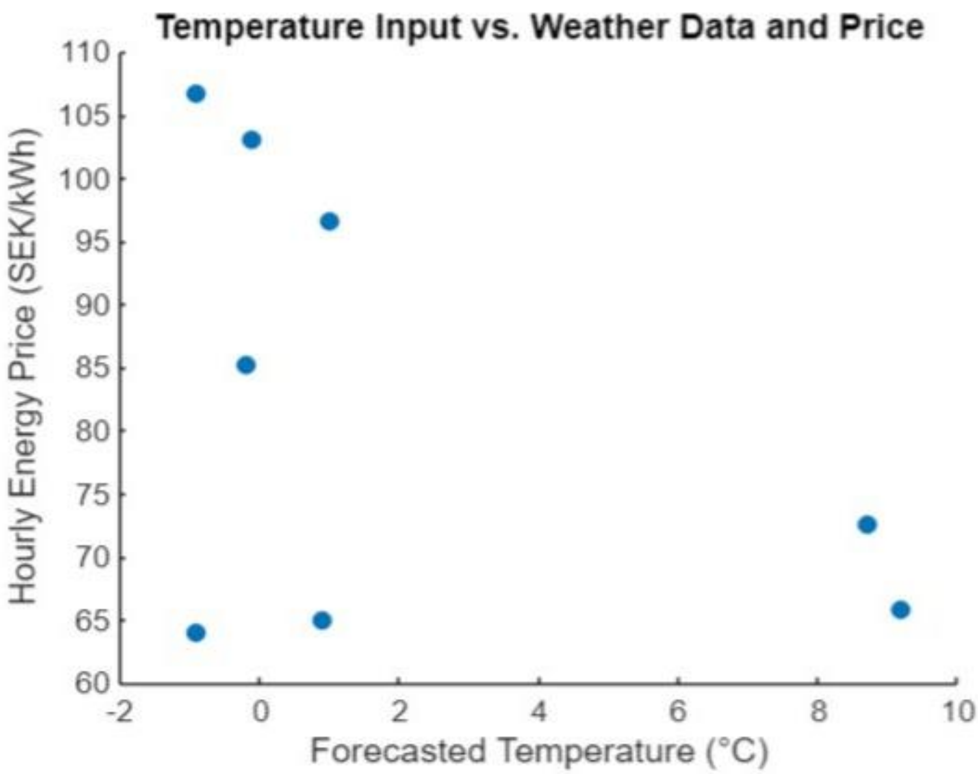


Figure 3.13 Heat input over time vs weather and spot price

The Figure 3.13 above displays how the heat input to the house dynamically adjusts over time in response to changes in weather conditions and spot electricity prices. It visually represents the system's ability to modulate heating input in real-time, directly responding to external factors to maintain energy efficiency and occupant comfort. In essence, below heat input vs. price and weather dual plot represents the relationship between weather driven heating demand and cost optimization, highlighting how the system modulates heat input to maintain comfort while minimizing energy costs.

The dual-axis plot in Figure 3.14, Figure 3.15 demonstrates how the system's power output varies in response to changes in spot electricity prices and weather price respectively. One axis represents weather data, while the other tracks fluctuations in electricity prices, allowing a direct comparison with power output. This visualization highlights how the system adjusts its power generation dynamically to optimize both energy efficiency and cost-effectiveness in response to external conditions.

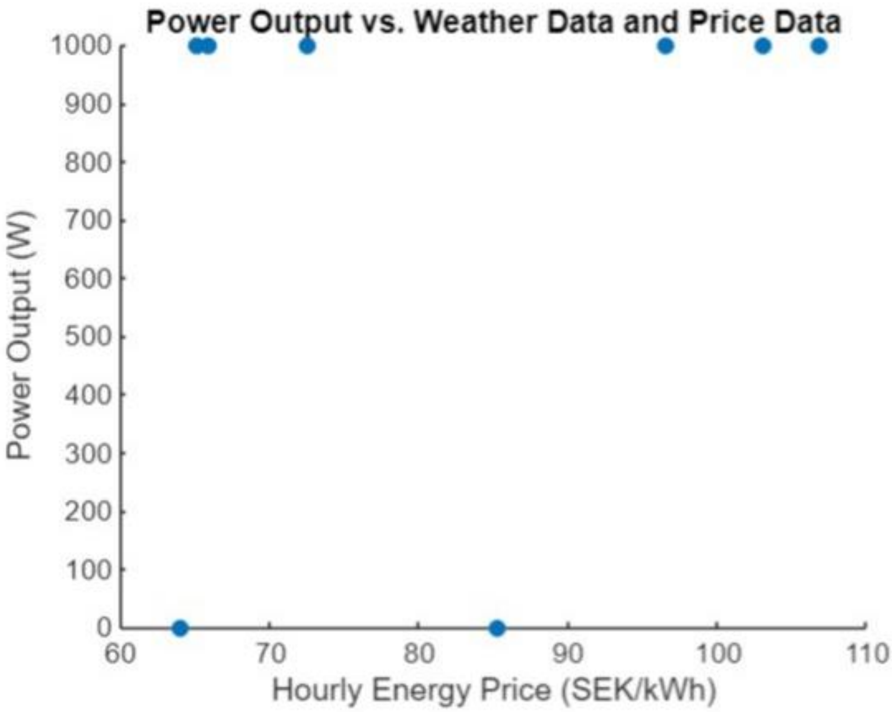


Figure 3.14 Power output over time Vs spot price

By analyzing the interplay between weather conditions and energy prices, the model facilitates more informed decision-making, potentially leading to enhanced energy efficiency and cost savings. Major takeaways are:

1. Adaptive Response: The model demonstrates the heating system's capability to adjust in real-time to changing external conditions, optimizing energy use while consistently maintaining the desired indoor temperature.
2. Cost Optimization: By incorporating spot price data, the model enables the heating system to operate more cost-effectively, minimizing energy expenses during periods of high electricity prices.
3. Weather Responsiveness: The model illustrates how varying weather conditions influence the heating system's energy demands, allowing for proactive and efficient adjustments to maintain comfort and efficiency.

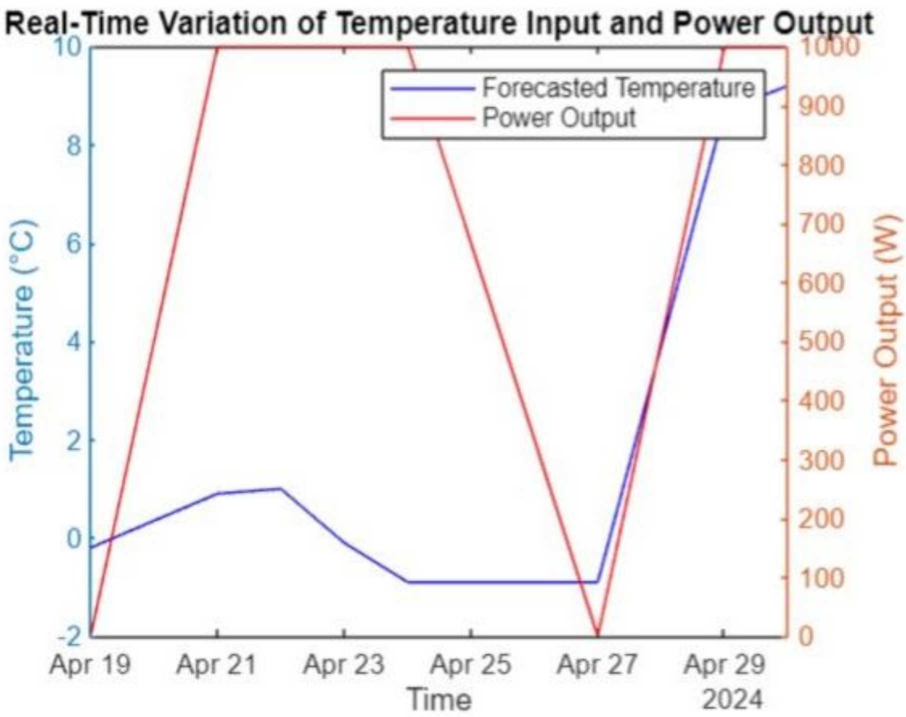


Figure 3.15 Power output over time Vs weather data

In conclusion, this chapter effectively demonstrates the thermal behavior of the house by replicating a first-order RC model integrated with controller in MATLAB Simulink (MATLAB Simulink replication of complete system is represented in Figure 3.16. The effectiveness of control strategy keeps indoor temperatures comfortably high to ensure immediate user comfort and to build a thermal buffer for times when energy prices are high, and temperatures are low. By heating the building during off-peak periods, the system minimizes energy use during peak times, achieving a balance between comfort and cost efficiency. This approach harnesses predictive technology to effectively manage fluctuations in weather and energy prices, optimizing both comfort and cost savings. The accompanying plots clearly illustrate the system's dynamic adjustments, highlighting its ability to respond to changing inputs.

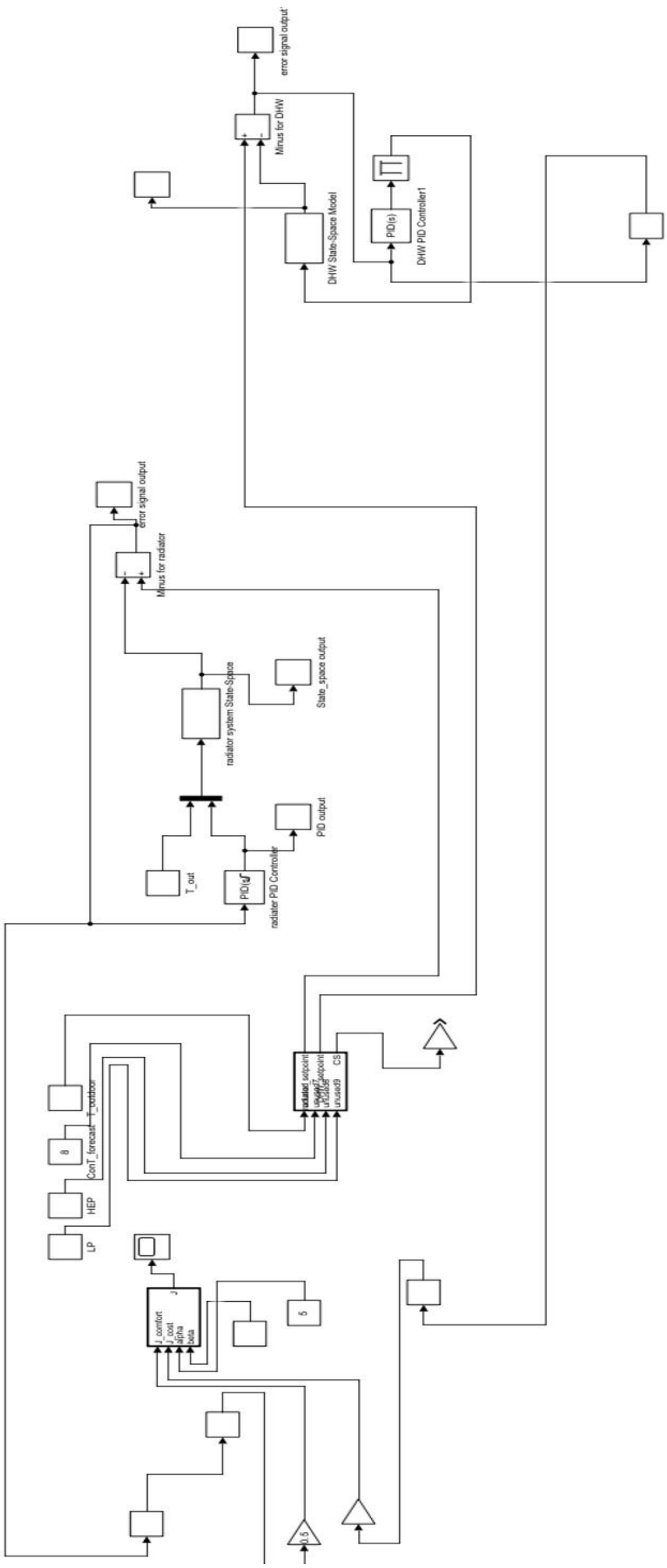


Figure 3.16 Simulink final model

The Predictive models optimize energy use by adjusting system operations based on weather and electricity price fluctuations. This allows the system to run more during cheaper periods, while still maintaining optimal room temperatures by anticipating higher energy demand during cold weather or high-price hours. The system modulates energy output based on forecasted demand, ensuring a stable Coefficient of Performance (COP) and preventing energy overuse. By reacting to changes in weather and energy prices, system effectively during low-price and cold periods.

3.8 Pseudocode representation of matlab code for predictive model control

% Pseudocode for indoor temperature control based on forecasted weather and energy prices

BEGIN HeatingSystemControl

% Load datasets

Load weather_data from 'April 2024 weather data.xlsx'

Load price_data from 'April Day-ahead prices.xlsx'

% Extract relevant columns forecasted_temperatures = Extract(weather_data, 'ForecastedTemperatureValue') energy_prices = Extract(price_data, 'EE')

% Find common timestamps common_times = INTERSECT(forecasted_temperatures, energy_prices)

% Initialize control parameters

Set Tset_current = 21 °C

Set Tset_max_radiator = 22 °C

Set Tset_max_DHW = 60 °C

Set Tset_min_DHW = 45 °C

LP = AVERAGE(energy_prices) % Calculate Limited Price

```
% Initialize arrays

Initialize CS and indoor_temperature arrays

% Control loop for each time step

FOR each time t in common_times DO

Adjust modulated setpoint based on forecasted temperature change

% Determine control signal based on temperature and price conditions

IF (Condition1: Forecast < Current outdoor temperature AND Average Price < LP) THEN

CS[t] = 1

Set temperature setpoints

ELSE IF (Condition2: Forecast > Current outdoor temperature AND Average Price < LP)
THEN

CS[t] = 1

Set temperature setpoints

ELSE IF (Condition3: Forecast < Current outdoor temperature AND Average Price > LP)
THEN

CS[t] = 1

Set temperature setpoints

ELSE IF (Condition4: Forecast > Current outdoor temperature AND Average Price > LP)
THEN

CS[t] = 1

Set temperature setpoints

ELSE

CS[t] = 0 % No heating

END IF
```

% Predict indoor temperature indoor_temperature[t] = PredictIndoorTemperature(previous_temperature, forecasted_temperature, heating_power) END FOR

END HeatingSystemControl

% Function: PredictIndoorTemperature

FUNCTION PredictIndoorTemperature(previous_temp, forecast_temp, heating_power)

% Calculate new indoor temperature

temperature_change = (heating_power / R - (previous_temp - forecast_temp)) * dt / C

RETURN previous_temp + temperature_change END FUNCTION

Listing 3.1. Pseudocode for Predictive Model Control

4. CONTROL ALGORITHM

This chapter begins with a brief overview of the previous algorithm, followed by a thorough exploration of the proposed algorithm. It includes detailed explanation of different algorithmic conditions, their rationale, and the implementation procedure utilizing the Ouflex BA tool tool. The objective of this chapter is to demonstrate how the newly devised algorithm ensures optimization of residential heating systems.

4.1 Previous control algorithm

The mechanism in the building's heating system is in place to dynamically modulate room temperature with fluctuating hourly energy prices. The system continuously monitors hourly electricity prices, anticipating potential fluctuations. When the projected electricity price for the upcoming hours exceeds the 100 Euro threshold, the system initiates a subtle reduction in the indoor temperature by 1°C, where the system's operation principle is a proportional adjustment mechanism of user set points based on energy price. For every 100 Euro increase in the hourly energy price, the system orchestrates a corresponding 1°C reduction in room set point temperature. Extended periods of elevated energy prices can significantly diminish indoor comfort levels, as gradual reductions in room temperature may compromise overall comfort. Additionally, the system's response to fluctuating energy prices might take time, leading to discomfort during sudden or rapid price increases, as temperature adjustments may lag the changes in energy costs. Furthermore, the algorithm needs more consideration for individual user preferences or comfort requirements, potentially resulting in dissatisfaction among occupants who prioritize a stable indoor temperature, irrespective of energy prices. It is crucial to integrate additional mechanisms that prioritize comfort and accommodate user preferences during significant energy price fluctuations. Ensuring a balanced approach that meets both economic and comfort-related needs is essential. Figure 4.1 flowchart representation of the control strategy utilized previously in building.

- The heating system incorporates a 10kW HP as its primary heat source, effectively transitioning from a conventional system. A tank with a total capacity of 1000L is utilized for DHW needs.
- Gebwell's HP features an internal controller responsible for managing a controlling.
- its processes. However, the signals to operate the HP are provided by Ouman controllers, which are configured to function on an ON/OFF logic basis. These controllers receive control signals from Ouflex.

- The control signals, transmitted via the Modbus communication protocol, regulate the HP's operation, employing a hysteresis approach to determine when to switch the unit on and off.
- The demand for DHW in the tank is calculated by assessing the temperature difference within the tank, ensuring efficient heating.

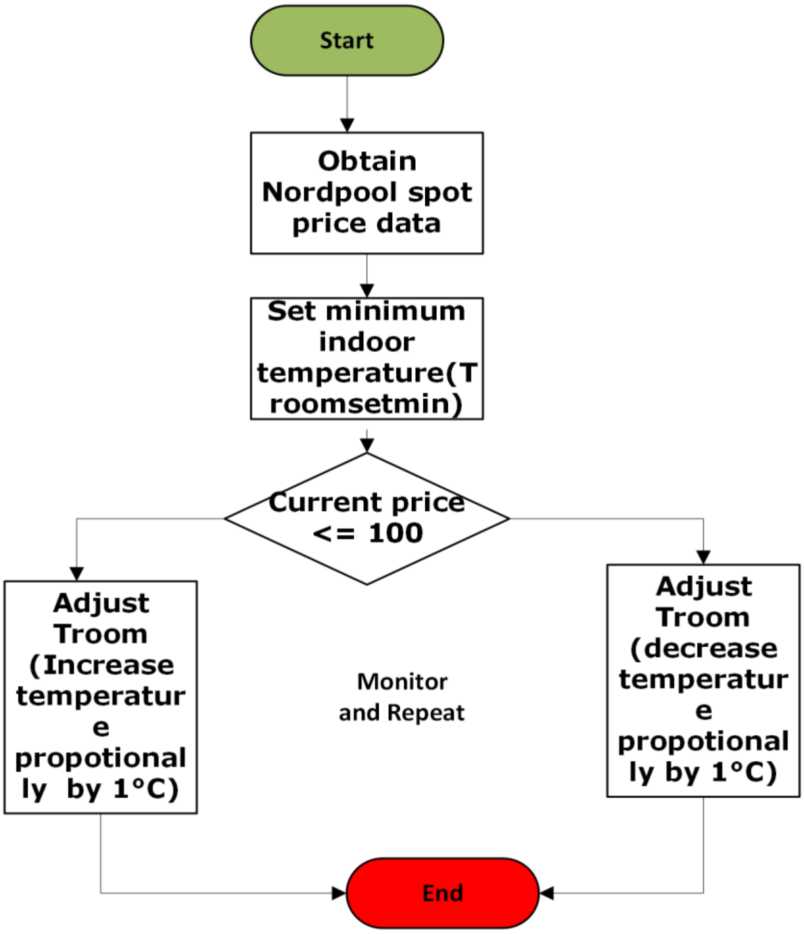


Figure 4.1 Previous control algorithm

4.2 Proposed control algorithm

The study introduced a control algorithm to regulate the set point temperature for space heating and the hot water storage tank, incorporating real-time hourly electricity Prices (HEP) and weather forecasts. The prediction-based model consistently prioritizes better room comfort by setting up RH over DHW, anticipating and preparing for periods of high heating demand, and peak pricing within the building.

