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Article

Simultaneous Energy Optimization of Heating Systems by Multi-Zone Predictive Control—Application to a Residential Building

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Abstract: Climate change has made energy management a global priority. In France, the Grenelle Environment has set very ambitious progress targets for positive-energy buildings, particularly in terms of reducing and managing energy consumption. However, effective energy management in multi-zone buildings presents significant challenges, particularly when considering the inter-zone dynamics and heat transfer. This study examines multi-zone heating control, using a data-driven model for predictive indoor temperature modeling in intelligent buildings taking into account the influence of interconnected adjacent zones. The research methodology uses dynamic thermal simulation, parallel predictive models based on multiple linear regressions, and a multi-objective non-dominated sorting genetic algorithm II (NSGA-II) for the optimization process, which evaluates various generated heating strategies. This research introduces an approach to improve building energy efficiency by considering inter-zone dynamics and reducing heating-related energy consumption compared to a conventional heating strategy. By applying this model predictive control on a simulated case, a reduction in energy consumption due to heating is observed while respecting thermal comfort. This work contributes by implementing a method that independently controls temperatures in different building zones simultaneously while applying distinct constraints to each zone. This approach empowers occupants to manage heating consumption based on their preferences, ensuring personalized comfort. In addition, a comparison was made using a model that did not account for inter-zone interactions. This comparison demonstrates that incorporating these interactions into the predictive model enhances the effectiveness of the model predictive control approach. The multi-zone approach was also validated experimentally by using real experimental data, demonstrating significant reductions in energy consumption.

Keywords: energy efficiency; thermal comfort; model predictive control; inter-zone thermal interactions; multiple linear regression; genetic algorithm



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1. Introduction

Due to global socio-economic developments, growing environmental concerns, and limited land resources, managing energy consumption in buildings is becoming a major priority in today's energy transition [1,2]. Population growth, increased urbanization, and growing demand for occupant comfort in buildings all point to a rapid rise in energy consumption [3]. Worldwide, buildings account for 30% of total energy consumption [4]. In France, the building sector is responsible for around 44% of total final energy consumption [5]. More than half of this energy is used by heating, ventilation, and air-conditioning (HVAC) systems [6–8]. At the same time, residents have increasingly demanded improved

indoor thermal comfort, while seeking to reduce energy consumption and CO₂ emissions [9]. Recently, advanced control solutions have been developed to create sustainable buildings, subsequently improving performance during building operation [10], such as the application of intelligent energy management strategies. In this context, the model predictive control (MPC) aims to maximize energy efficiency or minimize costs while meeting comfort requirements. MPC can handle a variety of constraints, multivariable models, and operational objectives [7,11]. MPC is an optimization-based control process that uses dynamic building models and forecasts. It anticipates disturbances such as weather and occupancy [12] in order to avoid overconsumption and discomfort by exploiting the thermal inertia of the building and it proved to have enormous potential in the field of building heating control [12]. Numerous studies have been carried out to minimize energy consumption in buildings while ensuring thermal comfort. Hazyuk et al. presented a methodology for evaluating controller performance under normal conditions, demonstrating that the MPC consistently outperforms PID controllers in building energy management, reducing occupant discomfort by up to 97%, energy consumption by up to 18%, and the number of heat pump on-off cycles by up to 78% [13]. Taheri et al. optimized installations in a commercial building in the USA, implementing an MPC-based predictive control framework for the HVAC system, with significant energy savings of up to 19.21% [12]. T. Hilliard et al. implemented an experimental trial of MPC-based predictive control over a four-month period, achieving a 29% reduction in HVAC electrical energy and a 63% reduction in thermal energy compared to previous years for the same period [14]. Table 1 presents an overview of recent publications, highlighting their key findings, limitations, and proposed solutions.

To develop MPCs, it is generally necessary to model the building in order to assess its performance. In research, system modeling approaches fall into three categories: white-box, grey-box, and black-box. White-box models are based on a complete understanding of the physical laws and mechanisms underlying the system. They use mathematical equations to accurately describe physical phenomena, such as heat exchange in a building, providing complete transparency into how they work [15]. Grey-box models are models that require less learning data and less knowledge of physical phenomena [16,17]. Black-box models are entirely data-driven and require no prior knowledge of physical mechanisms. This makes black-box or data-driven predictive control models an alternative to physics-based models, as they do not require knowledge of the physical laws of the system [6], thus reducing complexity and computing time.

AI and machine learning have been widely applied in the literature to conduct energy-saving studies in recent years [18–21], due to their ease of use and adaptability for quickly searching for optimal solutions [22]. A significant advantage of AI-based approaches is their superiority in solving non-linear problems with large datasets [23]. They are considered adaptive, self-organizing, real-time learning networks, making it easy to build network models. These methods are capable of predicting the indoor temperature of a building with good accuracy [24]. For example, D’Amico et al. applied neural networks to analyze a portfolio of non-residential properties in Italy, effectively predicting the heating and cooling loads of the buildings [25]. Yalcintas et al. developed a model using machine learning to estimate energy savings from equipment retrofit projects, leveraging energy-consumption data collected before and after retrofitting [26]. Magnier et al. integrated a neural network with a multi-objective genetic algorithm (NSGA-II) to enhance thermal comfort and energy efficiency in a building. Through their multi-objective approach, they uncovered a variety of potential configurations, presenting multiple trade-offs between thermal comfort and energy consumption [27].

Table 1. An overview of recent publications, presenting their key findings, limitations, and proposed solutions.