4.2.1 Modulated room set point calculation

The building's room set point adjusts based on weather conditions, following an algorithm that considers the difference between outdoor and forecasted temperatures (Toutdoor and Tforecast). The author set a limit of 2°C for this difference. By analyzing the average day temperature over a three-month research period (January 1st to March 15th), the author observed that the difference between current outdoor temperature and forecasted temperature for the next three hours typically stays within this 2°C range. When the outdoor temperature is expected to drop by 2°C in the upcoming hours, increase the room temperature by 1°C. If it is projected to rise by 4°C or more, increment the room temperature by 2°C. This helps us efficiently manage indoor temperature in response to changing weather conditions. Figure 4.2 gives a flowchart representation of modulated set point calculation.

4.2.2 Algorithm conditions

The control algorithm primarily operates based on two conditions. Initially, it evaluates the forecasted weather compared to the current outdoor temperature, using a set point difference range of 2°C. This range was established by studying the correlation between outdoor and predicted temperatures for the next three hours; for this purpose, the day average temperature is calculated from forecasted temperature data over three months (from January 1st to March 15th). The second segment assesses the influence of HEP energy prices, employing a predefined parameter known as the limited price (LP). The limited price is determined by averaging hourly energy prices over a day and can be represented by LP. Utilizing these two conditions, the controller enhances heating comfort in the building by regulating radiator and DHW operations within acceptable limits. By integrating spot price and weather forecasts, the controller will determine an appropriate modulated room temperature within the building. The control algorithm calculates the control signal and manages the heating system by selecting the set point temperatures for space heating(radiator) and the hot water storage tank. This approach involves sorting HEPs to comprehend their rise, fall, and stabilization patterns. Based on these trends, corresponding control signals are assigned to anticipate limited future prices. Figure 4.3 represents the proposed control algorithm used for optimizing heating system.

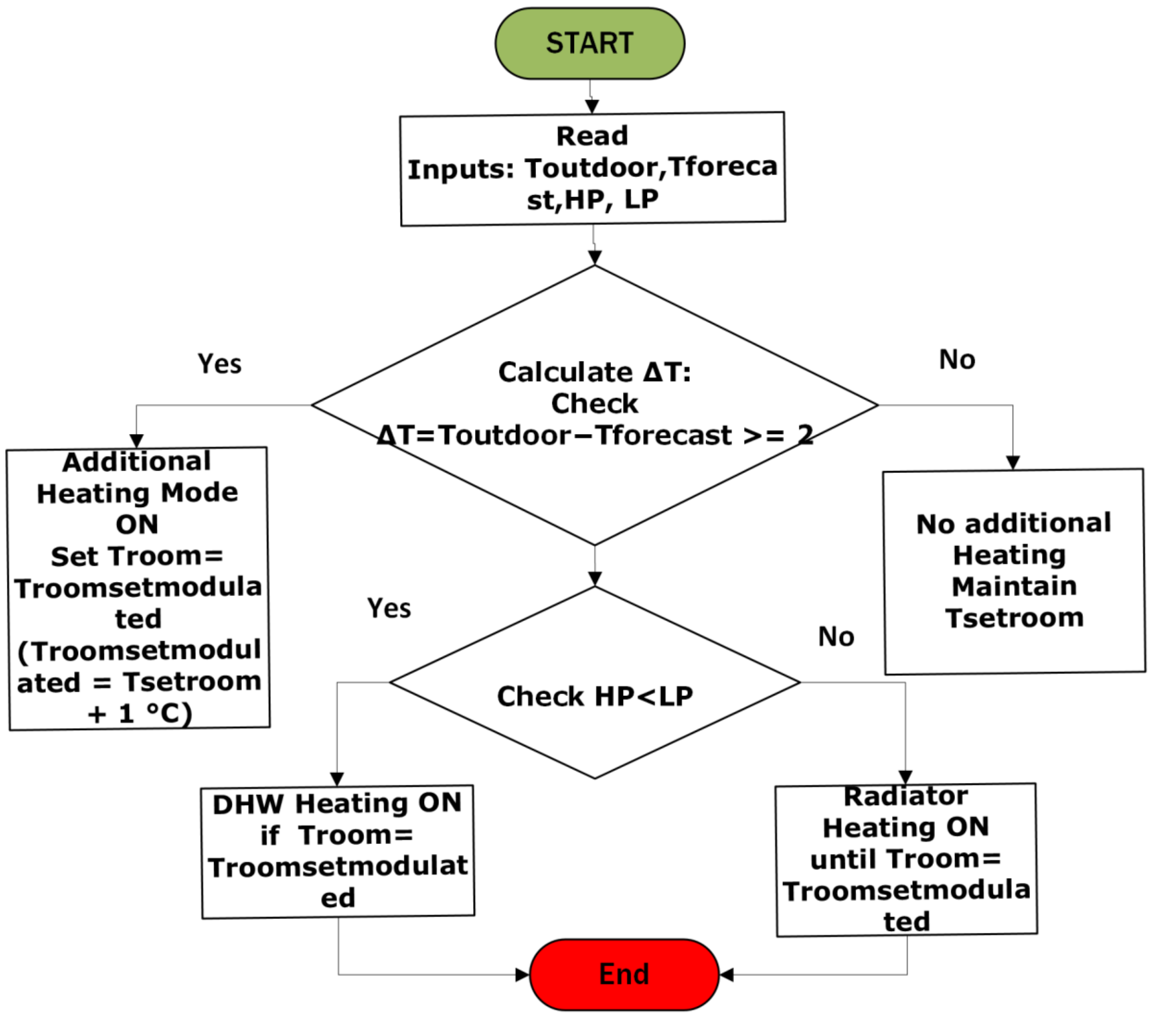


Figure 4.2 Modulated room set point

This scenario involves a four-part process:

1. When the forecasted temperature is less than outdoor, and hourly energy prices fall (HEP<LP), the heating system will be activated (CS+ 1) until it achieves a maximum set point temperature for radiator and DHW heating.
2. When the forecasted temperature is more than outdoor, and hourly energy prices fall (HEP<LP), the heating system will be activated (CS+ 1) until it achieves modulated set point temperature for RH and maximum set point temperature for DHW heating.
3. When the forecasted temperature is less than outdoor, and hourly energy prices rise (HEP>LP), the heating system will be activated (CS+ 1) until it achieves a modulated set point temperature for the radiator and minimum set point for DHW heating.
4. When the forecasted temperature is more significant than outdoor, and hourly energy prices are rise (HEP<LP), the heating system will be activated (CS+ 1)

until it achieves modulated set point temperature for RH and minimum set point temperature for DHW heating.

5. Where'' (CS + 1)" basically indicates the activation of additional heating mode in our system.

4.2.3 RH priority

The heating system prioritizes RH over DHW. This scenario involves a 4 basic criteria's:

- **Criteria 1**: When the forecasted temperature is lower than the outdoor temperature and hourly energy prices are decreasing (HEP < LP), the radiator heating (RH) will be activated until the room temperature reaches the maximum room set point. Upon achieving this maximum set point for both the radiator and domestic hot water (DHW), the heat pump will be deactivated.
- **Criteria 2**: When the forecasted temperature is higher than the outdoor temperature and hourly energy prices are decreasing (HEP < LP), the RH will be activated until the room temperature reaches the modulated room set point. Once this modulated set point for the radiator and the maximum set point for DHW are reached, the heat pump will be deactivated.
- **Criteria 3**: When the forecasted temperature is lower than the outdoor temperature and hourly energy prices are increasing (HEP > LP), the RH will be activated until the room temperature reaches the modulated room set point. The heat pump will be deactivated once the modulated set point for the radiator and the minimum set point for DHW are achieved.
- **Criteria 4**: When the forecasted temperature is higher than the outdoor temperature and hourly energy prices are increasing (HEP > LP), the RH will be activated until the room temperature reaches the modulated room set point. Once this modulated set point is achieved for the radiator and the minimum set point for DHW, the heat pump will be turned off. Algorithm flow chart is shown in below (Figure 4.3). The operational modes and truth table representation of algorithm is given in Table 4.1 and 4.2 respectively.

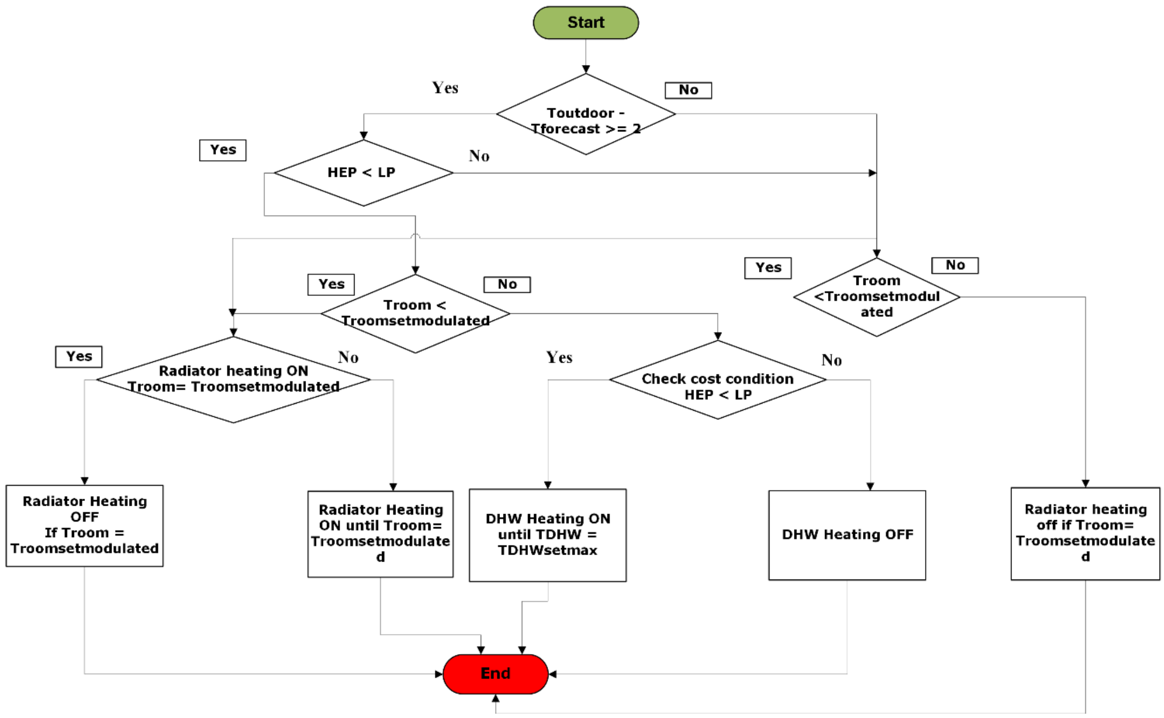


Figure 4.3 Algorithm flowchart

Table 4.1 Heating system operational modes

Temperature vs Price	Low	High
Low	Heat boost mode. (optimal)	Heat Economical mode
High	Heat comfort mode. (Balanced comfort)	Heat protection mode

4.2.4 Algorithm execution on ouflex tool

This section provides an overview of applying the developed control algorithm in the Ouman Ouflex tool, focusing on prioritizing RH. The methodology outlines crucial design considerations, highlighting the integration of the Ouflex tool for practical applications. This concise summary creates an opportunity for a detailed exploration of the newly developed algorithm's impact on the system's overall efficiency, Figure A6.7, Figure A6.6, gives a detailed idea of application of algorithm in Ouflex tool. Inputs: Outdoor temperature, Forecasted temperature, Hourly electricity price and Average day price.

Table 4.2 Truth table representation of algorithm

Tforc > Tout	Tforc < Tout	Tout = Tforc	HEP < LP	HEP > LP	HEP = LP	Output
1	0	0	1	0	0	Heating mode activated until the radiator and DHW reach their modulated and maximum values respectively
1	0	0	0	1	0	Heating mode activated until the radiator and DHW reach modulated room temperature. and minimum setpoint value, respectively
0	1	0	1	0	0	Heating mode activated until the radiator and DHW reach their maximum acceptable values
0	1	0	0	1	0	Heating mode activated until the radiator and DHW reach modulated room temperature and minimum setpoint value, respectively

System parameters: Maximum room set point, Modulated Room set point, Minimum, DHW setpoint, Normal DHW setpoint, Maximum DHW setpoint.

Conditions to check:

Toutdoor - Tforecast>= 2°C,

Hourly electricity price < Limited price

- **Scenario 1**:

  Condition: Forecasted temperature is lower than outdoors, and hourly energy prices are falling (HEP < LP).

  Action: RH will remain active until the room temperature attains the maximum room set point.
- **Scenario 2**:

  Condition: Forecasted temperature exceeds outdoor temperature, and hourly energy prices are falling (HEP < LP).

  Action: RH will remain active until the room temperature attains the modulated room set point.
- **Scenario 3**:

  Condition: Forecasted temperature is lower than outdoors, and hourly energy prices are rising (HEP > LP).

  Action: RH will remain active until the room temperature attains the modulated room set point.
- **Scenario 4**:

  Condition: Forecasted temperature is lower than outdoors, and hourly energy prices are falling (HEP < LP).

Action: RH will remain active until the room temperature attains the modulated room set point.

4.2.5 Optimization problem and solution

Previous system logic flow diagram

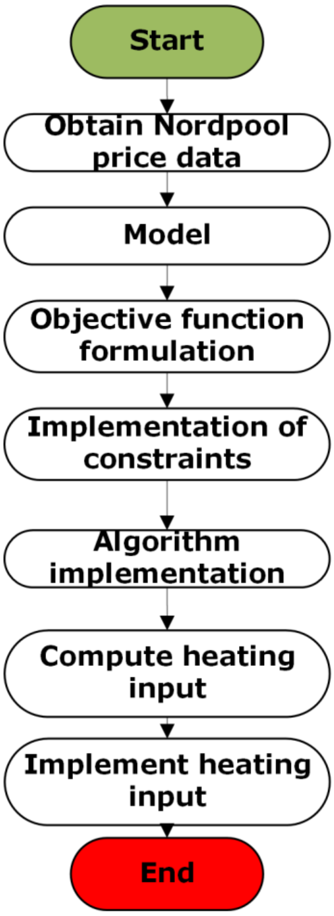


Figure 4.4 Optimization process with previous control algorithm optimization

The optimization process in the previous system starts with collecting real-time price data from Nordpool. The model then forecasts indoor temperatures based on the heating input. The system formulates an objective function to minimize costs, applying constraints to ensure that the heating system operates within its physical and operational limits. An optimization algorithm solves this problem to determine the optimal heating input. This optimal input is then implemented in the heating system, completing the process. Figure 4.4 is a graphical flowchart depicting the control optimization process in the previous system.

Proposed system

The proposed system improves optimization by incorporating weather forecasts and utilizing predictive Control strategy. It begins by gathering weather forecast data along with real-time and forecasted electricity price data from Nordpool. The prediction model leverages these inputs to forecast indoor temperatures more accurately. An objective function is then created to balance user comfort and energy costs, assigning specific weights to each. Constraints are applied to ensure the system operates within physical, operational, and comfort limits. The predictive method addresses the optimization problem by taking system dynamics into account. This process computes the optimal heating input that balances comfort and costs, which is then implemented in the heating system, resulting in a more adaptive and responsive approach to maintaining indoor comfort. Figure 4.5 a graphical flowchart depicting the control optimization process in the proposed system.

4.2.6 Description of logical operation

- First, I compared the outdoor temperature with the forecasted temperature. I use a subtract block to find the difference. The result is inserted into a comparator block, which checks if it is more significant than, equal to, or less than 2°C.
- The comparator output is then fed into an OR gate, which gives an accurate value if either condition (greater than or equal to) is met. This step helps us simplify our decision-making. Then, I move on to our second condition regarding changes in energy prices. We take the hourly energy and set limit prices as inputs for a comparator. This comparator helps us decide if the hourly energy price is more significant than, equal to, or less than the set limit price, as the first condition comparator output will be given to an OR gate block.
- I have executed all the scenarios using various combinations by feeding output from an OR gate to an AND gate.
- The output of and gates were then given to the compensator to execute increments and decrements of the control signal.
- I used an absolute block for the compensator to fine-tune and give a precise value. There are two compensators, one to increase the temperature and the other to decrease it. These compensators react to specific conditions, warming up or cooling the temperature. Two switches are in place for each compensator to carry out these adjustments, which directs the control flow and helps to increase or decrease the temperature.

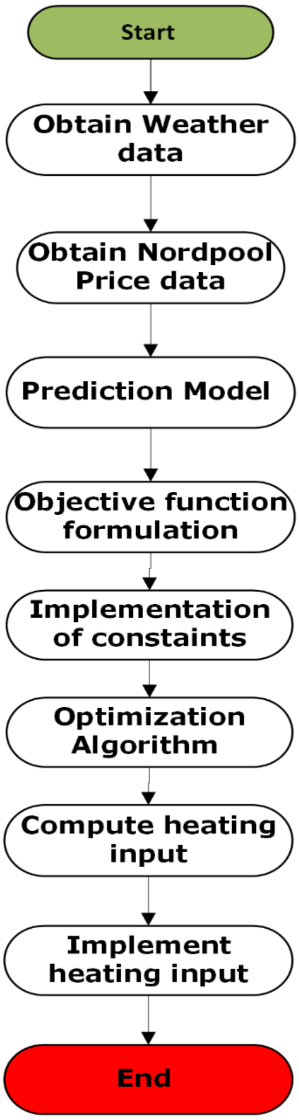


Figure 4.5 Optimization process with proposed control algorithm

4.2.7 Application

After implementing set point modulation, I proceeded to the overall application section. By implementing a priority block, the author has established a system where RH takes precedence over DHW. The system prioritizes heating the radiators, regardless of energy prices or outdoor temperatures. The DHW function becomes active only when the indoor temperatures reach predetermined acceptable levels.

In this chapter, we compare the optimization techniques used in the previous and proposed residential heating systems. The previous system solely relied on Nordpool spot prices, compromising user comfort by decreasing the indoor temperature by 1°C proportionally for every 100-euro increase in energy price. This method lacked the capability to ensure user desired comfort levels. The proposed system, on the other hand, incorporates both real-time energy prices and weather forecast data using predictive control methodology. This advanced approach enables more dynamic and predictive adjustments by anticipating future weather conditions and price fluctuations.

5. RESULTS AND BENCHMARKS

5.1 Data acquisition

This section compares how well the heating system performs. We are looking at monthly energy reports to see how the algorithm impacts energy use and costs. To compare the building or its heating system performance, I took reports for the study period (January 1 - March 15) and compared them with last year, 2023. This section comprehensively examines the energy consumption patterns of the heat pump, its total heat production, and associated expenditures during the specified periods, elucidating the impact of the control algorithm on the building's operational performance. Through analysis and comparison of the 2023 and 2024 data sets, insights are drawn regarding the effectiveness of the algorithm in optimizing heating system operation and its consequent implications on energy utilization and financial outlays. The findings explain the tangible benefits and potential challenges of implementing such control strategies in real-world building environments.

Numerous factors influence how I compare this year's energy usage and heating system performance with last year's. One crucial aspect is the fluctuation in outdoor temperature and varying weather conditions. These directly affect how much heat our system needs to maintain comfortable indoor levels, which I always prioritize. For instance, January and February 2024 were notably colder than in 2023, and March 2024 had much higher temperatures.

In this study, I compared the performance of our heating system using a method that prioritizes RH heating through our proposed algorithm. By analyzing monthly energy reports from January 1st to March 15th for 2023 and 2024, I looked closely at how the system used energy, produced heat, and incurred costs. This method helped us understand how our algorithm influenced the system's operation and its impact on energy consumption and corresponding expenses. The monthly energy reports for the target building for the years 2023 and 2024 are shown in Figure A1.1, Figure A1.2, Figure A1.3, Figure A1.4, Figure A1.5, and Figure A1.6. Numerical breakdown of the results is given in below Table 5.1.

Table 5.1 Heating system performance comparison

Factor	January 2023	January 2024	February 2023	February 2024	March 2023	March 2024
HP Heat Production (kWh)	3473	4712	2579	3564	1543	1765
HP Consumed Electricity (kWh)	1076	1415.5	855.5	1097.2	494.6	531
Outdoor Temperature (°C)	-0.47	-5.11	-0.02	-0.27	0.23	1.82
Floor 1 Temperature (°C)	16.91	6.80	18.05	18.28	17.36	18.05
Floor 2 Temperature (°C)	20.70	20.59	21.47	21.17	21.30	22.06
COP	3.23	3.33	3.01	3.25	3.12	3.31
HP Consumed Energy Consumption Equivalent Price (Euros)	193.68	169.86	153.99	131.66	89.03	63.94
Energy Efficiency Ratio (EER)	3.23	3.33	3.01	3.25	3.12	3.32
Comfort Index	0.20	-1.07	0.44	0.43	0.33	0.52
Operational Cost Savings (%)	-	12.27	-	14.51	-	28.33
Nord Pool Avg Price Per Month (€)	99.27	126.48	113.12	75.52	120.18	73.14

The analysis of heating system performance between 2023 and 2024 reveals considerable advancements, particularly in heat production, which increased from 3,473 kWh in January2023 to 4,712 kWh in January 2024, and from 2,579 kWh to 3,564 kWh in February. March also showed growth, rising from 1,543 kWh to 1,765 kWh. Electricity consumption followed a similar trend, with January consumption increasing from 1,076 kWh to 1,415.5 kWh, February from 855.5 kWh to 1,097.2 kWh, and March from 494.6 kWh to 531 kWh. The Coefficient of Performance (COP) improved, moving from 3.23 to 3.33 in January, 3.01 to 3.25 in February, and 3.12 in March 2023 to 3.31 in March 2024.

In 2024, the proposed heating system demonstrated notable advancements in energy efficiency and user comfort compared to 2023. In January, the Energy Efficiency Ratio (EER) increased significantly from 3.23 to 3.33, indicating a more effective conversion of energy into heating output. However, the Comfort Index decreased from 0.20 to -1.07 due to maintenance work on Floor 1. In February, the EER rose from 3.01 to 3.25, while the Comfort Index remained stable, showcasing the system's ability to maintain a consistent indoor environment despite similar outdoor temperatures. By March, the EER further improved from 3.12 to 3.32, while the Comfort Index increased from 0.33 to 0.52, emphasizing the system's consistent performance in delivering efficient heating and ensuring a comfortable indoor climate throughout the colder months. These enhancements underscore the effectiveness of the proposed system in optimizing energy usage while prioritizing occupant comfort. ERR and CI can be calculated by basic formula shown in 5.1 and 5.2.

$$\text{EER} = \frac{\text{HP Heat Production (kWh)}}{\text{HP Consumed Electricity (kWh)}} \tag{5.1}$$

$$\text{CI} = \frac{\text{Average Indoor Temperature} - \text{Lower Comfort Threshold}}{\text{Upper Comfort Threshold} - \text{Lower Comfort Threshold}} \tag{5.2}$$

were lower comfort threshold of 18◦C and higher comfort threshold of 22◦C is used for calculation. The operation savings cost can be calculated by Equation 5.3.

$$\text{Operational Cost Savings (\%)} = \frac{\text{Cost in 2023} - \text{Cost in 2024}}{\text{Cost in 2023}} \times 100 \tag{5.3}$$

The outdoor temperatures in both years have varied significantly, with some months in January 2024 being much colder than in 2023, and vice versa. The proposed system prioritizes maintaining user comfort within acceptable levels, regardless of fluctuations in outdoor temperatures or hourly electricity prices. In January 2024, despite the colder conditions, the heating system successfully maintained nearly the same indoor temperature on floor 2 (floor 1 was undergoing maintenance during this period). The system's improved Coefficient of Performance (COP) in 2024 enabled it to achieve better energy efficiency and reduce operational costs, even in colder weather. In February, when outdoor temperatures were like those in 2023, the system maintained a COP of 3.25, representing a 0.24 increase from the previous year, while keeping indoor temperatures steady and comfortable for users. The heat pump produced more heat during this period, which demonstrates the system's performance stability and efficiency. Overall, this showcases the system's ability to adapt to changing outdoor temperatures, using energy more efficiently while ensuring consistent indoor comfort for occupants.

This data suggests that there is a considerable rise in operational cost savings in 2024 compared to 2023. For instance, in January 2024, operational cost savings reached 12.27%, despite rising electricity prices, which increased from €99.27 to €126.48. In

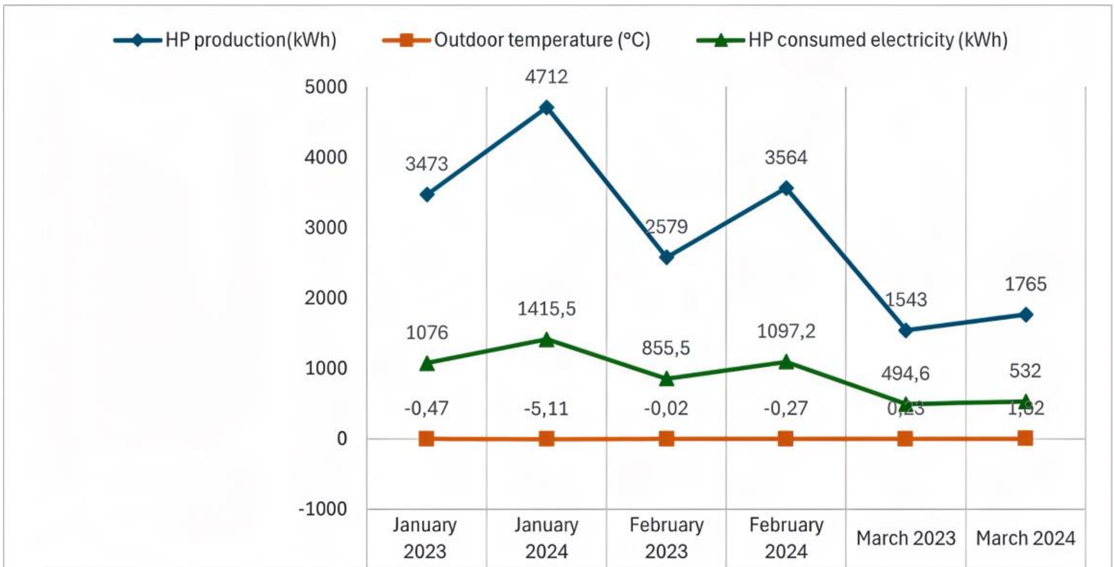
February, operational cost savings improved to 14.51%, coinciding with a drop in prices from €113.12 to €75.52. By March, it increased to 28.33%, as prices decreased from €120.18 to €73.14. It is essential to recognize that while the efficiency of the heating system has improved as indicated by COP, fluctuating electricity costs impact the effectiveness of energy savings. This creates a complex relationship among energy savings, operational costs, and market pricing. The enhanced system performance observed in 2024 demonstrates that the heating system operates more efficiently, irrespective of variations in electricity prices, resulting in considerable cost savings in 2024 compared to 2023.

5.2 Performance analysis: hourly electricity price, comfort, and COP

This section comprehensively analyses our heating system's performance, focusing on four key factors: Outdoor temperature, hourly electricity price, User comfort and COP. Through detailed examination, the author aims to gain insights into the system's efficiency, ability to maintain optimal comfort levels for occupants and cost-effectiveness. Considering these critical aspects, the author provides valuable findings that contribute to a deeper understanding of the system's effectiveness in real-world applications.

Analyzing the fluctuation in outdoor temperature between 2023 and 2024 during the study period from January 1st to March 15th is crucial. The building is situated in Tallinn, which experiences harsh weather, leading to a drop in outdoor temperatures from 2023 to 2024. As I prioritize RH in our system, this colder weather will surely lead to higher HP production and electricity consumption by the heat pump in 2024 compared to 2023. Figure 5.1 illustrates how heating system requires more operating hours for the heat pump due to the prioritized RH heating to meet user comfort requirements with changing outdoor temperature in 2024. The heating system and control algorithm are designed to prioritize user comfort, regardless of external conditions, by taking forecasted weather and hourly electricity price into account. This predictive model prompts the heating system to generate additional heat, which in turn consumes more electricity, to prepare the building for unfavorable conditions characterized by low temperatures and high costs by effectively managing the HP operation. It's crucial to recognize that changes in outdoor temperature can influence the heat production needs of the heat pump. However, the essence of this predictive model lies in its ability to anticipate and prepare for future conditions, ultimately minimizing the impact of fluctuating costs and varying weather.

In addition to the observed increase in heat pump energy consumption and production, it is noteworthy that despite these heightened demands, our system has managed to optimize energy consumption costs, as shown in Figure 5.2. This optimization is reflected in the reduced energy cost throughout 2024. This achievement underscores the effectiveness of our system's control strategies in efficiently managing energy usage. By acknowledging the impact of lower average monthly hourly electricity price in 2024 compared to 2023, it is important to note that although the heat pump has operated for more hours, this has not negatively impacted the system's performance, as it maintains a higher and stable COP than in 2024 than 2023. Overall, the system has ensured user comfort without compromising its performance.



	January 2023	January 2024	February 2023	February 2024	March 2023	March 2024
HP production(kWh)	3473	4712	2579	3564	1543	1765
Outdoor temperature (°C)	-0,47	-5,11	-0,02	-0,27	0,23	1,82
HP consumed electricity (kWh)	1076	1415,5	855,5	1097,2	494,6	532

Figure 5.1 Outdoor temperature as a vital factor influencing heating demands

By prioritizing RH heating through new control algorithm, our system demonstrates its capability to adapt to varying environmental conditions while simultaneously reducing operational expenses. The primary limitation of the previous system lies in its narrow focus on fluctuating hourly electricity prices as the sole determinant for adjusting the room's set point temperature, disregarding crucial factors such as current weather conditions and forecasted trends. This system does not use weather forecasts to pre-emptively adjust for anticipated outdoor temperature changes. Consequently, it cannot develop efficient heating or cooling strategies, leading to inadequate room temperature regulation and potential discomfort for occupants. Moreover, the system’s linear response to hourly electricity price changes, reducing the room temperature by 1°C for every 100 euros increase in hourly electricity price, oversimplifies the complex relationship between energy costs and comfort requirements. This simplistic approach might not accurately reflect the true cost-effectiveness of energy-saving measures and varying comfort preferences of occupants.

Coming to user-comfort factor, in January 2024, despite the outdoor temperature being nearly 5◦C lower than January 2023, the system ensures that the temperature on Floor 2 remains consistent with that of January 2023. This indicates the system’s ability to effectively compensate for the colder weather, preserving indoor comfort levels despite external temperature fluctuations. It is not all about minimizing operating expenses; the system employs efficient energy management to ensure better comfort by keeping hourly electricity prices within the limit. It is visible in Figure 5.4 that our heating system

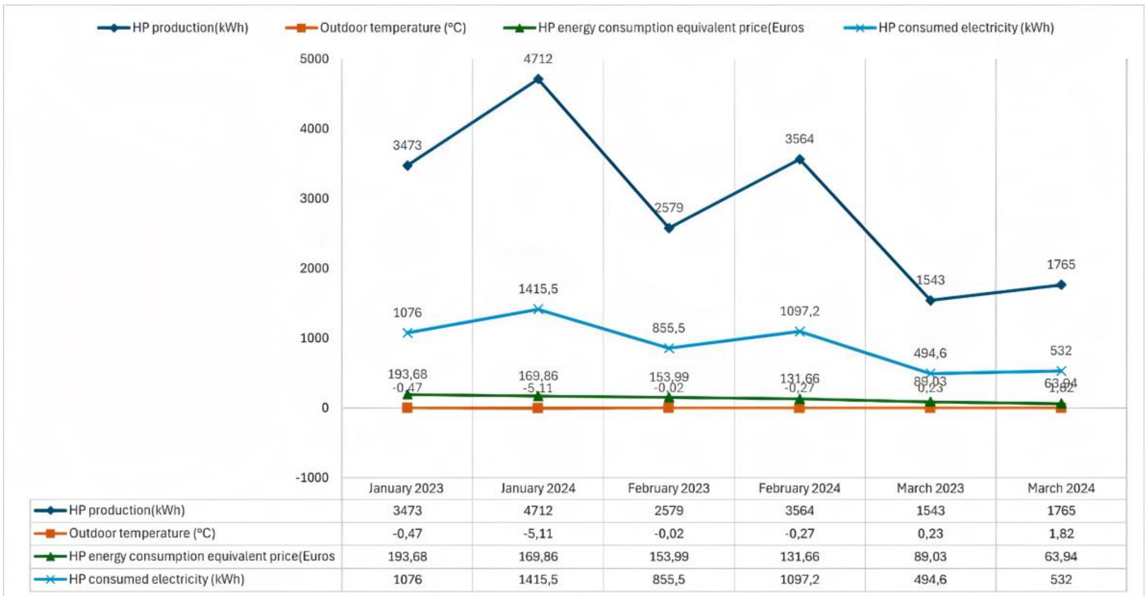


Figure 5.2 Analysis of HP operation and its consumed hourly electricity price

maintains almost the same indoor temperature on Floor 1 and Floor 2 compared to 2023. Particularly in January 2024, which is significantly colder than January 2023, the system maintains nearly the same levels of user comfort as in 2023. Importantly, it achieves this without negatively affecting system performance, as evidenced by a slightly higher COP.

Generally, when there is a higher heat demand, and the heat pump operates for longer hours, the COP tends to decrease. This occurs because the heat pump works harder to meet the increased demand, which can affect its efficiency. However, this decrease in COP might not be permanent, as the system could adjust and become more efficient over time. Thus, high heat demand and longer operating hours initially lower the COP. Integrating this concept into our research, Figure 5.3 shows that our system ensures almost a constant COP, even though we have higher heating demands in 2024. Compared to 2023, system has produced more heat which obviously demands more working hours. In summary, despite high heat demand and longer running times, our system maintains a nearly stable COP. This indicates that our system effectively adapts to varying demands and environmental conditions, maintaining efficiency even under challenging circumstances.

Figure 5.3 Analysis of variation of COP of HP

Benchmarking heating system performance characteristics

In January 2024, heat production significantly increased compared to January 2023, indicating higher demand (Figure 5.5). In January 2024, despite much lower outdoor temperatures than in 2023, the system maintained nearly the same indoor comfort level on Floor 2, even as Floor 1 remained unoccupied due to renovations. This was achieved with a slight increase in COP, indicating improved efficiency. Overall, in January 2024, the system effectively ensured user indoor comfort requirements, despite the substantially lower outdoor temperatures compared to 2023.

In 2023 and 2024, February saw nearly identical outdoor temperatures, were the system maintained similar indoor comfort levels on both building floors (Figure 5.6) with a significant increase in COP compared to 2023. In essence, the system kept the building comfortable while maintaining steady performance. Figure 5.7 illustrates the characteristics of the heating system in March 2023 and 2024. Compared to 2023, March 2024 experienced higher outdoor temperatures (March 1-15) and a better user comfort levels is maintained in both floors in 2024 by maintaining a better COP. Despite higher outdoor temperatures during these months, the system produced significantly more heat, with the heat pump working harder to prepare the building for the anticipated high prices and harsher outdoor conditions expected in the coming hours.