Reference	Key Findings	Limitations	Solutions
[12]	<ul style="list-style-type: none"> Implementation of a universally applicable MPC model in a commercial building Significant improvement in thermal comfort Energy consumption reduction of 12.83%, 19.21%, and 14.98% for 3 different strategies, respectively 	<ul style="list-style-type: none"> Inflexibility of traditional HVAC system High upfront costs of advanced control system Lack of real-world demonstrations 	<ul style="list-style-type: none"> Implementation of cloud-based microservices based on three strategies: <ol style="list-style-type: none"> Proportional integral (PI)+Preheating MPC Occupancy-based control
[2]	<ul style="list-style-type: none"> Importance of sensitivity analysis, particularly the Morris method, in identifying key parameters that affect building energy performance Efficient handling of multiple parameters with providing interpretable results for optimizing heating, cooling, and total thermal loads 	<ul style="list-style-type: none"> Data availability issues Limited input factors and no consideration of interactions between them 	<ul style="list-style-type: none"> Employment of global sensitivity analysis (GSA) methods to assess a broader range of parameters and account for correlations between inputs Implementation of sufficient simulations to guarantee convergence of results Incorporation of real-world conditions for more accurate BEMs
[28]	<ul style="list-style-type: none"> Energy savings of 8.8% and a 23.4% reduction in carbon footprint for a representative winter test day 	<ul style="list-style-type: none"> Higher computational complexity in the implementation of the MAC system, compared to simpler control systems, potentially posing challenges for real-time applications 	<ul style="list-style-type: none"> Use of a heuristic search based on a genetic algorithm for local agents and an ILP model for the coordinator problem, allowing for optimization of control sequences and addressing the complexity of multi-zone control while maintaining flexibility
[29]	<ul style="list-style-type: none"> A reduction of total energy consumption by up to 8.8% compared to conventional robust MPC approaches while satisfying thermal constraints more effectively 	<ul style="list-style-type: none"> Complexity of hybrid physics-based and data-driven approaches and requirement of computational resources and expertise for implementation 	<ul style="list-style-type: none"> Employment of an affine disturbance feedback rule, providing a tractable approximation for the robust MPC problem and enhancing feasibility and stability
[15]	<ul style="list-style-type: none"> Lumped building modeling approach for MPC in multi-zone buildings demonstrating good control performance, achieving energy savings of approximately 8.6% compared to feedback control 	<ul style="list-style-type: none"> HVAC efficiency improvements considered a saturated field, with limited additional potential for energy savings Challenges of estimating parameters in grey-box models due to non-linear optimization, making the modeling phase costly (up to 70% of total costs) 	<ul style="list-style-type: none"> Development of decentralized MPC approaches, like the lumped model, reducing computational complexity and engineering costs while maintaining effective control performance Combination of grey-box models with machine learning improving prediction accuracy for specific thermal zones and streamlining the control process
[11]	<ul style="list-style-type: none"> Incorporation of reference models into Bayesian optimization (BO) for MPC tuning, reducing the computational time by 28% from 14 iterations (28 h) to 3 iterations Use of a reference model, allowing BO to focus on learning residual errors and improving the search for optimal solutions 	<ul style="list-style-type: none"> Sensitivity to initials conditions, which can slow down the optimization process Lack of convergence guarantees, which can hinder the effectiveness of the framework 	<ul style="list-style-type: none"> Use of low-fidelity, closed-loop simulations to create a reference model for BO Focus on residual error learning to efficiently navigate the parameter space

Table 1. Cont.

Reference	Key Findings	Limitations	Solutions
[30]	<ul style="list-style-type: none"> A reduction in overheating and underheating periods, enhancing overall energy consumption and improving thermal comfort by up to 43% compared to conventional methods 	<ul style="list-style-type: none"> Accuracy of the predictive model is determined by the collection and pre-processing of measured and forecasted data, highlighting the importance of data quality and granularity in achieving reliable results 	<ul style="list-style-type: none"> Enhancing data collection systems to ensure high-quality and detailed historical data Development of adaptive algorithms that can adjust predictions based on real-time data, helping to mitigate the effects of sudden external changes
[25]	<ul style="list-style-type: none"> Implementation of artificial neural networks (ANNs) provides a reliable, efficient, and user-friendly method to predict heating and cooling loads in buildings with minimal input data and computational cost, validated through error analysis and ASHRAE performance criteria 	<ul style="list-style-type: none"> Accuracy of the neural network model, highly dependent on the quality and availability of input data, which may limit its effectiveness in cases with insufficient or poor-quality data Lower computational costs compared to traditional methods, which may still involve some trade-offs in terms of precision when compared to more detailed physical modeling approaches 	<ul style="list-style-type: none"> Expansion of the dataset to include a broader range of building types and geographical regions, enhancing the model's generalizability and accuracy Combination of the ANN-based approach with other modeling tools, helping to balance the trade-off between computational efficiency and detailed accuracy when necessary
[31]	<ul style="list-style-type: none"> MPC-GA's achievement of over 50% reduction in energy consumption and 80% reduction in discomfort compared to traditional rule-based control (RBC) systems 	<ul style="list-style-type: none"> Complexity of accurate modeling Time-consuming and costly nature of building accurate models of the physical system dynamics 	<ul style="list-style-type: none"> Use of neural network models named CAM-LSTM Development of accessible tools that facilitate the modeling process and reduce the time and cost associated with system dynamics modeling
[32]	<ul style="list-style-type: none"> Reduction in computational costs is achieved through the hybrid approach, which maintains prediction errors below 0.52% Results demonstrate that replacing one-third of the network leads to a 9% reduction in the computational time required by a physics-based MPC 	<ul style="list-style-type: none"> Traditional dynamic models used in MPC for district heating networks result in high computational costs, making them impractical for real-time control in large-scale applications 	<ul style="list-style-type: none"> A novel hybrid MPC approach has been proposed that integrates dynamic simulation with machine learning, utilizing neural network models to replicate the physical behavior of substation clusters and significantly reduce computational costs

In the literature, implementations of MPC studies using a black-box model on multi-zone buildings have increased within the last few years. Huang et al. applied an artificial neural network (ANN)-based modeling approach for multi-zone building, considering several factors such as mechanical cooling, ventilation, weather conditions, and heat transfer between the adjacent zones and achieving more accurate prediction results than a single-zone model [33]. Moreover, a data-driven robust MPC model was developed by Hu et al. for a multi-zone building considering thermal comfort and uncertain weather forecast errors. They found reductions of up to 8.8% in total energy consumption compared to conventional robust MPC approaches [29]. Zeng et al. investigate the energy savings of a multi-zone HVAC system by applying a data-driven approach while simultaneously controlling the temperature and humidity. Results showed that considering humidity constraints limited the potential of saving HVAC energy [34]. Mtibaa et al. developed an online data-driven MPC control via genetic algorithm (MPC-GA) allowing the optimal operation of the heating, ventilation, and air conditioning system, which was experimentally validated in a multi-zone retail building. The results showed that the MPC-GA system used was leading to more than 50% and 80% reduction in energy consumption and discomfort, respectively [31]. In another study investigated by Mtibaa et al., a multi-agent control framework was implemented to optimize operations of the HVAC system, resulting in energy savings of 8.8% and a reduction in the carbon footprint by 23.4% [28].

Therefore, due to their superior performance in prediction, as well as their adaptability and flexibility, the current paper proposes a black-box, data-driven model that uses simulation data and is subsequently tested on real data. This model accounts for

the inter-dynamics in a multi-zone environment by explicitly incorporating the influence of neighboring zones on the predictive model for each zone's behavior. Multiple linear regression models were created for each zone to predict the interior temperature, selected for their low computation time, adaptability, and generalizability. Linear regression was also used in a previous study conducted by the research team of the presenting authors [30]. The models consider factors such as outdoor temperature, outdoor relative humidity, global horizontal solar radiation, and zone heating consumption. Next, the NSGA-II optimization algorithm, a multi-objective genetic algorithm, is developed to optimize control strategies based on multiple criteria, such as energy consumption and thermal comfort. This algorithm is employed to provide flexibility, allowing users to select from several optimal strategies according to their priorities, which enhances adaptability to individual needs and varied objectives. Then, this paper validates the effect of considering adjacent zones on the MPC system, comparing it to using the system without accounting for these zones. Finally, an experimental validation was included to confirm the results obtained.