Figure 5.4 Optimizing indoor comfort

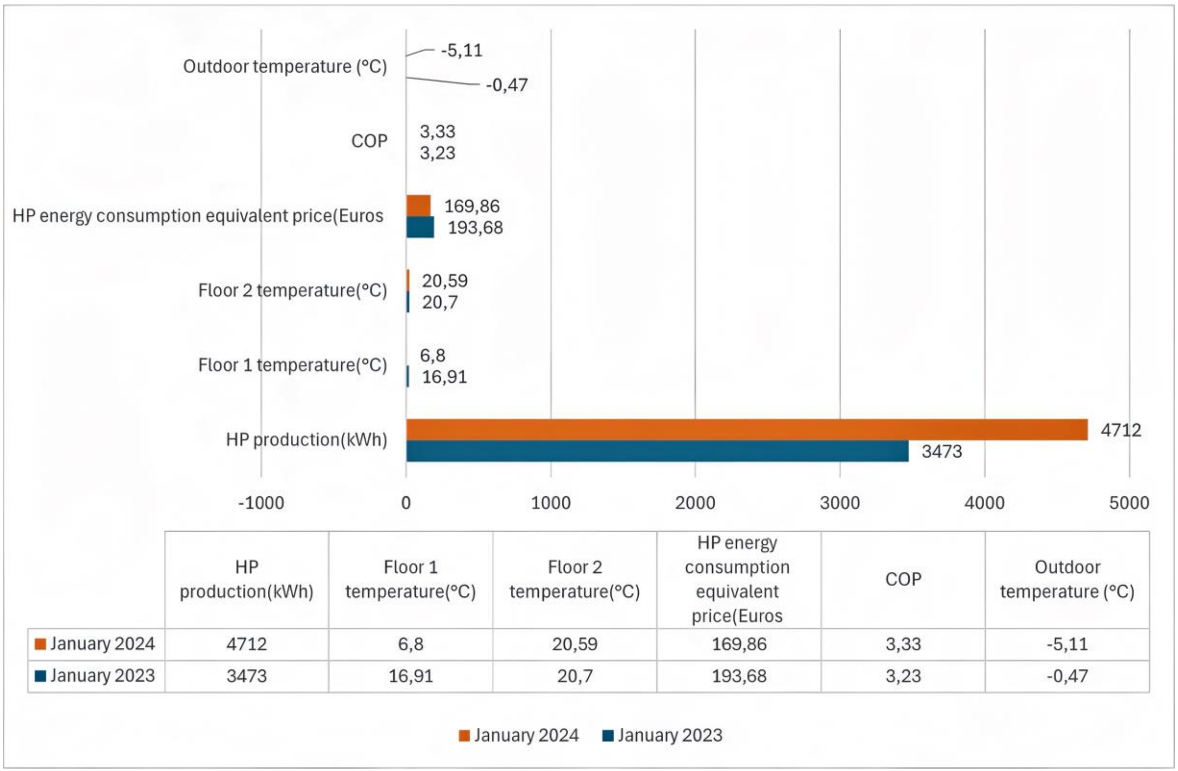
The comparison between 2024 and 2023 shows a significant rise in heating demand as the system always prioritize user comfort. This has led to a considerable increase in heat production and electricity consumption. Despite fluctuating outdoor temperatures within this unfavorable condition, the system consistently preserves indoor user comfort levels. This highlights its strong ability to adjust and control indoor environments, ensuring that occupants' comfort is maintained regardless of external weather changes. A comprehensive visual representation of the above-mentioned system's characteristics can be found in the figure below Figure 5.8.

5.3 Discussion of results

Analysis of user comfort and hp consumed energy cost

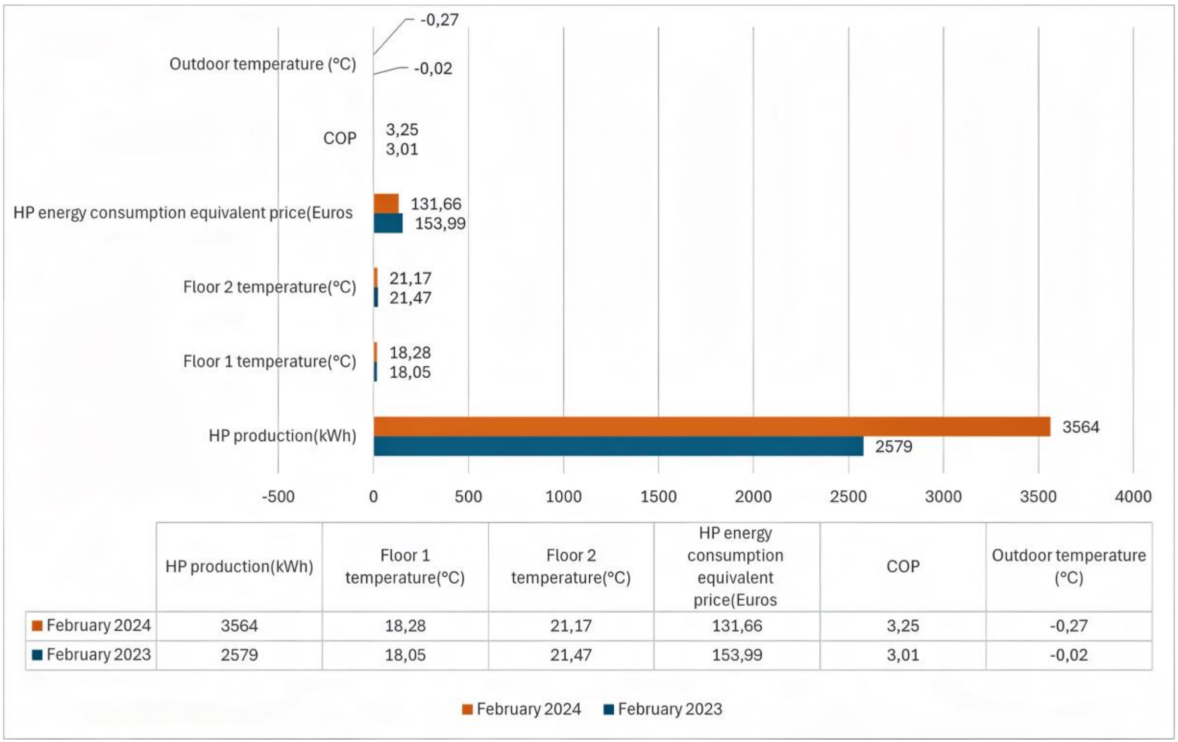
The optimized control algorithm developed was implemented in a real building and tested over a three-month period, from January 1 to April 15, 2024. The primary objectives of the algorithm were to maintain user comfort while minimizing energy costs. All results were derived from monthly utility bills obtained from the Ouman platform, considering fluctuations in Nord Pool prices. Consequently, results were analyzed based on monthly utility bills, where the control algorithm used a predictive model that incorporated forecasted intra-hour spot prices. This approach allows for optimized heating adjustments in response to anticipated price fluctuations. The results represented in Figure in 5.6,5.7,5.8 and 5.9 indicate that the algorithm successfully achieved following objectives.

1. Maintained user Comfort: The algorithm effectively maintained the required comfort levels for the building occupants.
2. Reduced Energy Costs: The energy consumption costs for the heat pump in 2024 were significantly lower compared to 2023, without compromising user comfort.
3. Stable COP: The algorithm maintained a stable coefficient of performance (COP), which was slightly higher than in 2023, ensuring efficiency of system.



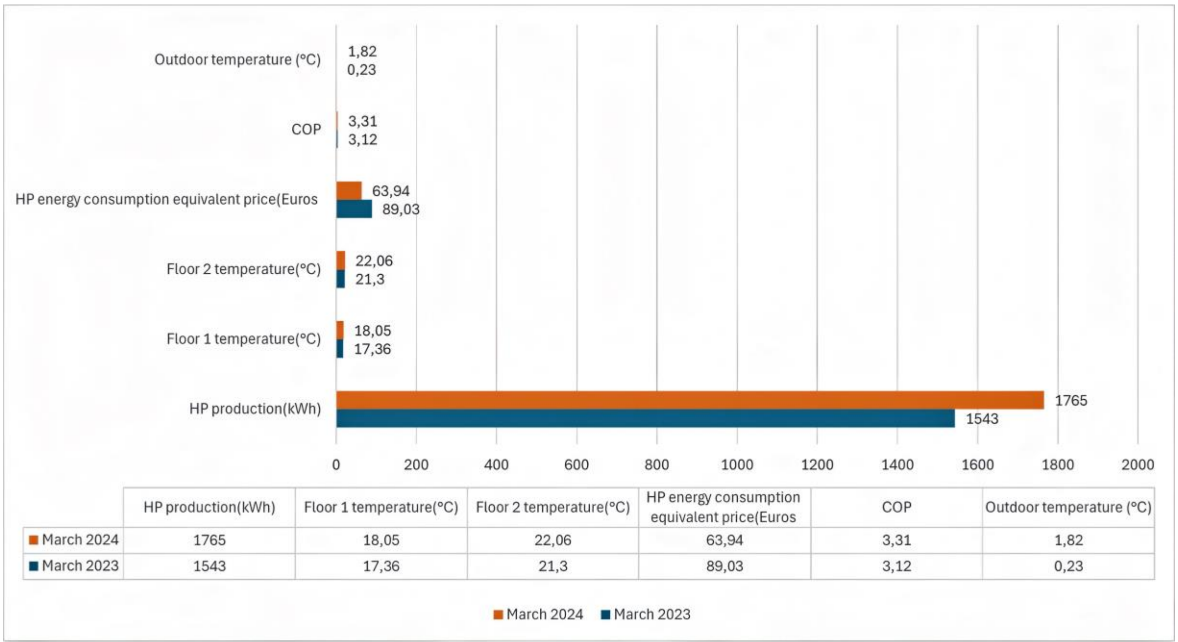
	HP production(kWh)	Floor 1 temperature(°C)	Floor 2 temperature(°C)	HP energy consumption equivalent price(Euros	COP	Outdoor temperature (°C)
January 2024	4712	6,8	20,59	169,86	3,33	-5,11
January 2023	3473	16,91	20,7	193,68	3,23	-0,47

Figure 5.5 Heating system characteristics January 2023 & 2024



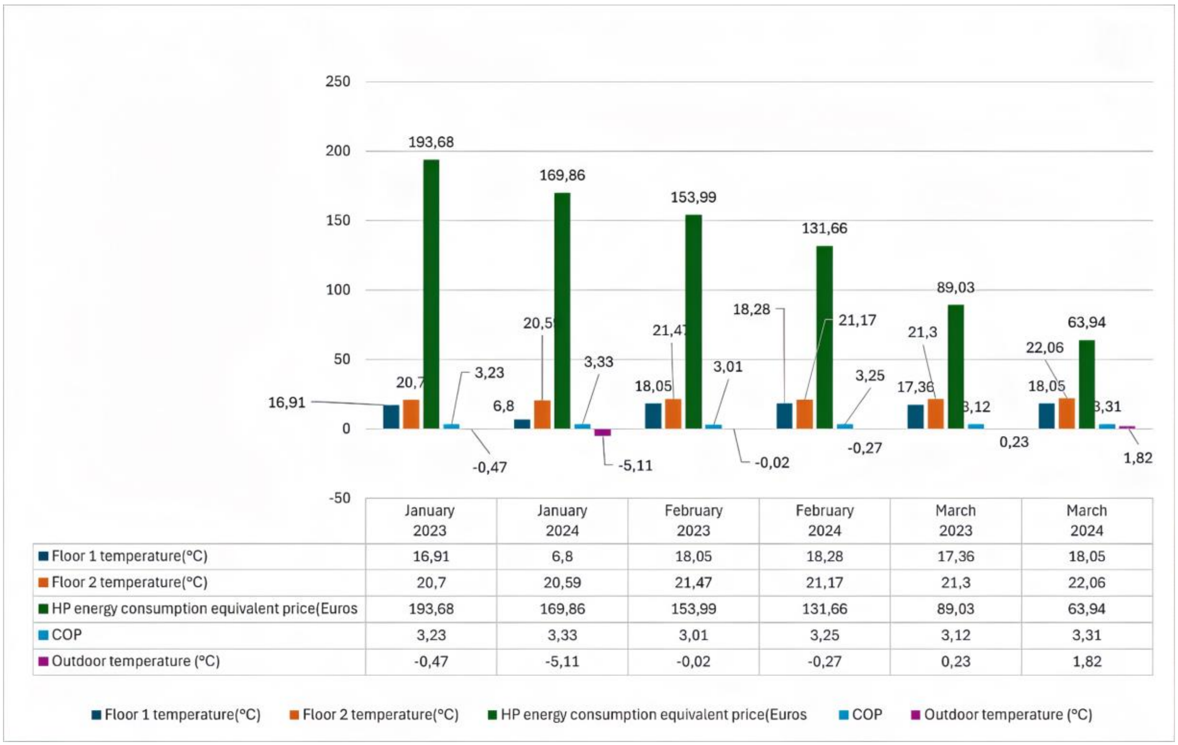
	HP production(kWh)	Floor 1 temperature(°C)	Floor 2 temperature(°C)	HP energy consumption equivalent price(Euros	COP	Outdoor temperature (°C)
February 2024	3564	18,28	21,17	131,66	3,25	-0,27
February 2023	2579	18,05	21,47	153,99	3,01	-0,02

Figure 5.6 Heating system characteristics February 2023 & 2024



	HP production(kWh)	Floor 1 temperature(°C)	Floor 2 temperature(°C)	HP energy consumption equivalent price(Euros	COP	Outdoor temperature (°C)
March 2024	1765	18,05	22,06	63,94	3,31	1,82
March 2023	1543	17,36	21,3	89,03	3,12	0,23

Figure 5.7 Heating system characteristics March 2023-2024



	January 2023	January 2024	February 2023	February 2024	March 2023	March 2024
Floor 1 temperature(°C)	16,91	6,8	18,05	18,28	17,36	18,05
Floor 2 temperature(°C)	20,7	20,59	21,47	21,17	21,3	22,06
HP energy consumption equivalent price(Euros	193,68	169,86	153,99	131,66	89,03	63,94
COP	3,23	3,33	3,01	3,25	3,12	3,31
Outdoor temperature (°C)	-0,47	-5,11	-0,02	-0,27	0,23	1,82

Figure 5.8 Overall system characteristics for a simulation period

Comparison with previous Year

To evaluate the effectiveness of the algorithm, a comparative analysis was performed using utility bills from the same period in the previous year (1 January to 15 April 2023). It is important to highlight that:

- Focus on Relative Performance: The key performance indicators for this project are maintaining user comfort levels, minimizing energy costs, and ensuring COP stability. Although the difference in hourly electricity prices between the two years is acknowledged, it should be understood as an external variable that does not affect the core evaluation of the optimization algorithm itself.
- Scope of Provided Data: There is a noticeable decrease in hourly electricity prices in 2024 compared to 2023. The data sets for hourly electricity prices and weather forecasts used in this work were provided by the company. Therefore, the observed decrease in hourly electricity prices in 2024 is an external factor beyond the control and scope of the project.

Implications

In evaluating the performance of the developed control algorithm, it is important to acknowledge the impact of varying hourly electricity prices between 2023 and 2024. At the same time, it is necessary to recognize that the performance of the heating system and the resulting cost changes cannot be attributed solely to fluctuations in hourly electricity prices, due to the influence of building-specific factors like thermal resistance and inertia. Compared to 2023, HP heat production and electricity consumption have increased, while maintaining a nearly stable COP, highlighting the algorithm's effectiveness in adapting to changing weather conditions and maintaining indoor comfort. This stable COP indicates that the algorithm has successfully optimized heating efficiency and performance, despite the increased electricity consumption. Unlike previous algorithms that primarily focused on minimizing costs by leveraging lower-priced hours, this proposed algorithm prioritizes user comfort while effectively balancing cost considerations.

In summary, the control algorithm has proven effective in achieving a balance between comfort and efficiency. While the decrease in hourly electricity prices in 2024 is a beneficial external factor, it does not detract from the algorithm's performance. The data sets were provided by the company, and the focus of the project was on achieving relative improvements in the specified metrics.

5.4 Conclusion

This study explored how predictive control strategies can improve performance with a residential heating system featuring a heat pump and thermal energy storage tank. The primary goal was to enhance comfort levels within the building while simultaneously managing energy costs. Unlike conventional approaches that aim to reduce energy consumption, this research focused on optimizing system operations by strategically scheduling energy delivery based on hourly electricity prices and weather forecasts. Weather conditions have a notable effect on the heating and cooling needs of the household in question. Quick changes in outdoor temperature led to adjustments in the algorithm's indoor comfort settings. Likewise, fluctuations in hourly electricity prices influence how the algorithm manages heating, cooling, and storage systems to improve energy efficiency and reduce costs. The algorithm's adaptability across different situations ensures efficient operation and prevents excessive energy use during peak demand periods.

The control algorithm considers the present and future electricity prices and weather data. It adapts space heating set point temperatures, accordingly, allowing for user-defined maximum room temperatures. Additionally, it calculates modulated set points based on hourly prices and weather conditions to meet the recommended thermal comfort levels for residential detached houses.

In 2024, the average indoor temperature on Floor 1 decreased to 14,37$^{\circ}C$ compared to 17,44$^{\circ}C$ in 2023, while Floor 2 maintained a similar average temperature of 21,27$^{\circ}C$ compared to 21,15$^{\circ}C$ in 2023(considering of no occupancy on Floor 1 in January 2024 due to renovation work). Despite the lower temperature on Floor 1, the heating system ensures user-set comfort levels for the whole house. Additionally, the proposed control algorithm led to a cost reduction of approximately 71 Euros in 2024 compared to 2023, saving about 19,47%. Moreover, the average COP increased by approximately 0,17 in 2024 compared to 2023, signifying a 5,45% improvement in energy efficiency. These enhancements suggest improved system performance and the potential for reduced energy expenses. To conclude, implementation of the control algorithm in the heating system has yielded notable improvements in both energy efficiency and cost savings, with a minor decline in the average indoor temperature on Floor 1 in 2024 compared to the preceding year, the heating system, with its reliable performance, continues to maintain user-defined comfort levels across the household. It underscores the effectiveness of the proposed algorithm in optimizing heating performance, even amidst challenging conditions.

It's crucial to recognize the pivotal role the control algorithm plays in achieving these outcomes. The algorithm, with its predictive control approach, optimizes energy usage and ensures effective operation in weather and cost conditions. It does so by dynamically adjusting heating system parameters based on real-time data and user preferences. This proactive control approach not only enhances comfort and cost-effectiveness but also lays the foundation for adaptable and resilient heating systems that can meet the evolving needs of a specific household. Therefore, the seamless integration of prediction-based methodology in heating systems is vital in shaping intelligent solutions.

While the findings of this study demonstrate promising outcomes for the targeted building, it's essential to acknowledge that the effectiveness of the proposed algorithm may vary when implemented in different households. The algorithm's performance is inherently influenced by the unique characteristics and properties of each building, including factors such as insulation levels, building layout, occupancy patterns, and climate conditions. Therefore, future implementations of the control algorithm should be designed and optimized according to the specific requirements and dynamics of each target building to ensure optimal energy efficiency and cost-effectiveness.

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APPENDICES

APPENDIX 1 IMPLEMENTATION OF PREDICTIVE CONTROL

```
% This is a simple MATLAB code to solve a system of linear equations
% Load the datasets weather_data =
readtable('April 2024 weather data.xlsx');
price_data = readtable('April Day-ahead
prices.xlsx');

% Extract relevant data from the tables
DayAndTime_weather = weather_data.DayAndTime; % Using the correct
column name
T_forecast_data = weather_data.ForecastedTemperatureValue; % Using the
    correct column name

DayAndTime_price = price_data.Var1; % Using the correct column name
HEP = price_data.EE; % Using the correct column name

% Convert to datetime if
necessary if
~isdatetime(DayAndTime_w
eather)
    DayAndTime_weather =
datetime(DayAndTime_weather); end
if ~isdatetime(DayAndTime_price)
    DayAndTime_price =
datetime(DayAndTime_price); end

% Find the common time range common_times =
intersect(DayAndTime_weather, DayAndTime_price);

% Align weather data
[~, idx_weather] = ismember(common_times, DayAndTime_weather);
T_forecast_data_aligned = T_forecast_data(idx_weather);

% Align price data
[~, idx_price] = ismember(common_times, DayAndTime_price);
HEP_aligned = HEP(idx_price);

% Update the DayAndTime to the common times
DayAndTime = common_times;
```

```
% Define the setpoints
Tset_max_radiator = 22; % Max setpoint for radiator (°C)
Tset_max_DHW = 60; % Max setpoint for DHW (°C)
Tset_min_DHW = 45; % Min setpoint for DHW (°C)
Tset_current = 21; % Current indoor temperature setpoint (°C)
Tset_modulated = Tset_current; % Initialize modulated setpoint

% Calculate the limited price (LP) as the average of the hourly energy prices
LP = mean(HEP_aligned);

% Initialize arrays for results
num_points = length(T_forecast_data_aligned); % Number of data points
CS = zeros(num_points, 1); % Control signal
Tset_radiator = zeros(num_points, 1); % Setpoint for radiator
Tset_DHW = zeros(num_points, 1); % Setpoint for DHW
Tindoor_pred = zeros(num_points, 1); % Indoor temperature prediction

% Define the RC model parameters
R = 1; % Thermal resistance
(°C/W) C = 500; % Thermal
capacitance (J/°C) dt = 1; %
Time step (hours)

% Initialize the indoor temperature prediction array
Tindoor_pred(1) = Tset_current; % Initial indoor temperature

% Implement the predictive-based control
algorithm for t = 2:num_points
    % Calculate the temperature difference between forecasted
    temperatures temp_diff = T_forecast_data_aligned(t) -
    T_forecast_data_aligned(t-1);

    % Adjust the modulated setpoint based on temperature
    difference if abs(temp_diff) > 2 && abs(temp_diff) <= 4
        Tset_modulated = Tset_current + 1; % Increase setpoint
    by 1°C elseif abs(temp_diff) > 4
        Tset_modulated = Tset_current + 2; % Increase setpoint
    by 2°C else
```

```
        Tset_modulated = Tset_current; % Keep the current
    setpoint end

    % Determine the control signal (CS) and setpoints based on HEP and
    temperature if T_forecast_data_aligned(t) < T_forecast_data_aligned(t-
    1) && HEP_aligned(t) < LP
        % Condition 1: Forecast < Previous Forecast, Price < Limited
        CS(t) = 1;
        Tset_radiator(t) = Tset_max_radiator;
        Tset_DHW(t) = Tset_max_DHW; elseif
    T_forecast_data_aligned(t) > T_forecast_data_aligned(t-1)
    && HEP_aligned(t) < LP
        % Condition 2: Forecast > Previous Forecast, Price < Limited
        CS(t) = 1;
        Tset_radiator(t) = Tset_modulated;
        Tset_DHW(t) = Tset_max_DHW; elseif
    T_forecast_data_aligned(t) < T_forecast_data_aligned(t-1)
    && HEP_aligned(t) > LP
        % Condition 3: Forecast < Previous Forecast, Price > Limited
        CS(t) = 1;
        Tset_radiator(t) = Tset_modulated;
        Tset_DHW(t) = Tset_min_DHW; elseif
    T_forecast_data_aligned(t) > T_forecast_data_aligned(t-1)
    && HEP_aligned(t) > LP
        % Condition 4: Forecast > Previous Forecast, Price > Limited
        CS(t) = 1;
        Tset_radiator(t) = Tset_modulated;
        Tset_DHW(t) =
    Tset_min_DHW; else
        CS(t) = 0; % No heating if conditions are
    not met end

    % Predict the indoor temperature using the RC thermal model
    Tindoor_pred(t) = RC_model(Tindoor_pred(t-1),
    T_forecast_data_aligned(t), CS(t)
         * 1000, R, C, dt);
end

% Visualization of results
```

```
% 1) Plot the control signal over time figure;
plot(DayAndTime, CS, '-k', 'DisplayName', 'Control
Signal'); xlabel('Time');

ylabel('Control Signal');
legend(); title('Control
Signal Over Time');

% 2) Plot the real-time variation of temperature input and
power output figure; yyaxis left;
plot(DayAndTime, T_forecast_data_aligned, '-b', 'DisplayName', 'Forecasted
    Temperature'); ylabel('Temperature (°C)'); yyaxis right;
plot(DayAndTime, CS * 1000, '-r', 'DisplayName', 'Power
Output'); ylabel('Power Output (W)'); xlabel('Time');
legend(); title('Real-Time Variation of Temperature Input
and Power Output');

% 3) Scatter plot of Temperature Input vs. Weather Data
and Price figure; scatter(T_forecast_data_aligned,
HEP_aligned, 'filled'); xlabel('Forecasted Temperature
(°C)'); ylabel('Hourly Energy Price (SEK/kWh)');
title('Temperature Input vs. Weather Data and Price');

% 4) Scatter plot of Control Signal vs. Weather Data and Price Data
figure; scatter(HEP_aligned(CS == 1), T_forecast_data_aligned(CS
== 1), 'filled'); xlabel('Hourly Energy Price (SEK/kWh)');
ylabel('Forecasted Temperature (°C)'); title('Control Signal vs.
Weather Data and Price Data');

% 5) Plot of Power Output vs. Weather Data and
Price Data figure; scatter(HEP_aligned, CS *
1000, 'filled'); xlabel('Hourly Energy Price
(SEK/kWh)'); ylabel('Power Output (W)');
title('Power Output vs. Weather Data and Price
Data');

% Optional: Save the updated results to an Excel file for further analysis
results_table = table(DayAndTime, T_forecast_data_aligned, HEP_aligned,
```

```
    Tset_radiator, Tset_DHW, Tindoor_pred, CS);
writetable(results_table,
'Updated_Heating_System_Control_Results.xlsx');

% Define the RC model function function Tindoor =
RC_model(Tindoor_prev, T_forecast, power_input, R, C, dt)
    % Calculate the temperature change based on the RC model
    % Tindoor_prev: Previous indoor temperature
    % T_forecast: Forecasted outdoor temperature
    % power_input: Heating power input (W)
    % R: Thermal resistance (°C/W)
    % C: Thermal capacitance (J/°C)
    % dt: Time step (hours)

    % Calculate the temperature difference delta_T =
    (power_input / R - (Tindoor_prev - T_forecast)) * (dt / C);

    % Update the indoor temperature
    Tindoor = Tindoor_prev +
delta_T; end
```

Listing 5.1. MATLAB code for predictive control algorithm implemention

APPENDIX 2 RESULTS (JANUARY 1 -APRIL 15)

OUMAN Report

Month:	Jaanuar				
Time selection:	01/01/2023 00:00	31/01/2023 00:01	Ok		
Tihase 19	*Start*	*End*	Total		
Heat pump production	128958.0 kWh	132431.0 kWh	3473.0 kWh		
Heat pump operating hours	13034.0 h	13401.0 h	367.0 h		
Heat pump start times	10493.0	10603.0	110.0	-	
Heat pump - Domestic water	35989.0 kWh	37261.0 kWh	1272.0 kWh		
Total thermal energy			3473.00 kWh		
Heat pump heat price [Eur/kWh]			0.04 Eur/kWh		
DHW total	1581.65 m3	1598.74 m3	17.086 m3	29.56 Eur	**100%**
Price for DHW					
Floor 1 & basement electricity			496.4 kWh	89.35 Eur	25.4 %
Floor 2 electricity	23570.2 kWh	23950.1 kWh	379.9 kWh	68.38 Eur	19.4 %
Electricity consumed by HP	38145.1 kWh	39221.1 kWh	1076.0 kWh	193.68 Eur	55.1 %
PV Panel	2128.1 kWh	2130.3 kWh	2.2 kWh	0.40 Eur	0.1 %
Purchased electricity	73474.8 kWh	75427.1 kWh	1952.3 kWh	351.41 Eur	99.9 %
Total consumed electrical energy			1954.50 MWh	351.81 Eur	**100.0 %**
Heatpump COP			3.23		

Saving energy
Creating comfort

Average temperatures for the selected period

Outdoor	Floor 1	Floor 2
-0.47 C	16.91 C	20.74 C

Figure A2.1 January 2023

OUMAN Report

Month:	Veebruar
Time selection:	01/02/2023 ... 00:01 ... 01/03/2023 ... 00:00 ... Ok

Tihase 19	*Start*	*End*	Total		
Heat pump production	132431.0 kWh	135010.0 kWh	2579.0 kWh		
Heat pump operating hours	13401.0 h	13676.0 h	275.0 h		
Heat pump start times	10603.0	10724.0	121.0	-	
Heat pump - Domestic water	37261.0 kWh	38756.0 kWh	1495.0 kWh		
Total thermal energy			2579.00 kWh		
Heat pump heat price [Eur/kWh]			0.04 Eur/kWh		
DHW total	1598.74 m3	1615.76 m3	17.022 m3	29.45 Eur	**100%**
Price for DHW					
Floor 1 & basement electricity			468.2 kWh	84.28 Eur	28.7 %
Floor 2 electricity	23950.2 kWh	24248.6 kWh	298.4 kWh	53.71 Eur	18.3 %
Electricity consumed by HP	39221.1 kWh	40076.6 kWh	855.5 kWh	153.99 Eur	52.5 %
PV Panel	2130.3 kWh	2139.1 kWh	8.8 kWh	1.58 Eur	0.5 %
Purchased electricity	75427.1 kWh	77049.2 kWh	1622.1 kWh	291.98 Eur	99.5 %
Total consumed electrical energy			1630.90 MWh	293.56 Eur	**100.0 %**
Heatpump COP			3.01		

Saving energy
Creating comfort

Average temperatures for the selected period

Outdoor	**Floor 1**	**Floor 2**
-0.02 C	18.05 C	21.41 C

Figure A2.2 February 2023

OUMAN Report

Month:	Märts				
Time selection:	01/03/2023 00:01	15/03/2023 23:59	Ok		
Tihase 19	*Start*	*End*	Total		
Heat pump production	135010.0 kWh	136553.0 kWh	1543.0 kWh		
Heat pump operating hours	13676.0 h	13842.0 h	166.0 h		
Heat pump start times	10724.0	10769.0	45.0	-	
Heat pump - Domestic water	38756.0 kWh	39480.0 kWh	724.0 kWh		
Total thermal energy			1543.00 kWh		
Heat pump heat price [Eur/kWh]			0.04 Eur/kWh		
DHW total	1615.76 m3	1624.11 m3	8.350 m3	14.45 Eur	**100%**
Price for DHW					
Floor 1 & basement electricity			192.1 kWh	34.58 Eur	21.3 %
Floor 2 electricity	24248.9 kWh	24447.5 kWh	198.6 kWh	35.75 Eur	22.0 %
Electricity consumed by HP	40076.6 kWh	40571.2 kWh	494.6 kWh	89.03 Eur	54.8 %
PV Panel	2139.1 kWh	2156.0 kWh	16.9 kWh	3.04 Eur	1.9 %
Purchased electricity	77049.3 kWh	77934.6 kWh	885.3 kWh	159.35 Eur	98.1 %
Total consumed electrical energy			902.20 MWh	162.40 Eur	**100.0 %**
Heatpump COP			3.12		

Saving energy
Creating comfort

Average temperatures for the selected period

Outdoor	Floor 1	Floor 2
0.23 C	17.36 C	21.30 C

Figure A2.3 March 1-15, 2023

OUMAN Report

Month:	Jaanuar
Time selection:	01/01/2024 00:00 31/01/2024 23:59 Ok

Tihase 19	*Start*	*End*	Total		
Heat pump production	152831.0 kWh	157543.0 kWh	4712.0 kWh		
Heat pump operating hours	15449.0 h	15951.0 h	502.0 h		
Heat pump start times	12164.0	12396.0	232.0	-	
Heat pump - Domestic water	45295.0 kWh	46212.0 kWh	917.0 kWh		
Total thermal energy			4712.00 kWh		
Heat pump heat price [Eur/kWh]			0.04 Eur/kWh		
DHW total	1762.54 m3	1775.05 m3	12.509 m3	21.64 Eur	**100%**
Price for DHW					
Floor 1 & basement electricity			408.4 kWh	49.01 Eur	18.5 %
Floor 2 electricity	29016.5 kWh	29394.1 kWh	377.6 kWh	45.31 Eur	17.1 %
Electricity consumed by HP	45555.5 kWh	46971.0 kWh	1415.5 kWh	169.86 Eur	64.2 %
PV Panel	2525.0 kWh	2528.5 kWh	3.5 kWh	0.42 Eur	0.2 %
Purchased electricity	89166.2 kWh	91367.7 kWh	2201.5 kWh	264.18 Eur	99.8 %
Total consumed electrical energy			2205.00 MWh	264.60 Eur	**100.0 %**
Heatpump COP			3.33		

Saving energy
Creating comfort

Average temperatures for the selected period

Outdoor	Floor 1	Floor 2
-5.11 C	6.80 C	20.59 C

Figure A2.4 January 2024

OUMAN Report

Month:	Veebruar				
Time selection:	01/02/2024 00:00	29/02/2024 23:59	Ok		
Tihase 19	*Start*	*End*	Total		
Heat pump production	157543.0 kWh	161107.0 kWh	3564.0 kWh		
Heat pump operating hours	15951.0 h	16335.0 h	384.0 h		
Heat pump start times	12396.0	12643.0	247.0	-	
Heat pump - Domestic water	46212.0 kWh	47237.0 kWh	1025.0 kWh		
Total thermal energy			3564.00 kWh		
Heat pump heat price [Eur/kWh]			0.04 Eur/kWh		
DHW total	1775.05 m3	1789.50 m3	14.453 m3	25.00 Eur	**100%**
Price for DHW					
Floor 1 & basement electricity			432.4 kWh	51.89 Eur	21.9 %
Floor 2 electricity	29394.1 kWh	29827.0 kWh	432.9 kWh	51.95 Eur	21.9 %
Electricity consumed by HP	46971.0 kWh	48068.2 kWh	1097.2 kWh	131.66 Eur	55.6 %
PV Panel	2528.5 kWh	2539.8 kWh	11.3 kWh	1.36 Eur	0.6 %
Purchased electricity	91367.8 kWh	93330.3 kWh	1962.5 kWh	235.50 Eur	99.4 %
Total consumed electrical energy			1973.80 MWh	236.86 Eur	**100.0 %**
Heatpump COP			3.25		

Saving energy
Creating comfort

Average temperatures for the selected period

Outdoor	**Floor 1**	**Floor 2**
-0.27 C	18.28 C	21.17 C

Figure A2.5 February 2024

OUMAN Report

Month:	Märts				
Time selection:	01/03/2024 00:00	15/03/2024 23:59	OK		
Tihase 19	*Start*	*End*	Total		
Heat pump production	161107.0 kWh	162872.0 kWh	1765.0 kWh		
Heat pump operating hours	16335.0 h	16525.0 h	190.0 h		
Heat pump start times	12643.0	12757.0	114.0	-	
Heat pump - Domestic water	47237.0 kWh	47619.0 kWh	382.0 kWh		
Total thermal energy			1765.00 kWh		
Heat pump heat price [Eur/kWh]			0.04 Eur/kWh		
DHW total	1789.50 m3	1795.01 m3	5.505 m3	9.52 Eur	**100%**
Price for DHW					
Floor 1 & basement electricity			157.7 kWh	18.92 Eur	17.7 %
Floor 2 electricity	29827.0 kWh	30012.3 kWh	185.3 kWh	22.24 Eur	20.8 %
Electricity consumed by HP	48068.3 kWh	48601.1 kWh	532.8 kWh	63.94 Eur	59.8 %
PV Panel	2539.8 kWh	2555.5 kWh	15.7 kWh	1.88 Eur	1.8 %
Purchased electricity	93330.3 kWh	94206.1 kWh	875.8 kWh	105.10 Eur	98.2 %
Total consumed electrical energy			891.50 MWh	106.98 Eur	**100.0 %**
Heatpump COP			3.31		

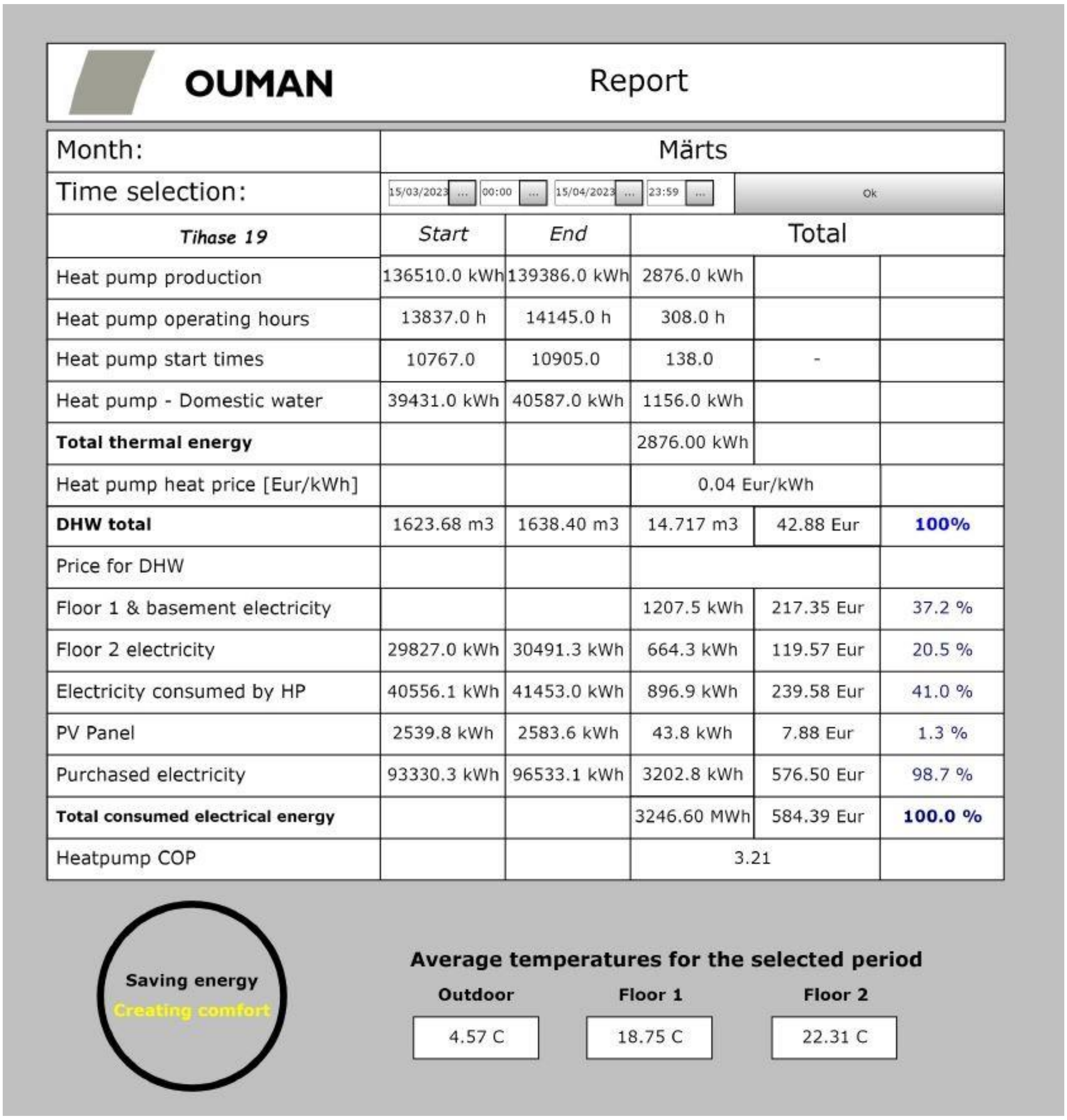
Saving energy
Creating comfort

Average temperatures for the selected period

Outdoor	Floor 1	Floor 2
1.82 C	18.05 C	22.06 C

Figure A2.6 March 1-15, 2024

After reviewing data from March 15 to April 15 in 2023 and 2024, I found significant improvements in terms of cost and comfort. In 2024, the outdoor temperature increased from $4.57^{\circ}C$ to $5.732^{\circ}C$, were both Floor 1 and Floor 2 temperatures increased slightly by 0.31°2$^{\circ}C$ and 0.16°2$^{\circ}C$, respectively, compared to 2023 (Figure A2.8). Additionally, the equivalent energy cost for the heat pump consumption reduced significantly, from 239.58 Euros in 2023 to 131.99 Euros in 2024, marking a 44.86% decrease in energy expenses. A slight increase in outdoor temperature may have contributed to the overall improvements in comfort in 2024.