This paper is structured as follows. Section 2 presents the development of the MPC in three parts: the first part describes the dynamic thermal simulation, the second part deals with the development of the indoor temperature prediction models and the results obtained, and the third part details the genetic algorithm (GA) optimization process for testing heating strategies and selecting an optimal strategy, capable of achieving energy savings while ensuring an acceptable level of comfort. Section 3 presents the results of the anticipatory approach by testing several case studies: (1) integrating adjacent zones into the indoor temperature modeling of the zone under consideration, (2) without integrating adjacent zones, (3) comparing these two approaches, and (4) testing a real experimental case. Finally, Section 4 provides a conclusion and perspectives for this work.

2. Materials and Methods

In this section, the various stages of the MPC are developed to facilitate the selection of a heating strategy that achieves energy savings. Each stage of the MPC process is presented to optimize the selection of an effective strategy for reducing energy consumption while guaranteeing an acceptable level of comfort.

2.1. Dynamic Thermal Simulation

The thermal optimization approaches discussed in this work are based on a dynamic thermal simulation of the study house. It is important to emphasize that studying a control method using a dynamic thermal simulation tool is a crucial step before applying it to a real case. During the development phase, implementing the method directly on a building is challenging. Simulation offers a secure environment for testing the MPC without posing any risk to the actual installation or occupant comfort.

This is a residential building consisting of a ground floor and a first floor. Built in 1989, located in northern France, near Lille, the individual house falls within a temperate climate zone characterized by mild summers and cool winters. It is a brick construction with 100 mm of interior insulation. The exterior walls are made up of 13 mm of plaster, 100 mm of polystyrene, and 210 mm of red brick. The floor consists of 250 mm of reinforced concrete. The ceiling at the top of the upper floor comprises 13 mm of plasterboard, 100 mm of glass wool, and 250 mm of rock wool. The house has an area of approximately 130 m² and a total volume of around 330 m³. It is oriented north, as shown in Figure 1, which impacts solar gains and thermal behavior, particularly concerning windows and facades exposed to sunlight. The windows cover a total area of 8 m², distributed across six windows. The ground floor comprises an office, kitchen, and a hall with a living room, while the first floor contains three bedrooms and a bathroom. The typical occupancy is four (two parents and two children), following a schedule from 4 p.m. to 8 a.m. on weekdays and all day on weekends, which is modeled in the control strategy.

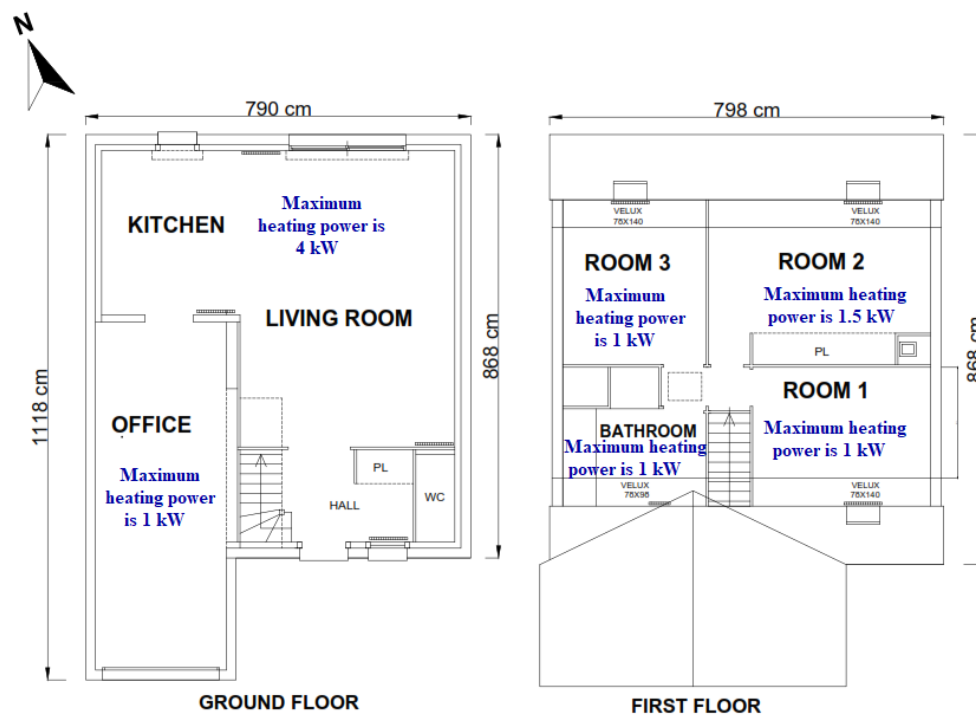


Figure 1. Plan of the study building.

Each room is equipped with individually controllable electric radiators, regulated by conventional heating strategies based on scenarios set by the occupants. The building is instrumented and will be used for experimental purposes. Referring to the building plan shown in Figure 1, the upstairs rooms were selected for the study, as rooms 1, 2, and 3 are adjacent to each other. This spatial arrangement was chosen in order to specifically examine the mutual influence of adjacent zones and assess the heat exchange between them. In this study, zones are defined by distinct physical spaces (rooms or compartments separated by partitions) equipped with independent heating systems. Each zone represents an autonomous thermal entity, influenced by its own heating, occupancy, and exposure conditions. Although the walls between rooms have 100 mm of insulation, mainly for acoustic insulation, heat transfer is still possible, mainly by conduction through the walls and floors, as well as by convection and radiation.

The current study focuses specifically on the interactions between zones on the same level. In future work, the methodology proposed in this paper should be extended to all zones of the house.

The individual house employs a natural ventilation system and is surrounded by shading devices, overhangs, neighboring buildings, and trees. The building is equipped with various appliances that contribute to the internal heat gains within each room. In addition to electric heating radiators, whose maximum power is shown in Figure 1, other electrical devices such as televisions, washing machines, computers, refrigerators, and kitchen appliances like microwaves and ovens are also present. These devices generate additional heat, which can influence the thermal performance of the space. While managing heat gains from electric heating radiators can be straightforward, integrating these additional appliances presents a more complex scenario, particularly in common living areas. The varying usage patterns of these devices can lead to fluctuations in internal temperatures, necessitating careful consideration in thermal modeling and energy management strategies. Understanding and incorporating the contributions of all these appliances in simulations will enhance the accuracy of thermal performance assessments for the building.