OUMAN Report

Month:	Märts				
Time selection:	15/03/2023 00:00	15/04/2023 23:59	Ok		
Tihase 19	*Start*	*End*	Total		
Heat pump production	136510.0 kWh	139386.0 kWh	2876.0 kWh		
Heat pump operating hours	13837.0 h	14145.0 h	308.0 h		
Heat pump start times	10767.0	10905.0	138.0	-	
Heat pump - Domestic water	39431.0 kWh	40587.0 kWh	1156.0 kWh		
Total thermal energy			2876.00 kWh		
Heat pump heat price [Eur/kWh]			0.04 Eur/kWh		
DHW total	1623.68 m3	1638.40 m3	14.717 m3	42.88 Eur	**100%**
Price for DHW					
Floor 1 & basement electricity			1207.5 kWh	217.35 Eur	37.2 %
Floor 2 electricity	29827.0 kWh	30491.3 kWh	664.3 kWh	119.57 Eur	20.5 %
Electricity consumed by HP	40556.1 kWh	41453.0 kWh	896.9 kWh	239.58 Eur	41.0 %
PV Panel	2539.8 kWh	2583.6 kWh	43.8 kWh	7.88 Eur	1.3 %
Purchased electricity	93330.3 kWh	96533.1 kWh	3202.8 kWh	576.50 Eur	98.7 %
Total consumed electrical energy			3246.60 MWh	584.39 Eur	**100.0 %**
Heatpump COP			3.21		

Saving energy
Creating comfort

Average temperatures for the selected period

Outdoor	Floor 1	Floor 2
4.57 C	18.75 C	22.31 C

Figure A2.7 March 15- April 15 2023

OUMAN Report

Month:	Märts				
Time selection:	15/03/2024 00:00	15/04/2024 23:59	Ok		
Tihase 19	*Start*	*End*	Total		
Heat pump production	163023.0 kWh	165289.0 kWh	2266.0 kWh		
Heat pump operating hours	16541.0 h	16786.0 h	245.0 h		
Heat pump start times	12769.0	12946.0	177.0	-	
Heat pump - Domestic water	47660.0 kWh	49033.0 kWh	1373.0 kWh		
Total thermal energy			2266.00 kWh		
Heat pump heat price [Eur/kWh]			0.04 Eur/kWh		
DHW total	1795.73 m3	1813.87 m3	18.144 m3	31.39 Eur	**100%**
Price for DHW					
Floor 1 & basement electricity			1004.6 kWh	180.83 Eur	45.4 %
Floor 2 electricity	30032.9 kWh	30481.8 kWh	448.9 kWh	80.80 Eur	20.3 %
Electricity consumed by HP	48647.2 kWh	49380.5 kWh	733.3 kWh	131.99 Eur	33.1 %
PV Panel	2556.0 kWh	2582.4 kWh	26.4 kWh	4.75 Eur	1.2 %
Purchased electricity	94292.4 kWh	96479.2 kWh	2186.8 kWh	393.62 Eur	98.8 %
Total consumed electrical energy			2213.20 MWh	398.38 Eur	**100.0 %**
Heatpump COP			3.09		

Saving energy
Creating comfort

Average temperatures for the selected period

Outdoor	Floor 1	Floor 2
5.73 C	19.06 C	22.47 C

Figure A2.8 March 15- April 15 2024

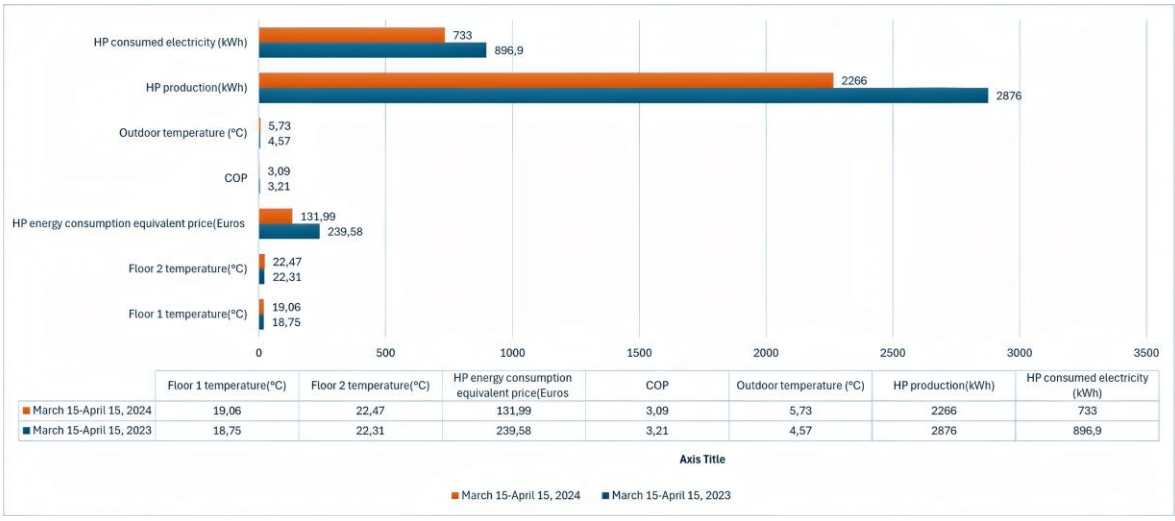


Figure A2.9 Heating system characteristics March 15- April 15

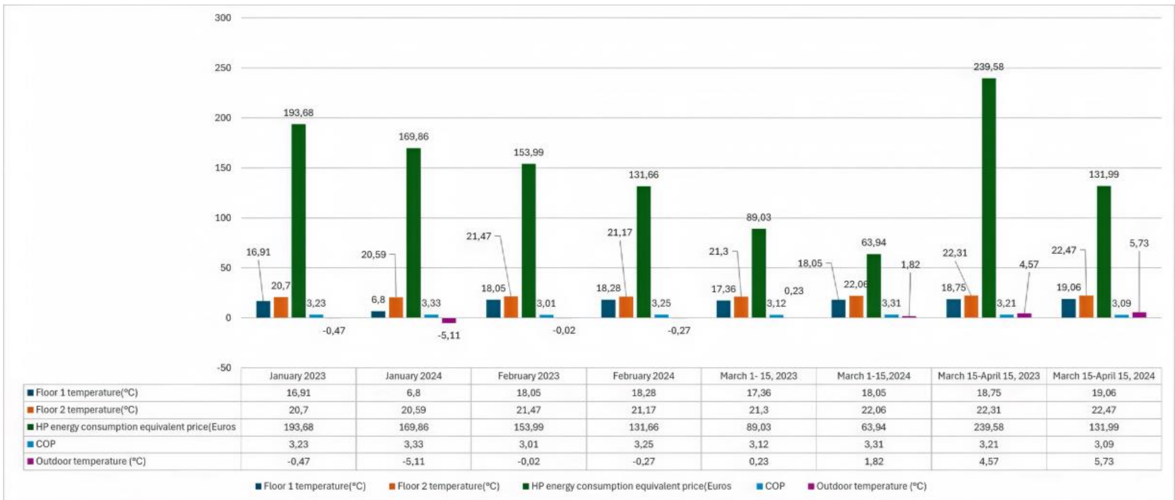


Figure A2.10 Overall system characteristics for a simulation period until 15th of April

Compared to previous months, there was a considerably higher outdoor temperature during this period. In 2023, from March 15 to April 15, the heat pump consumption was 2876kWh, while during the same period in 2024, it decreased to 2266kWh, indicating a significant reduction in energy usage by 610kWh or approximately 21.22%. This demonstrates that our system is responsive to changing outdoor temperatures and can anticipate and prepare the building for periods of high prices and cold weather in the future (Figure A2.9) (Figure A2.10).

APPENDIX 3 ALGORITHM TESTING AND VALIDATION

The proposed algorithm is executed in the BA Ouflex tool and tested for various scenarios. The solution prioritizes user comfort by incorporating weather forecasts and hourly electricity prices. Based on these two factors, the algorithm develops a suitable modulated room temperature.

- **Scenario 1**: If the forecasted temperature is lower than current outdoor temperature, and hourly energy prices are falling (HEP<LP), RH will be ON until room temperature reaches the maximum room set point. Once this temperature is reached, the RH will be switched off, and priority will shift to DHW until the DHW temperature reaches its maximum set point value.
- **Scenario 2:** If the forecasted temperature is higher than current outdoor temperature, and hourly energy prices falling (HEP<LP), RH will be ON until room temperature reaches the modulated room set point. Once this temperature is reached, the RH will be switched off, and priority will shift to DHW until the DHW temperature reaches its maximum set point value.
- **Scenario 3**: If the forecasted temperature is lower than current outdoor temperature and hourly energy prices are rising (HEP>LP), RH will be ON until the room temperature reaches the modulated room set point. Once this temperature is reached, the RH will be switched off and HP will be switched off.
- **Scenario 4**: If the forecasted temperature exceeds current outdoor temperature and hourly energy prices rising (HEP>LP), RH will be ON until the room temperature reaches the modulated room set point. Once this Temperature is reached, the RH will be switched off and HP will be switched off.

To sum up, this chapter re-evaluates the algorithm's conditions and its validation using the Ouflex simulation tool. All the above scenarios are represented in Figure A3.1, Figure A3.2, Figure A3.3, Figure A3.4, Figure A3.5, Figure A3.6, Figure A3.7, Figure A3.8.

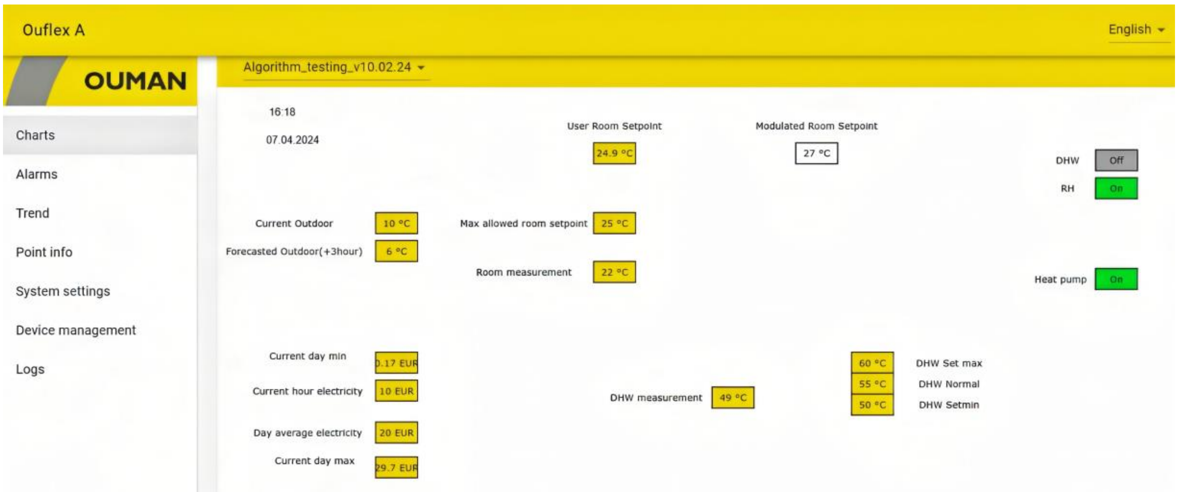


Figure A3.1 Scenario 1 RH during low-price hours anticipating cold hours

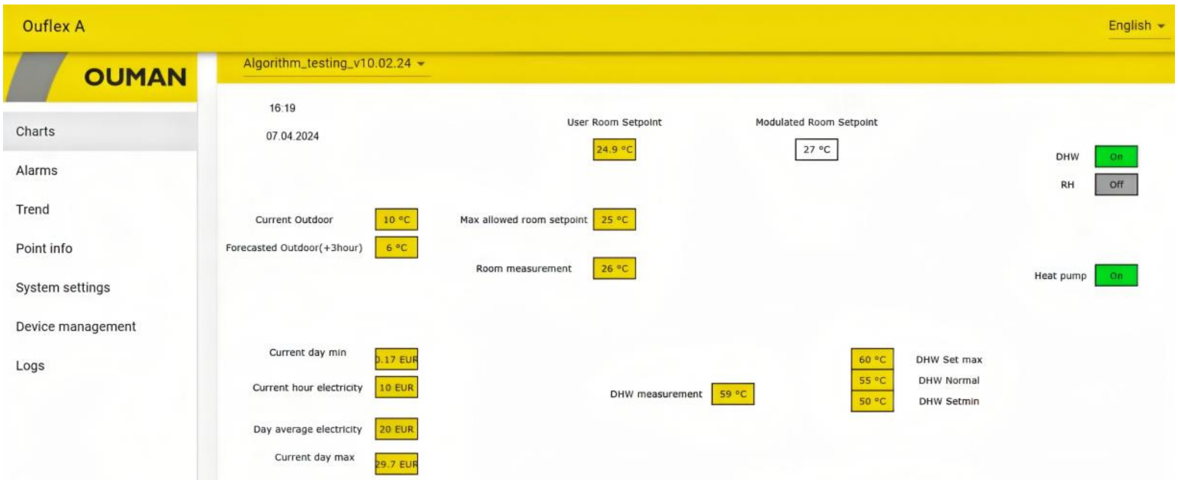


Figure A3.2 Scenario 1 DHW during low-price hours anticipating cold hours

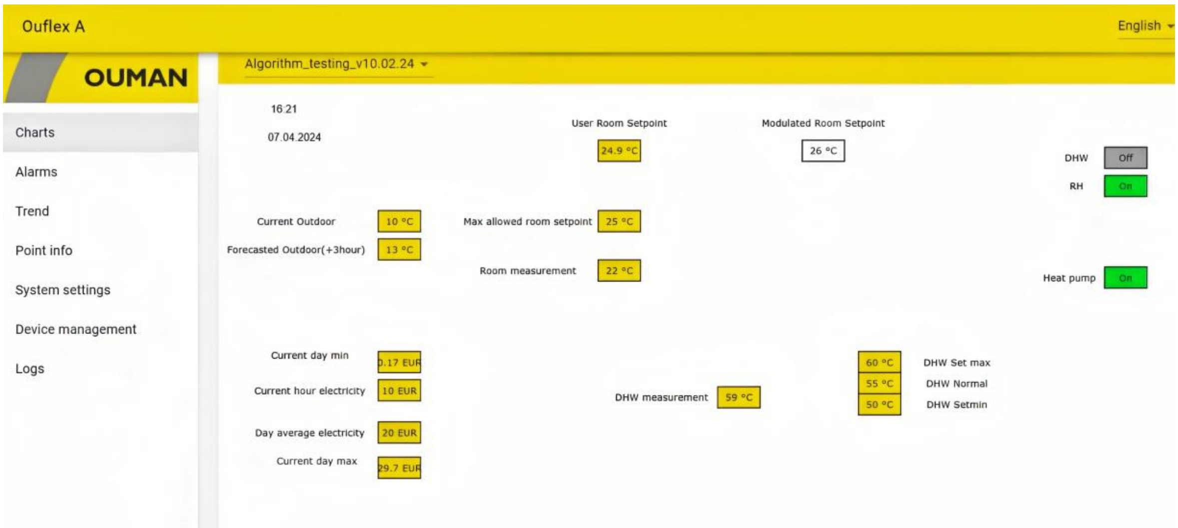


Figure A3.3 Scenario 2 RH during low-price hours anticipating warm hours

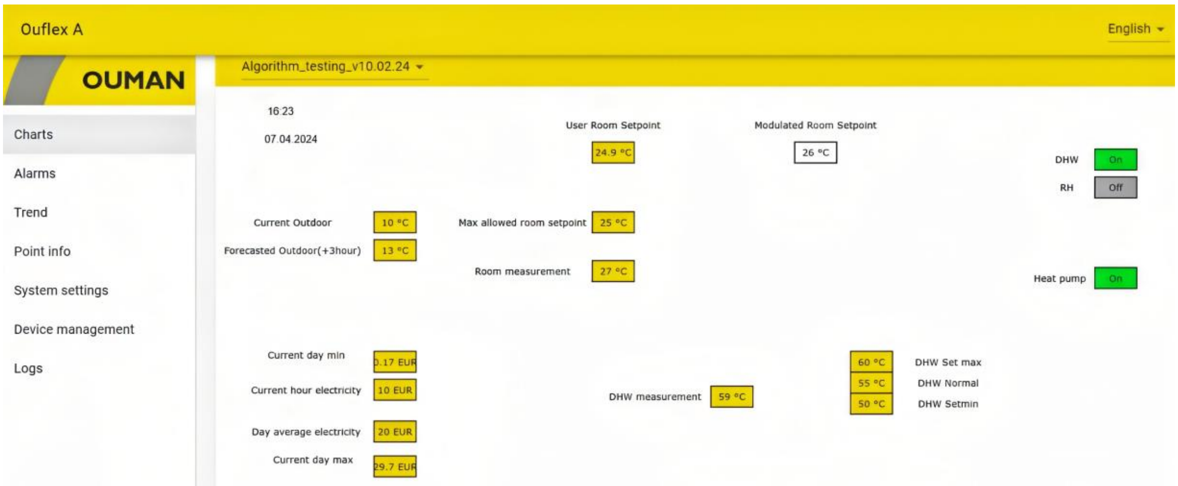


Figure A3.4 Scenario 2 DHW heating during low-price hours anticipating warm hours