The building was modeled using TRNSYS 18, a highly flexible graphical software package used to simulate the behavior of dynamic systems and perform dynamic thermal simulations (DTS). The purpose of the simulation is to develop a data-driven model for

forecasting the interior temperature of each room using data from the simulated building. The energy performance of buildings is subject to the influence of various parameters such as weather conditions, the structure, and characteristics of the building, its operation such as lighting and HVAC systems, as well as occupancy and occupant behavior [35]. So, the geometry, the various parameters of the building elements, and the characteristics of the heating systems were all taken into account. The various thermal zones and the corresponding temperature setpoint scenarios were defined in accordance with the building's operation. The simulation was conducted over one year with a time step of one hour. The building was subjected to meteorological constraints extracted from the Meteonorm 8 software, using the typical meteorological year weather file for Saint-Quentin, as it is near Lille and the Lille file was unavailable. The simulation results, which include variables such as the indoor temperature and heating consumptions of the three adjacent zones, in addition to the meteorological data, were then used as a training dataset to create a prediction model for each room. In this work, a data-driven modeling approach was chosen.

2.2. Indoor Temperature Modeling

2.2.1. Development of Prediction Models

The selection of explanatory variables is an important step in the development of predictive models, and reducing them to those that are significant facilitates the search for a robust solution [25]. First, a selection of physical variables that could be collected by sensors was thoroughly made. Only current data have been included in this study to avoid the need to add specific sensors. Next, the selection of predictors was based on a statistical analysis that identified those with the strongest correlations to the indoor temperature of each zone. These predictors included outdoor temperature, outdoor relative humidity, global horizontal solar radiation, and zone heating consumption. In addition, the indoor temperatures and heating consumptions of adjacent zones were taken into account, in order to incorporate the interactions between zones into the models. The data have been pre-processed. Pre-processing can improve data quality and enhance the accuracy of prediction results [23]. A multiple linear regression (MLR) model was developed for each of the three zones, and these predictors were incorporated as input data or explanatory variables in each zone's indoor temperature prediction model.

The general form of the MLR model is expressed as follows:

$$\hat{y} = \beta_0 + \beta_1x_1 + \beta_2x_2 + \dots + \beta_nx_n + \epsilon \quad (1)$$

where \hat{y} represents the dependent variable, which is the variable to be predicted. In this case, it is the indoor temperature in the considered zone.

β_0 is a constant term.

x_1, x_2, \dots, x_n are the independent or explanatory variables or predictors.

$\beta_1, \beta_2, \dots, \beta_n$ are coefficients corresponding to the independent variables $x_1, x_2 \dots x_n$, respectively. It is the role of the linear regression algorithm to determine these coefficients.

ϵ represents the error term, which accounts for the unobserved factors affecting the dependent variable that are not included in the model.

Linear regression assumes a linear relationship between the dependent variable and the independent variables. Its objective is to estimate the coefficients (β values) that minimize the dispersion between the values obtained from the simulation and the predicted values of the dependent variable.

The dataset generated at hourly intervals by TRNSYS extends from January 1 at 4:00 a.m. to 30 April at 4:00 p.m. It is divided into a training set representing 80% of the data and a test set containing 20% of the data. It is worth mentioning that a specific study was carried out as part of previous work, incorporating predictor historization to optimize the model. Past predictor values were therefore introduced as additional inputs. They were used to improve predictions by taking into account the inertia of the phenomena. Various historization windows ranging from 0 to 10 h were tested. It was therefore decided to continue with a 4 h historization [36].

2.2.2. Prediction Models Results and Discussion

Multiple linear regression showed a good ability to effectively capture the complex relationships between the input variables and the output variable (indoor temperature after 1 h) in the case of the electric heating system [37].

Figure 2 provides an explicit illustration of the inputs and output data for the model created for room 1. The two other multiple linear regression models created in parallel for rooms 2 and 3 each have a structure identical to that of the model for room 1, as well as similar input data. These models are used to simulate the indoor temperature of room 2 and room 3, respectively, for the next hour. Sequentially, the temperatures predicted for time $t + 1$ are then fed into the models to predict temperatures at time $t+2$, and so on, over the prediction horizon.

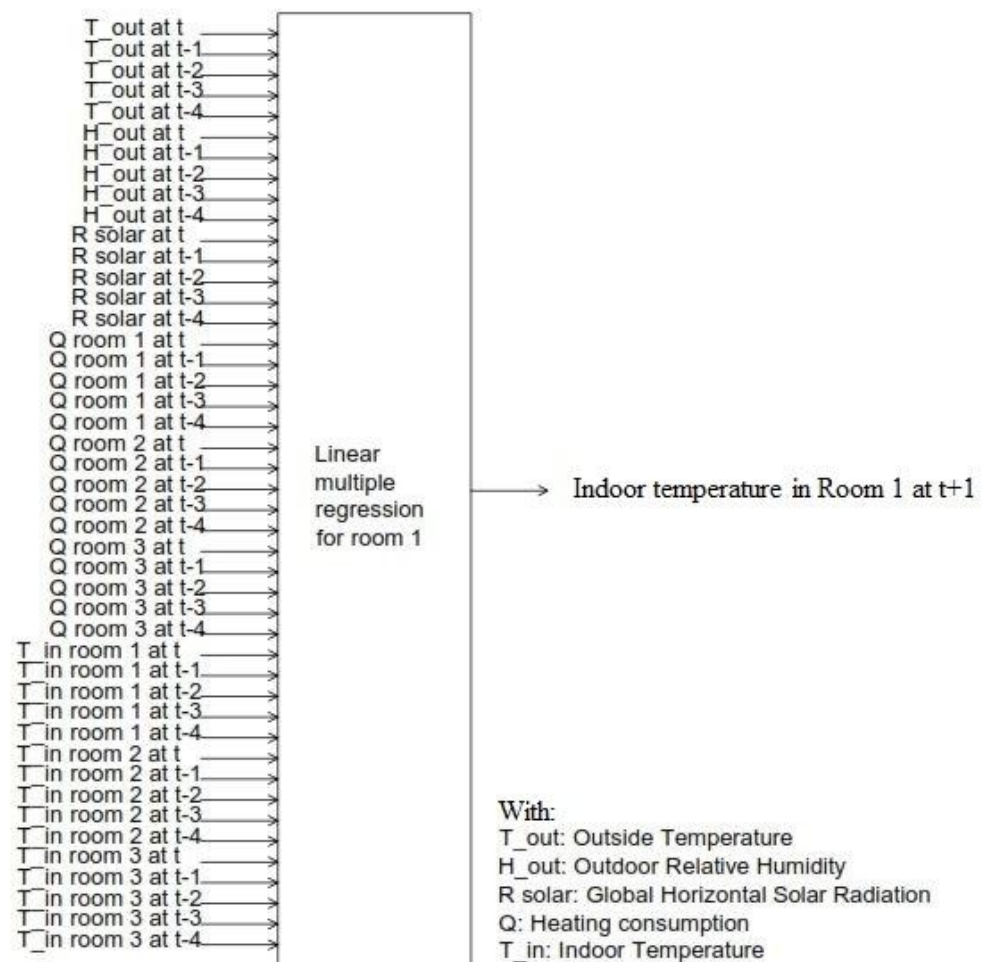


Figure 2. Prediction model for room 1.