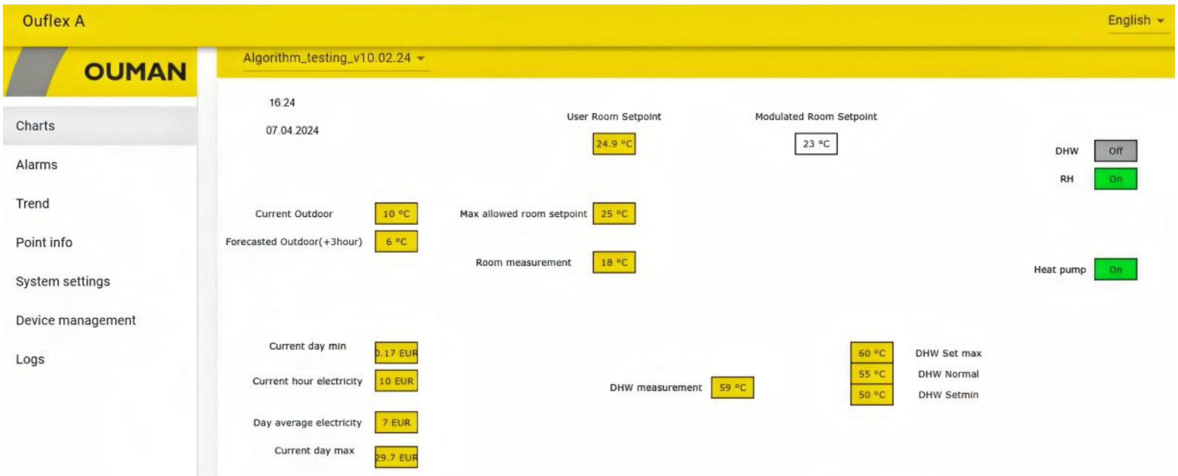


Figure A3.5 Scenario 3 RH during high-price hours anticipating cold hours

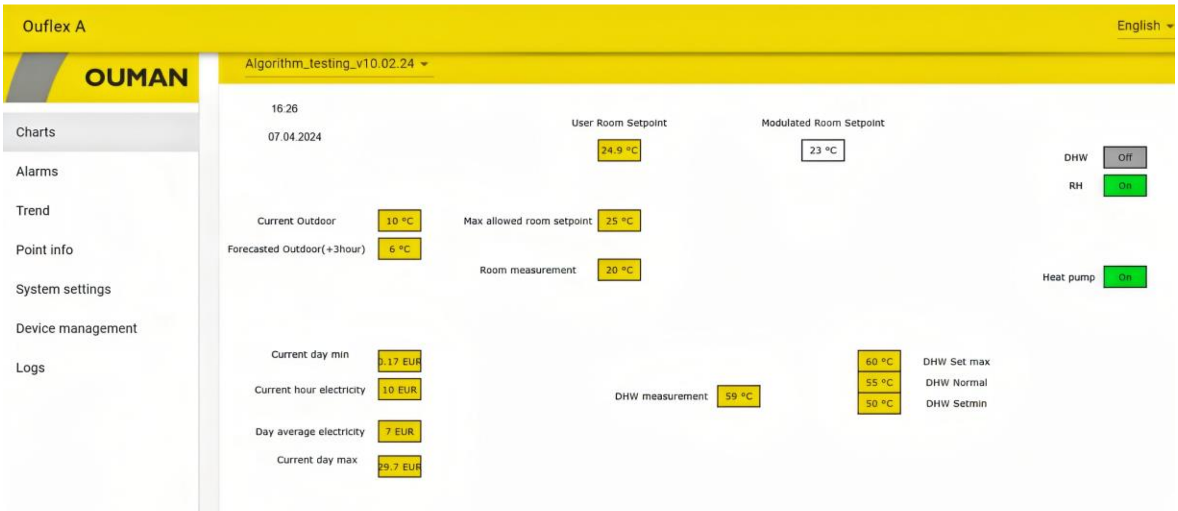


Figure A3.6 Scenario 3 DHW during high-price hours anticipating cold hours

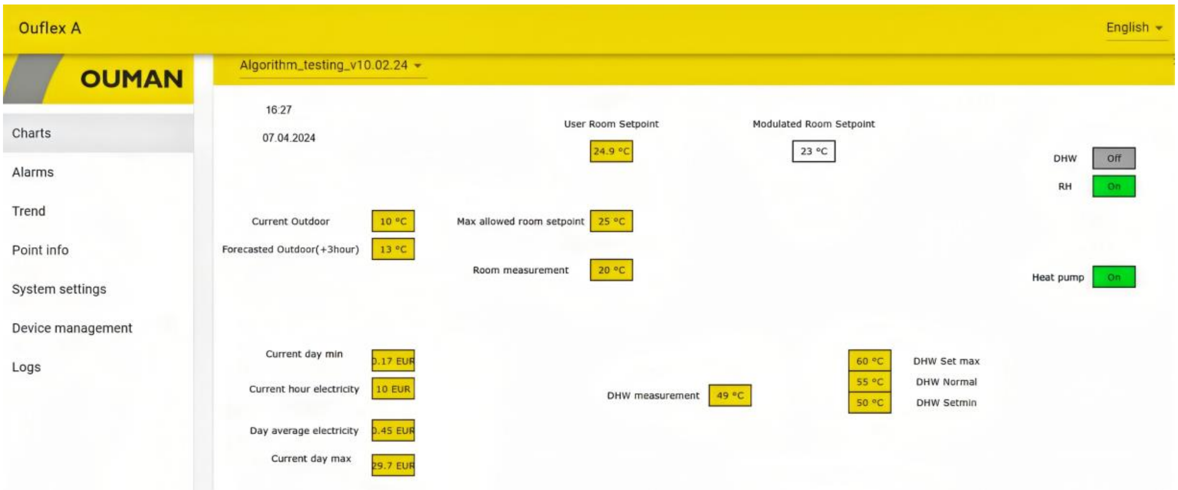


Figure A3.7 Scenario 4 RH during high-price hours anticipating warm hours

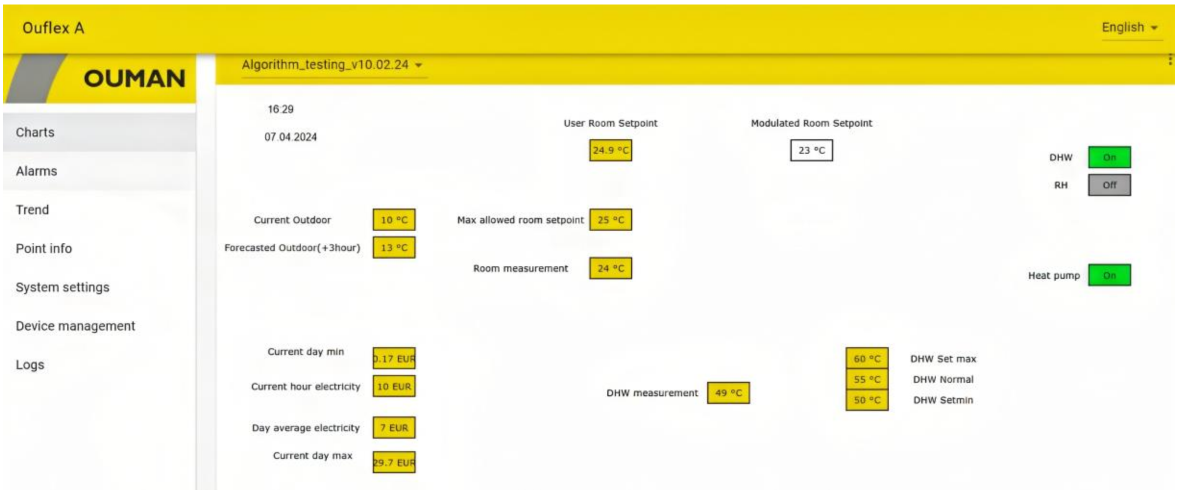


Figure A3.8 Scenario 4 DHW during high-price hours anticipating warm hours

This chapter extensively examines the benchmarking method and outcomes, with a specific emphasis on the operation and performance of the controller. Detailed discussions regarding the system's design and model, particularly about houses and controllers, focus on potential challenges. The implementation of the predictive approach in consumer products is explored, and specific aspects of the feasibility of real-world implementation are discussed. The conclusion is derived from evaluating problems, methodology, and results. Additionally, suggestions for future work are incorporated.

Impact of varying COP on predictive controller

The significance of keeping a consistent COP has pros and cons for controller performance. While it can sometimes cut costs compared to using a heat curve controller, using it in worst-case scenarios may mean less comfort for occupants and higher electricity bills. It is crucial to consider these advantages and disadvantages carefully when deciding whether to adopt a constant COP approach in HVAC systems. In direct comparison with a predictive controller, the constant COP approach consistently performs poorly. The intention is to concentrate power consumption during periods of low electricity prices. However, achieving better comfort in households may demand power consumption even during high-price hours. Traditional control methods yield more uneven power consumption patterns, favoring a significant amount of energy at once or not when needed. The COP is highest for low-power inputs and lowest for high-power inputs. From a COP perspective, it is always beneficial to maintain a low but steady power consumption.

Importance of radiation forecasting in prediction

A model considering global radiation based on sunshine and cloudiness, along with time of day and day of the year, has limitations. The cloudiness model could be more reliable, leading to occasional over- or underestimation, especially in winter. While excluding the radiation model improves simplicity, it may sacrifice accuracy, and including it increases complexity, requiring a careful balance between accuracy and model simplicity. Considering the importance of better heating comfort in buildings, it is decided to exclude the radiation model from the prediction.

Dimension of heating system

The thesis employed a COP model based on a real-world heat pump installed in the targeted building. This building has a GSHP with a 10-kW capacity. The recommended 10 kW heat pump effectively covers the outside temperature range considered in the analyzed cases. Specifically, a 10-kW heat pump can handle temperatures ranging from approximately -20 to 12 degrees Celsius without burst heating, as it would not operate at its lowest capacity. The fact that the heat pump predominantly operates at low power implies that the COP is generally favorable.

Comfort vs Cost balance

In heating systems, there is a balance between cost and comfort. It would help if you often decided how much you are willing to spend to keep warm while ensuring occupants are still comfortable. This trade-off depends on comfort, temperature range, insulation, and energy efficiency. Adjusting these parameters, such as lowering the thermostat, enhancing insulation, or upgrading to a more energy-efficient system, allows you to finetune this balance and strike the right compromise between cost savings and maintaining a comfortable environment.

Weight

The weight α is like a tuning knob for the predictive controller in heating systems. Consumers can choose its value based on their preferences. A larger α emphasizes keeping the comfort level high, while a smaller α prioritizes saving money on electricity. If α is set to 0, the user wants to minimize electricity costs as much as possible. In this scenario, the heat pump could be turned off entirely when it is unnecessary for comfort, emphasizing cost savings over maintaining a specific level of warmth.

Other Constraints

User preference plays a crucial role when designing constraints for heating system models. Keeping the indoor temperature within or close to the comfort range is entirely up to the user. Some users prioritize staying within the comfort range regardless of cost considerations. However, the spot price exceeds a specific limit. In that case, an opportunity arises to temporarily raise the indoor temperature above the comfort range or allow it to drop below, aiming to save on electricity costs. The most straightforward approach involves increasing the comfort range by accepting higher prices. In this thesis, a slightly higher priority is given to maximizing comfort over energy cost.

Controller implementation feasibility

This thesis has examined the theoretical and practical feasibility of employing a prediction controller for heat pump control through simulations on the Ouflex tool. Implementing the controller on a heat pump has revealed additional challenges, mainly related to the complex house modeling process, particularly related to the complex house modeling process. While identifying a heating system model for a GSHP is relatively straightforward and has sufficient data, challenges arise due to variations in power output to the heat pump at different flow temperatures depending on the size of the radiator system.