For optimal MPC performance, reliable model predictions are crucial [38]. In the evaluation process, Figures 3–5 show a graphical comparison between the predictions of the three models and the values generated by simulation over a 10-day period. The curves of the predicted and DTS-generated values are almost superimposed and follow similar dynamics, with a root mean square error (RMSE) of less than $0.2\text{ }^{\circ}\text{C}$. The RMSE is a widely used metric for assessing the accuracy of a predictive model. It measures the difference between predicted and observed values by taking the square root of the average of the squared differences. A lower RMSE indicates better predictive accuracy. The resulting RMSE offers a clear indication of the prediction models' performance. The results underline the relevance of MLR as the preferred choice for these prediction objectives, demonstrating the high accuracy of the prediction.

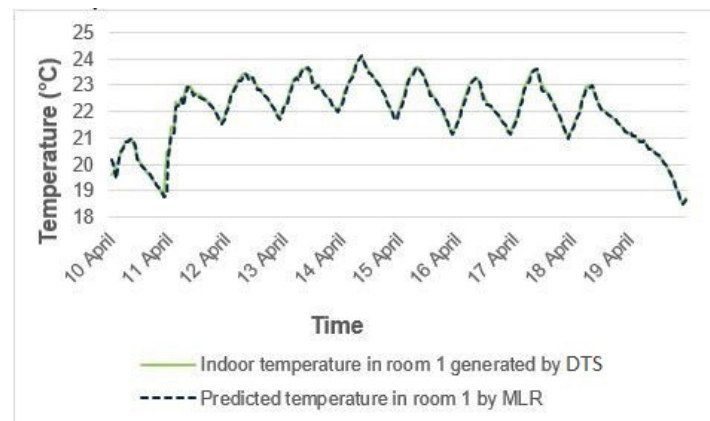


Figure 3. Values predicted by MLR versus actual values generated by DTS for room 1.

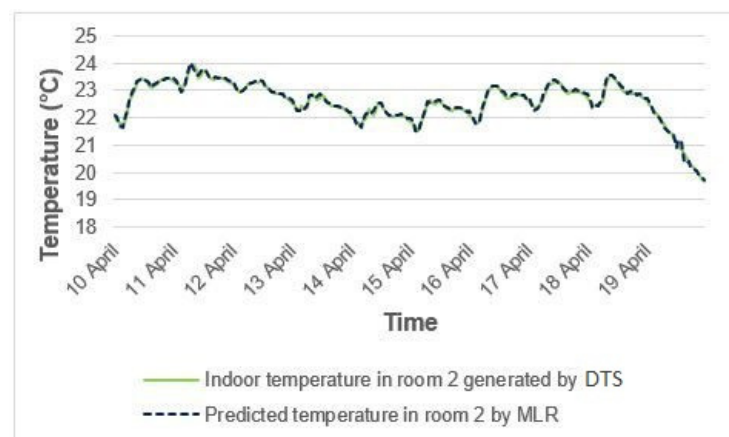


Figure 4. Values predicted by MLR versus actual values generated by DTS for room 2.

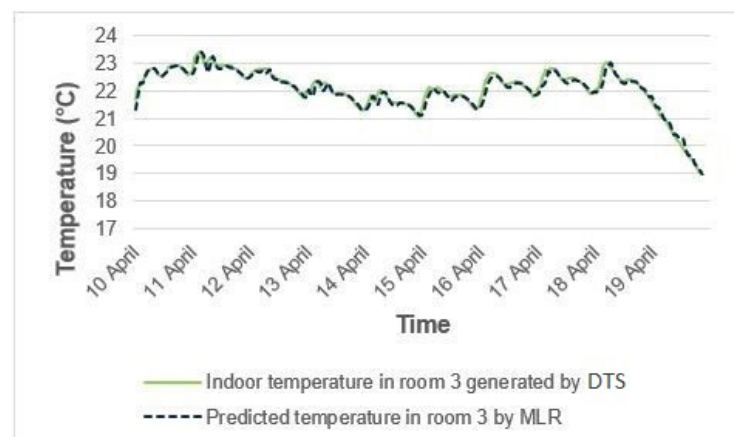


Figure 5. Values predicted by MLR versus actual values generated by DTS for room 3.

2.3. Optimization Process for Selecting the Appropriate Heating Strategy Using Genetic Algorithms

In an optimization process, the choice between deterministic and heuristic methods depends on the priority given to finding the optimum solution. If this quest is considered essential, deterministic methods may be preferred, although this can be very time-consuming in this particular context. However, if the main objective is to obtain an acceptable solution quickly, even if it is not necessarily optimal, heuristic methods such as genetic and evolutionary algorithms prove more suitable, offering greater efficiency for solving computationally expensive problems [39]. Various research projects have explored the application

of metaheuristic algorithms to determine the best design for building envelopes when designing or renovating buildings [40]. J. Reynolds et al. have combined a neural network prediction model with a genetic algorithm [41], while Abdellatif et al. have integrated a multiple linear regression model into a MPC using a genetic algorithm [30].

Genetic algorithms (GA), inspired by Darwin's theory of evolution and based on genetic crossing, are optimization methods designed to tackle complex problems by simulating the process of evolution. They operate on a population of individuals, each representing a potential solution encoded as binary genes (0 and 1). In the context of on/off electric heater control, an individual corresponds to a sequence of setpoints, where a '0' indicates that the heater is off and a '1' signifies that it is operating at full power. The algorithm iteratively applies processes such as selection, crossover, and mutation to evolve the population over multiple generations. Selection prioritizes individuals that demonstrate better performance, while crossover combines genetic information from pairs of individuals to create offspring with new characteristics. Mutation introduces random variations, enhancing the diversity of the population. By evaluating the fitness of each individual based on a specific objective, GAs effectively search through large solution spaces to identify optimal or near-optimal solutions to various optimization problems.

In this study, the NSGA-II algorithm was chosen, which is an evolutionary algorithm used to solve multi-objective optimization problems, such as the search for a compromise between heating consumption and thermal comfort. The algorithm's parameters are set as follows: 200 individuals per population, 60 generations, a crossover probability of 80%, and a mutation probability of 1%. The process begins with a randomly generated population, which then evolves through three operations—crossover, mutation, and selection—continuing until the predefined number of generations is reached. Crossover renews the population by combining the genetic information of two parent solutions to create a new child with the same size (in this case, 18 genes corresponding to 18 setpoints). Mutation introduces random changes to individual solutions, promoting diversity and preventing premature convergence. Selection keeps the best individuals based on the fitness function, ensuring that only the most promising solutions are retained for the next generation. In NSGA-II, the fitness function incorporates both the forecasting model and the score calculation function, addressing multiple objectives. Each generated heating strategy is tested using the forecasting model to determine the corresponding interior temperature. Based on predefined equations, two objective scores are assigned to each heating strategy: the energy score, which represents the amount of energy this strategy will consume, and the comfort score, which calculates how far it deviates from comfort. NSGA-II then evaluates these strategies. Its main objective is to find a Pareto front, which represents a set of solutions that are not dominated by others. In other words, these solutions are a compromise between comfort and consumption. The algorithm seeks to explore the solution space in order to find a set of optimal solutions that cover different trade-offs between these conflicting objectives.

Optimizing the anticipatory heating strategy of the 3 adjacent rooms is a crucial step in this process. To illustrate this approach, a specific date and time were selected: 30 April at 5:00 p.m.. This is the start of the period for which the data were not used for the training phase of the 3 prediction models, thus ensuring the objectivity of the results. In this case, all the weather data, heating consumption, and indoor temperatures in the house's three rooms are available. All these data are taken from the simulation. This initial time and these simulated data are crucial, as they form the starting point for anticipatory optimization of the heating strategy for the 3 rooms. From this simulated hour, six consecutive hours of simulation data are considered: 6 p.m., 7 p.m., 8 p.m., 9 p.m., 10 p.m., and 11 p.m. on 30 April, representing a relevant time window for assessing and anticipating heating requirements while ensuring comfort. Each candidate strategy is then integrated as input data into the prediction model. This iterative process then predicts the indoor temperature in the three rooms for each strategy. The individuals or strategies correspond to the heating scenarios for the 3 rooms during 6 one-hour periods. In this work, periods of one hour

have been chosen to reduce the frequency of switching. This approach prevents excessive switching, which could lead to higher energy consumption and reduce the lifespan of the heating equipment due to wear and tear. So, a strategy consists of 18 heating setpoints. At the end of this process, predictive control aims to satisfy the user's comfort requirements while anticipating disturbances, thus avoiding periods of discomfort [42]. Thermal comfort is difficult to assess. As in the vast majority of research work and for control systems, its assessment is limited, in this study, to observing whether the indoor temperature value lies within an acceptable temperature range. Within this range, for room 1, this corresponds to an inside temperature of between 17 °C and 19 °C, and between 20 °C and 23 °C for rooms 2 and 3. These limits were set in line with occupant habits. The various stages of this approach are shown in Figure 6, where the ComfortScore and EnergyScore are calculated according to Equations (2), (2a), (2b) and (3).

$$\text{ComfortScore} = \sum_{i=1}^{18} C[i] \quad (2)$$

$$\text{If } T_{\text{indoorMin}} \geq T_{\text{indoor}[i]}: C[i] = |T_{\text{indoorMin}} - T_{\text{indoor}[i]}| \quad (2a)$$

$$\text{If } T_{\text{indoor}[i]} \geq T_{\text{indoorMax}}: C[i] = |T_{\text{indoorMax}} - T_{\text{indoor}[i]}| \quad (2b)$$

where

$T_{\text{indoorMin}}$ and $T_{\text{indoorMax}}$ correspond to the acceptable temperature range;

$T_{\text{indoor}[i]}$ corresponds to the indoor temperature at the setpoint i ;

$C[i]$ corresponds to the comfort score for setpoint i .

$$\text{EnergyScore} = \text{the sum of energy consumption across the three rooms over the six hours} \quad (3)$$

A good comfort score is a minimal score or a score close to zero, and a good energy score is a score with a lower number.

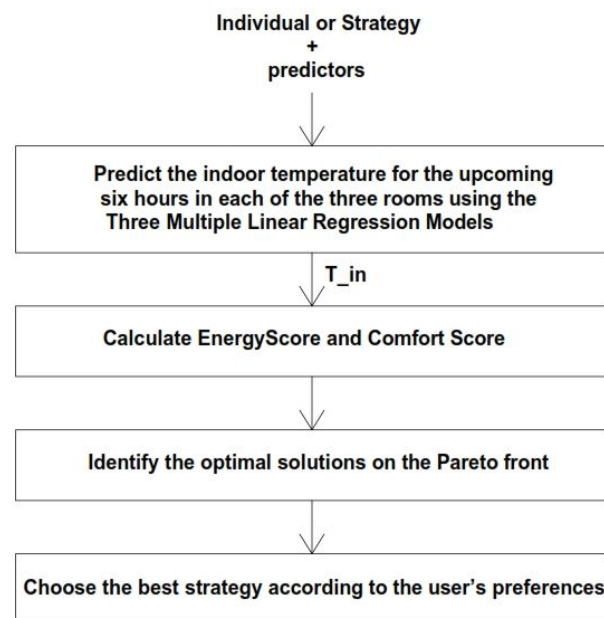


Figure 6. Schematic diagram of heating energy consumption optimization using genetic algorithms.

3. Results of the Anticipatory Heating Control Approach

3.1. Process Integrating Adjacent Zones

Using the NSGA-II predictive heating control model, the best-performing individuals on the Pareto front were identified; they are represented by the red dots in Figure 7. These represent the optimal heating strategies for the next six hours, considering both the weather forecast and the anticipated behavior of the studied rooms. In this situation, the choice of

the individual best suited to specific needs can be left to the user. Table 2 shows the three individuals obtained and their energy consumption and comfort scores.

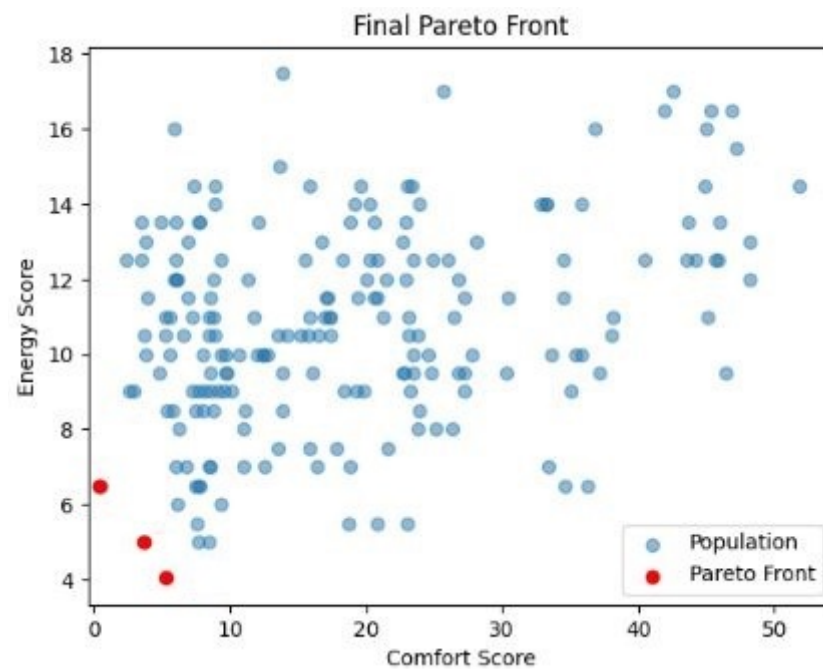


Figure 7. Final Pareto front for multi-zone optimization.