APPENDIX 5 – ADDITIONAL GRAPHICAL MATERIALS

Figure A5.1 Floor1 plan

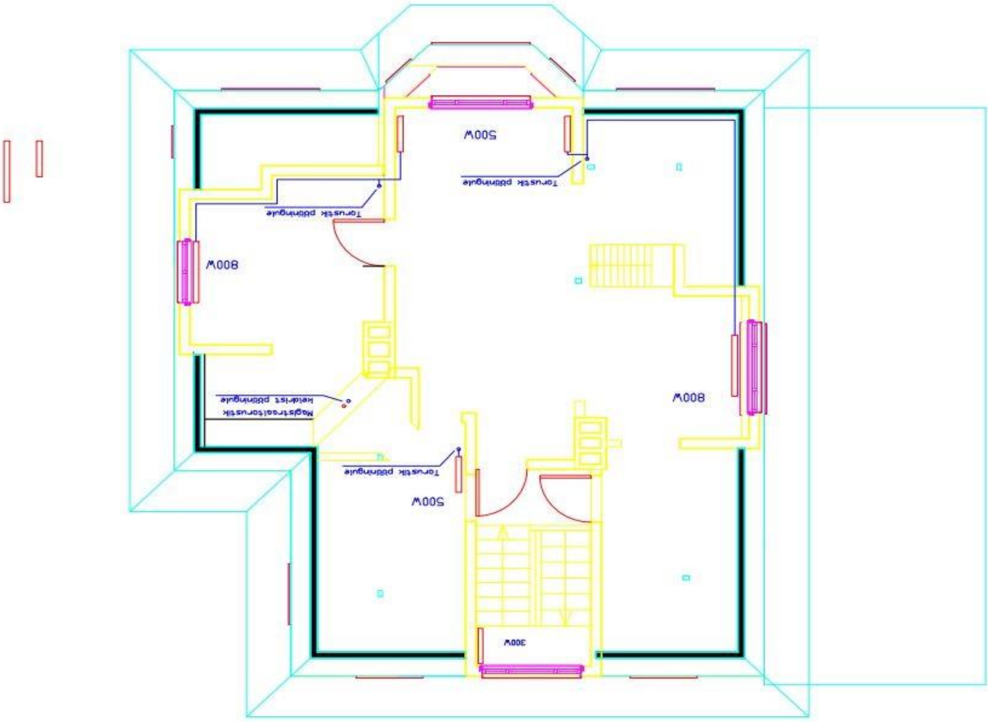


Figure A5.2 Floor2 layout

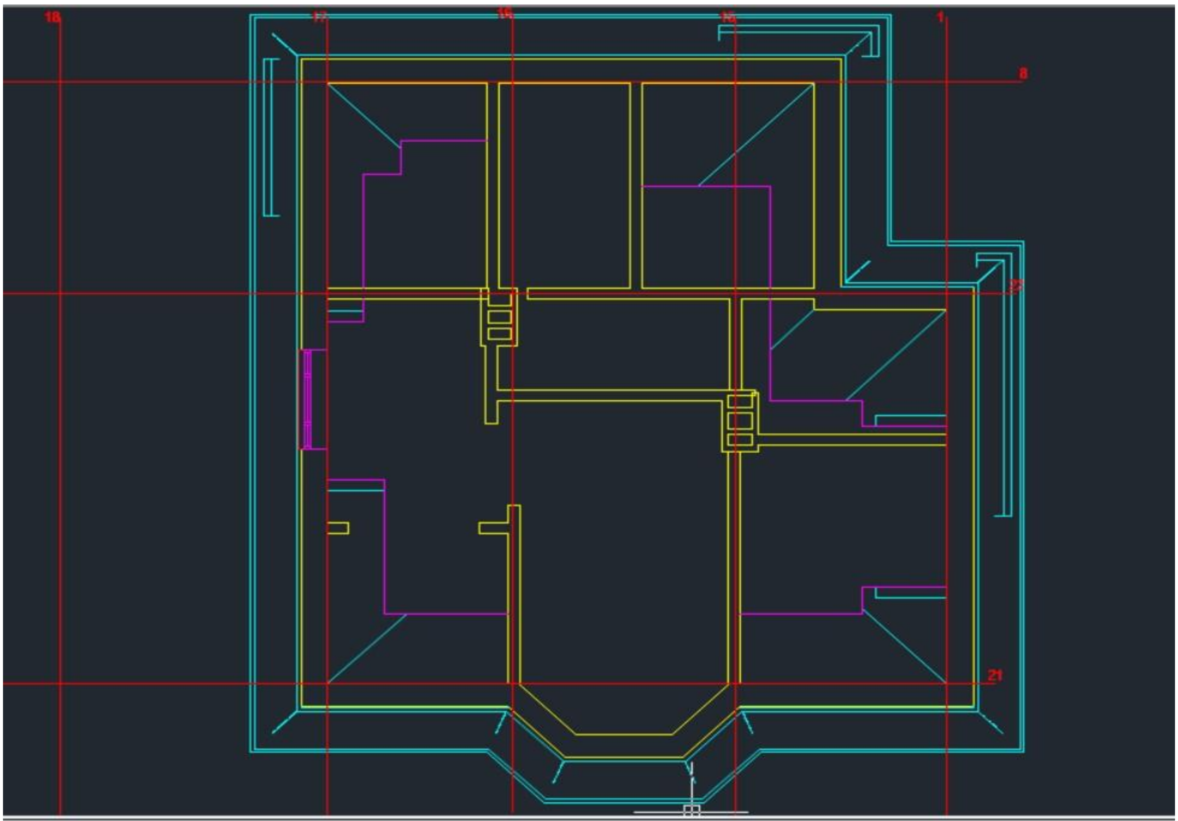


Figure A5.3 Ceiling plan

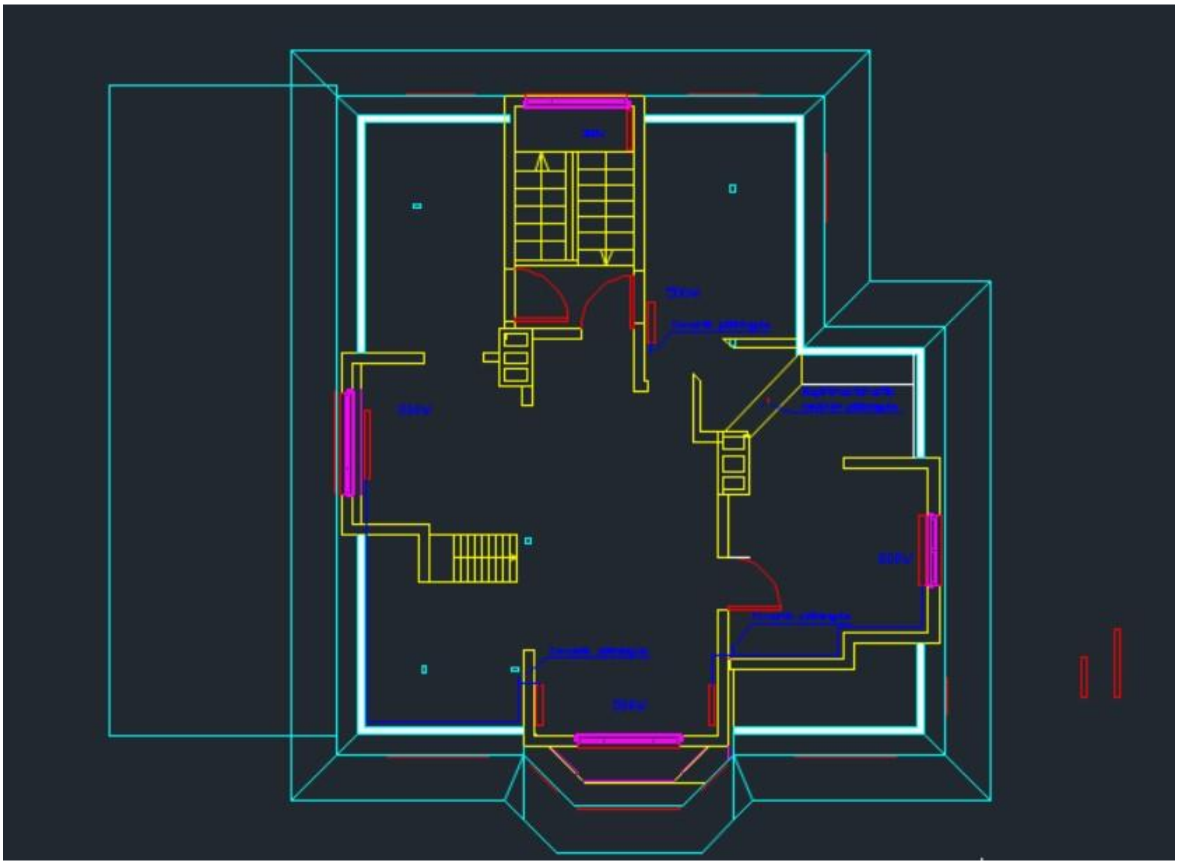


Figure A5.4 Overall house schematics

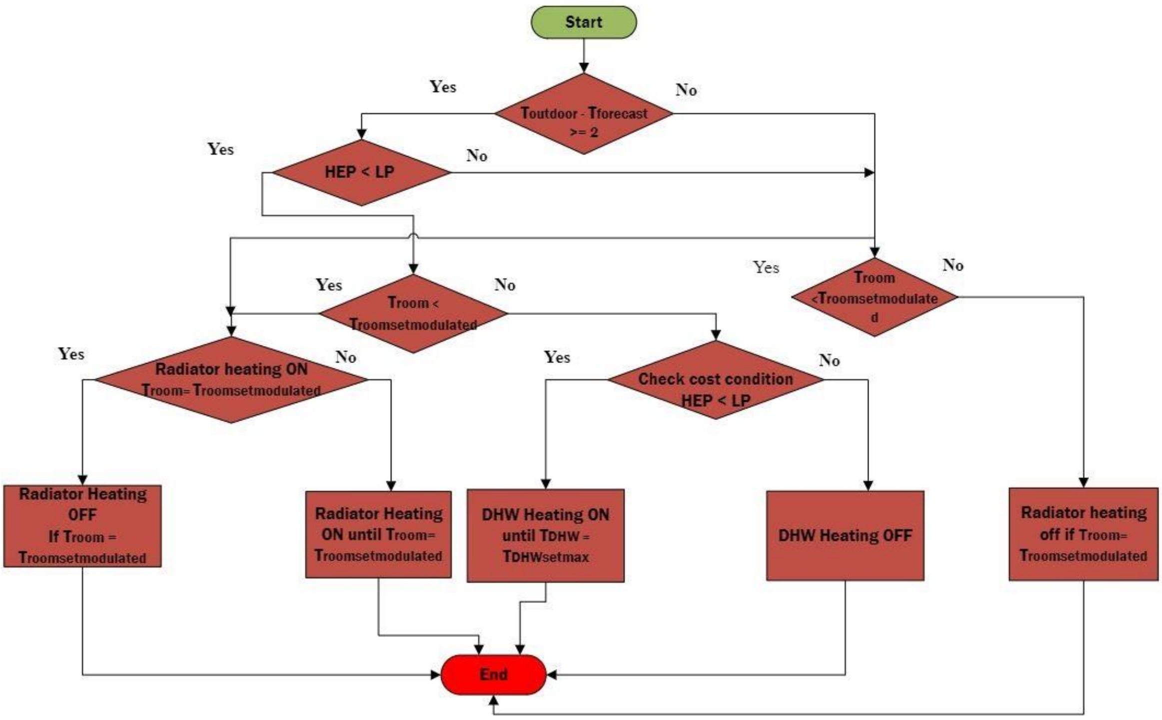


Figure A5.5 Algorithm flow chart

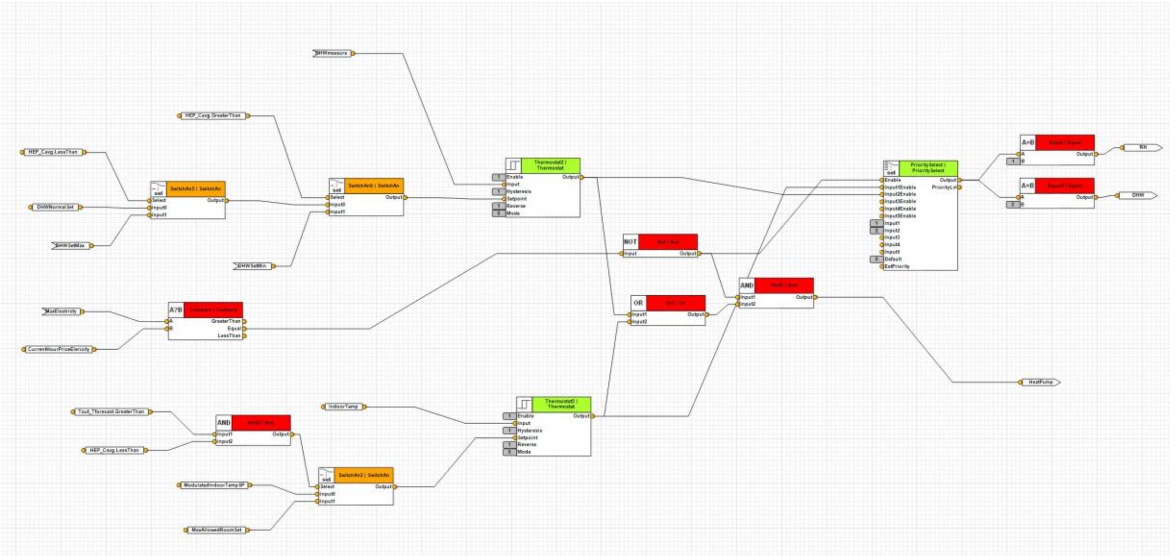


Figure A5.6 Application

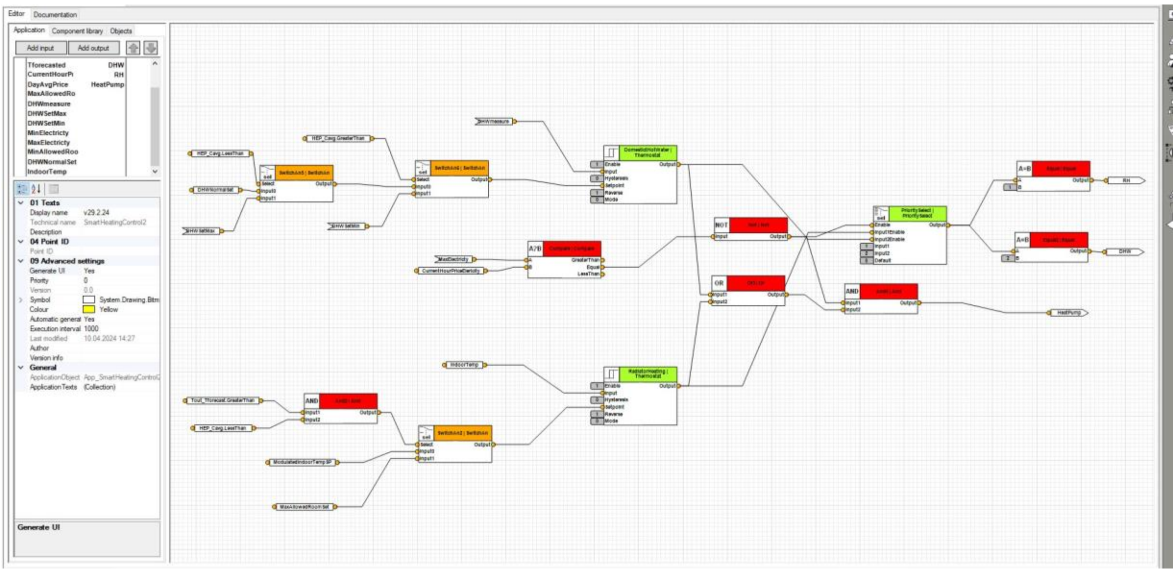


Figure A5.7 Set point modulation

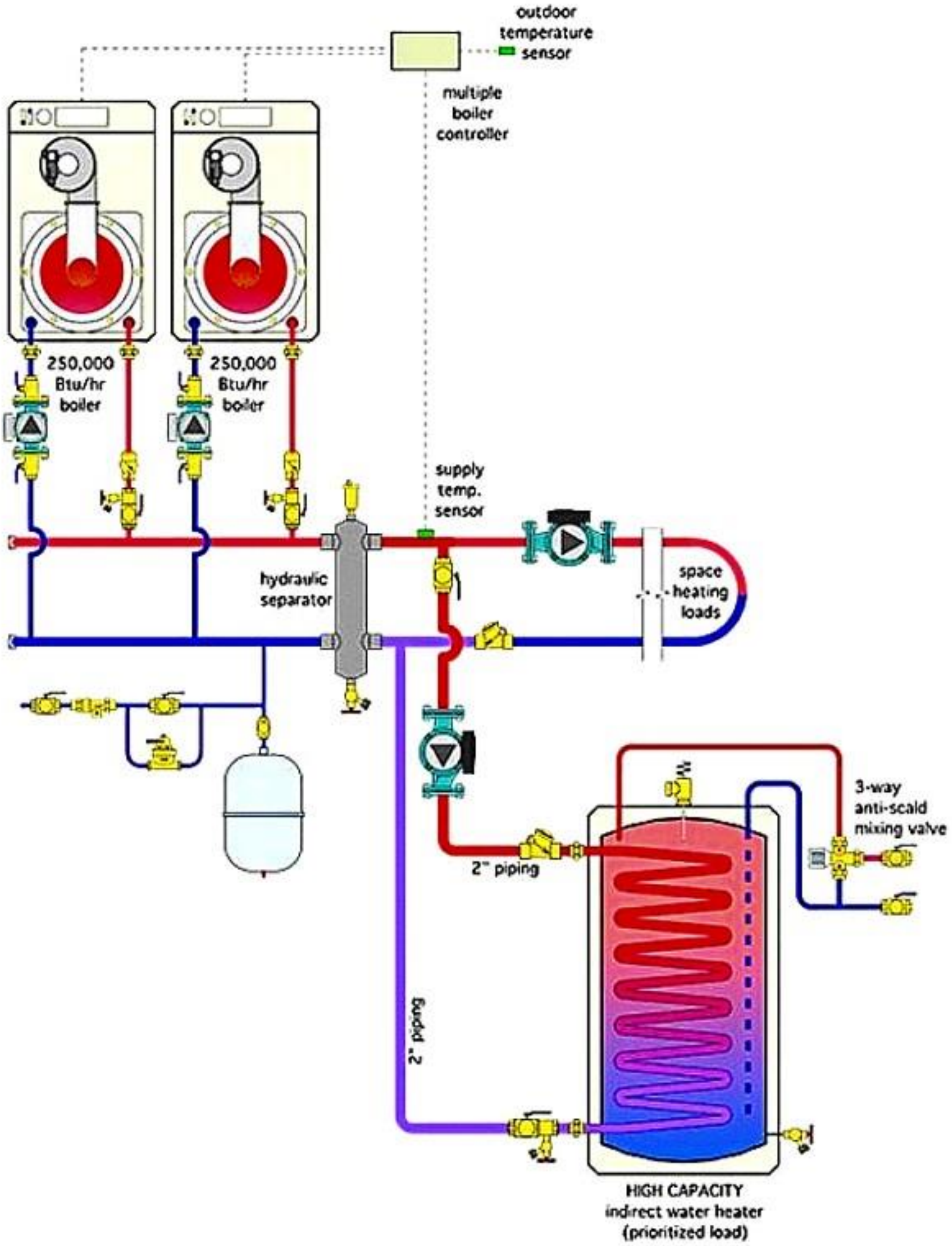


Figure A5.8 Typical DHW system[13]

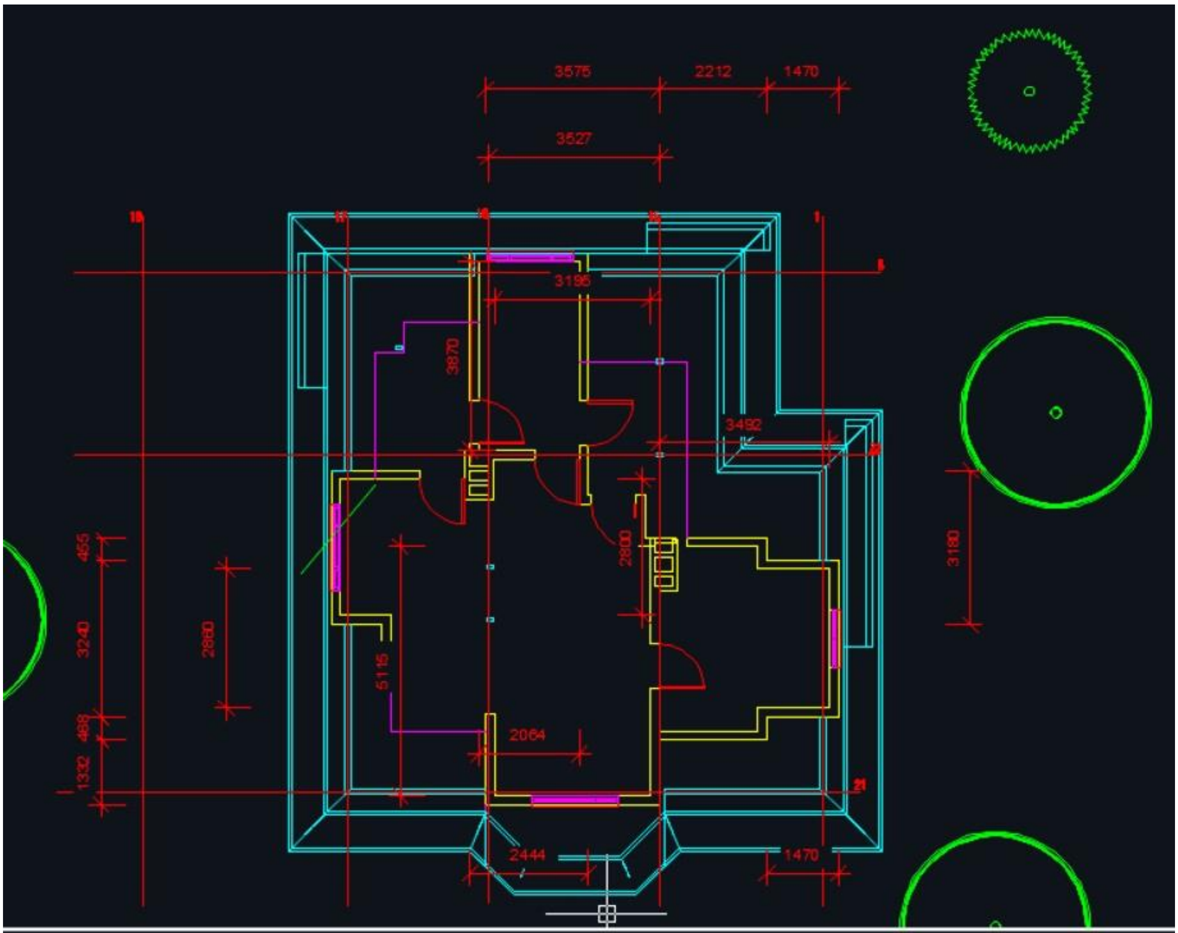


Figure A5.9 Floor2 layout with an area of each zone and window.

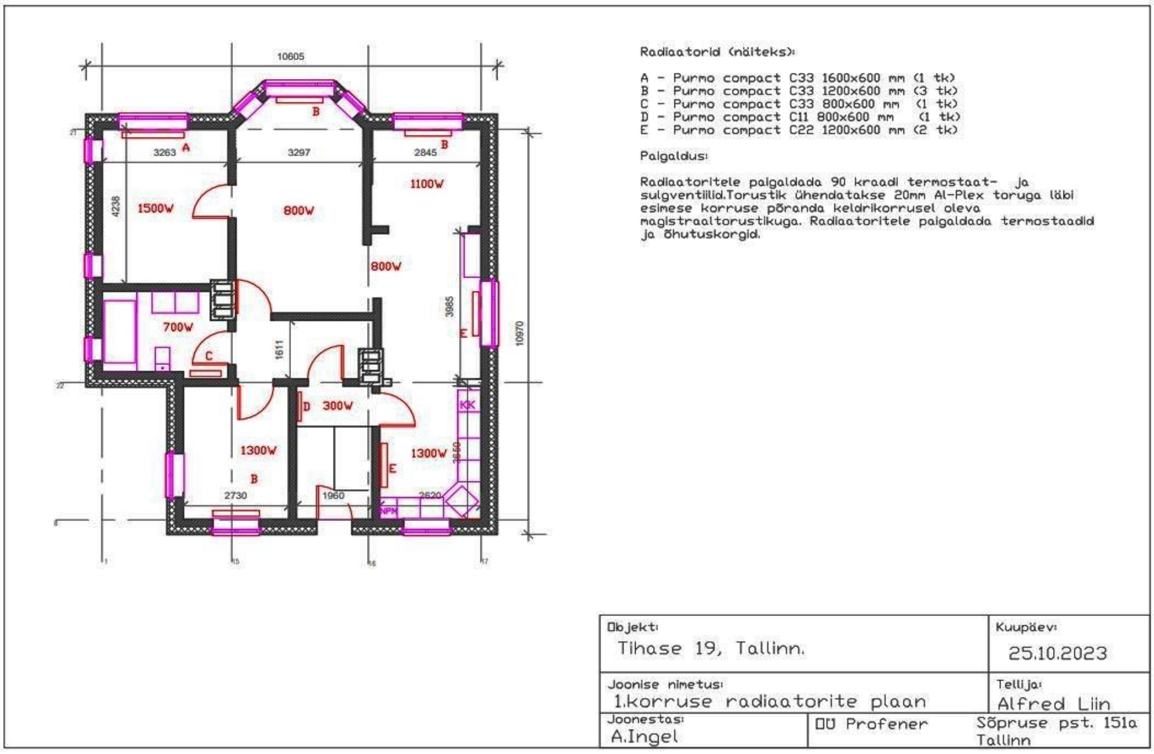


Figure A5.10 Floor1 layout with an area of each zone and window