Table 2. Non-dominated individuals on the Pareto front for multi-zone optimization.

Non-Dominated Individuals on the Pareto Front	ComfortScore	EnergyScore
[0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0]	3.64	5
[0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1]	0.28	6.5
[1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1]	5.42	4

By selecting the second individual, which guarantees the maximum comfort level, the results of the indoor temperature prediction correspond very well to the comfort range defined by the user, as shown in Figures 8–10, underlining the robustness of the predictive model in maintaining thermal comfort. The conventional heating strategy used in the simulation resulted in a consumption of 10.5 kWh. Comparing the energy consumption resulting from the strategy selected by the heating control optimization process with that resulting from the simulation in Table 3, a 38% reduction in heating energy consumption has been observed over the studied period of six hours.

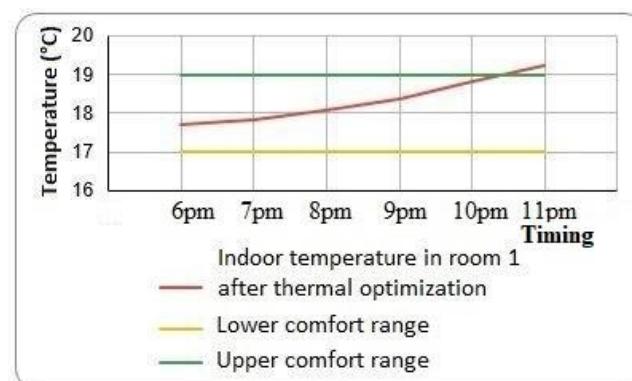


Figure 8. Predicted indoor temperature values for the next 6 h on 30 April by the optimization process in room 1.

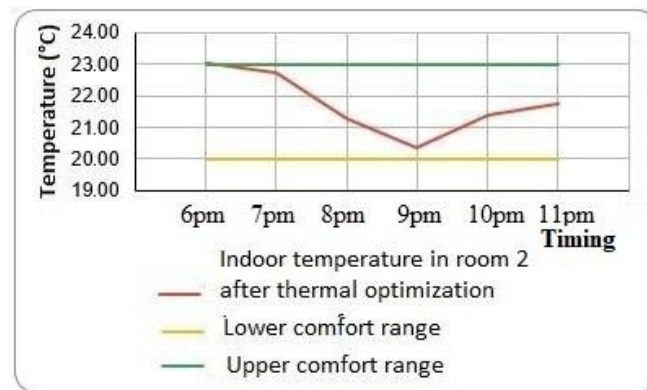


Figure 9. Predicted indoor temperature values for the next 6 h on 30 April by the optimization process in room 2.

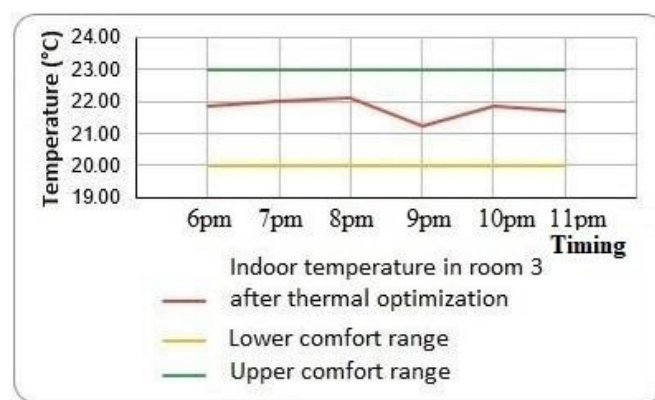


Figure 10. Predicted indoor temperature values for the next 6 h on 30 April by the optimization process in the room.

Table 3. Heating consumption.

Type of Strategy	Consumption (KWh)
Strategy selected by the heating control optimization process	6.5
Strategy selected from simulation	10.5

Similarly, selecting the third individual, which has a low consumption score of 4, allows for a substantial reduction of 62% over the studied period of six hours compared to the consumption generated by the simulation strategy based on a deterministic occupancy scenario. However, in this case, the comfort score is equal to 5.42. Choosing this individual option results in a significant reduction in energy consumption, though it may involve some discomfort for a brief period, amounting to 16% of the study period. The decision depends on specific needs and preferences, allowing for the selection of the most suitable option.

3.2. Process Not Integrating Adjacent Zones

In addition, to emphasize the importance of adjacent zones in this study, the process, without taking adjacent zones into account, was repeated. In other words, each prediction model depended solely on the weather data, indoor temperature, and heating consumption of the room under consideration, without taking the other two rooms into account. Thus, Figure 11 illustrates the Pareto front identifying the best individuals in this case, and Table 4 lists the non-dominated individuals with their scores.

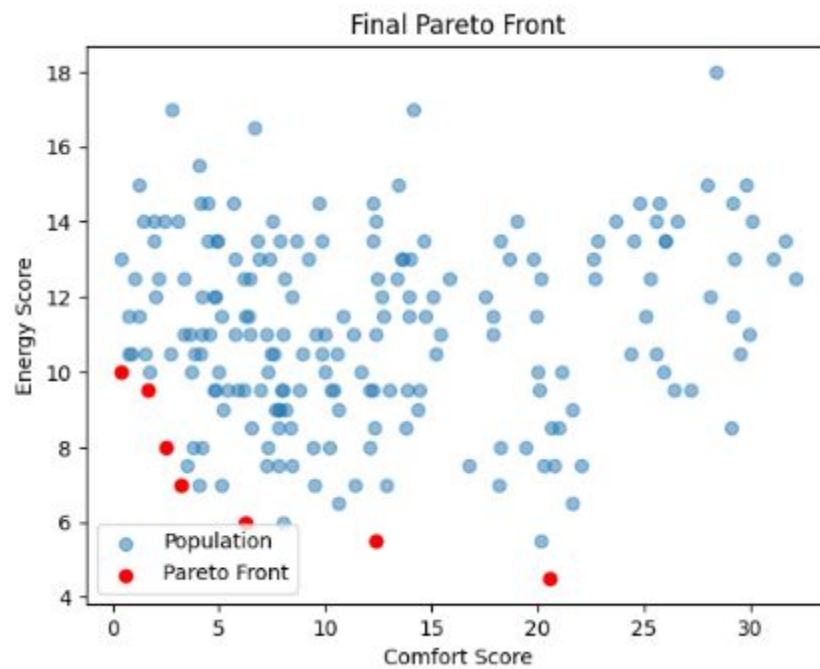


Figure 11. Final Pareto front without taking adjacent zones into account.

Table 4. Individuals on the Pareto front by a process not integrating adjacent zones.

Non-Dominated Individuals on the Pareto Front	ComfortScore	EnergyScore
[0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0]	0.36	10
[0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0]	2.47	8
[0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1]	20.56	4.5
[0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0]	6.22	6
[0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0]	3.19	7
[0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1]	1.67	9.5
[0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0]	12.37	5.5

3.3. Comparison between the Two Processes

Figure 12 provides an evaluation of the influence of the integration of adjacent zones on the performance of the model predictive control with regard to the optimal solutions identified. The strategies identified by the optimization process, which take adjacent zones into account, have lower scores, indicating an improvement over strategies identified by the MPC that do not take these zones into account, since the aim of this study is to minimize both scores for energy consumption and discomfort.

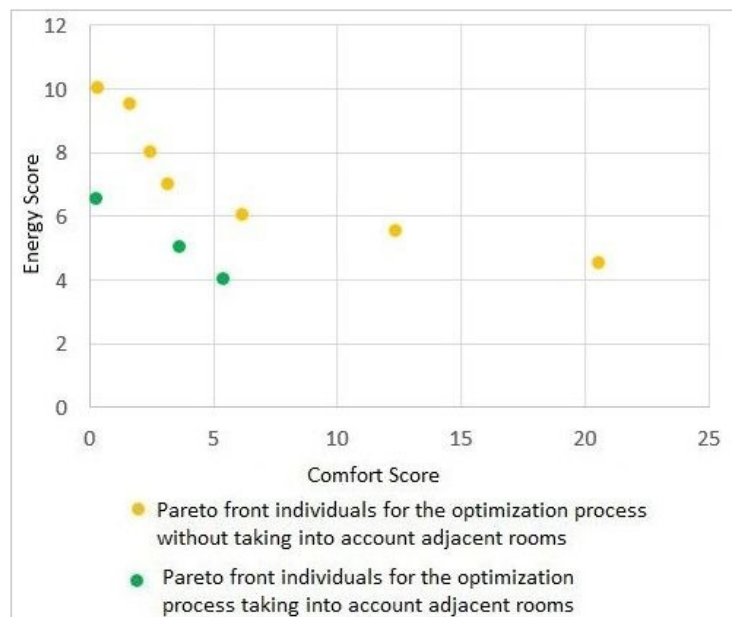


Figure 12. Comparison of the two Pareto fronts.

These results indicate that the predictive approach, integrating the influence of adjacent zones on thermal inertia, enhances energy efficiency in this case study by reducing energy consumption.

3.4. Experimental Test for the Process Integrating Adjacent Zones

The study house has been instrumented since 2021. Sensors have been installed in the various thermal zones of the house, enabling indoor temperatures to be recorded. The study of heating control, taking into account adjacent zones in the predictive modeling of indoor temperature, is repeated for experimental validation. Data are retrieved and pre-processed. Multiple linear regression models were developed for the three upstairs rooms, with data training from over the full year of 2023. The date of January 3 at 12:00 p.m. was chosen to determine the best anticipatory strategy this approach could offer for the next six hours. Using the predictive heating control model optimized by NSGA-II, the individuals on the Pareto front were identified and represented by the red dots in Figure 13. Table 5 illustrates the three Pareto front individuals found, along with their energy consumption and comfort scores. It also shows the energy reduction each individual could achieve if selected and applied, given that the actual consumption of the three rooms for those six hours was 12.5 kWh.

Table 5. Individuals on the Pareto front for the experimental test.

Non-Dominated Individuals on the Pareto Front	ComfortScore	EnergyScore	Energy Reduction
[0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0]	5.27	5.5	56%
[0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0]	3.42	7.0	44%
[0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0]	9.62	5.0	60%

In this case study, if this approach had been applied to this residential building in real time, the three strategies found could have achieved energy reductions. By prioritizing comfort, the user could have opted for individual 2 and realized an energy reduction of 44%.

This process validates the theoretical results obtained by simulation using real experimental data.

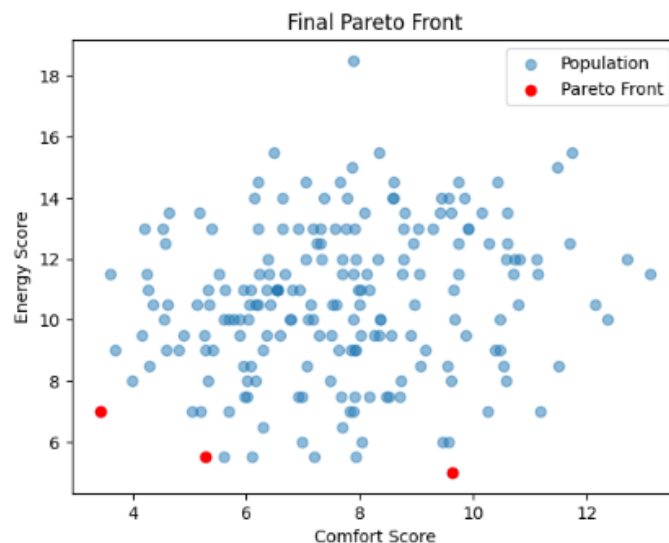


Figure 13. Final Pareto front for the experimental test.

4. Conclusions and Perspectives

This research focuses on building energy efficiency, taking into account heat exchanges between different zones to reduce heating-related energy consumption. This paper presents the development of a multi-zone model predictive control to estimate the best anticipatory strategy for efficient heating management while guaranteeing user comfort. The methodology used relies on dynamic thermal simulation, parallel predictive models based on multiple linear regressions to simulate temperatures in the different zones, and a NSGA-II to optimize heating control in each zone.

The application of this anticipatory optimization of heating control, taking into account the thermal inter-dynamics of the building's zones, to a simulated case study showed a significant reduction in energy consumption when exchanges between the different zones were taken into account. A 38% reduction in energy consumption was observed over the studied period of six hours while maintaining thermal comfort. In this case study, the reduction can reach up to 62% over the six hours, with a slight discomfort for a short period representing 16% of the study period. To emphasize the importance of adjacent zones in this study, the process was repeated without taking adjacent zones into account. The results showed that the predictive approach, which took into account the influence of adjacent zones on thermal inertia, offers a better solution for improving energy efficiency in buildings. The process, taking into account heat exchanges between different zones, was also validated experimentally by testing a real-life scenario, demonstrating significant reductions in energy consumption. This approach allows occupants to manage heating consumption according to their preferences by choosing the consumption/comfort trade-off that suits them best from among the individuals on the Pareto front resulting from GA optimization.

This work represents a first step towards the practical validation of the model. In the future, research will be conducted over the course of a year and in real residential buildings to assess the benefits of this anticipatory approach by actually controlling heating according to this multi-zone study.

In terms of future perspectives, this research could be extended through the development of a smart building control platform. Such a platform would have the capacity to collect data from residential buildings of various typologies, enabling the creation of predictive control models applicable to a broad range of buildings. This approach would enhance the generalizability of the MPC, moving beyond models tailored to specific types of residential buildings.

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