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Optimising energy flexibility in Finnish residential buildings: A comparative study of PI, rule-based and model predictive control strategies☆

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ABSTRACT

As integral components of urban infrastructure, buildings play a crucial role in maintaining occupant well-being, especially during extreme weather conditions. This research presents a model predictive control (MPC) approach to harnessing the energy flexibility of buildings by utilising their thermal mass to cost-effectively manage the energy use. The study compares two apartment buildings located in the Nordic climate of Helsinki, Finland: one built in the 1970s and a modern positive energy building (PEB) with a high-performance envelope exceeding the minimum requirements of national building regulations. Three control strategies are evaluated for building thermal mass activation: Proportional-Integral (PI) control as a standard strategy for thermal comfort, Rule-Based Control (RBC) as a cost-based benchmark strategy and an advanced MPC as an innovative energy-flexible strategy for cost-savings. The three investigated control strategies are implemented by interfacing IDA ICE building energy performance simulation software with the programming environment, Python as a master controller. The study aims to optimise the operation of the building's energy systems in real-time, minimising energy costs while maintaining comfort constraints by adjusting temperature setpoints based on dynamic weather conditions and occupant behaviour by applying the adaptive thermal comfort model. The results, obtained from simulations, demonstrate that the MPC provided the highest cost savings, particularly under high and fluctuating price conditions. In the 1970s building, MPC achieved up to 29.9 % cost savings compared to PI control, while RBC achieved up to 17.2 % savings. In the modern PEB, MPC resulted in up to 14.8 % cost savings, with RBC achieving up to 7.9 % savings. These findings highlight MPC's potential to improve energy efficiency and resilience in buildings, especially in cold climates.

1. Introduction & literature review

Climate change remains one of the most pressing global challenges of our time with profound implications for environmental, economic, and social systems. The building sector is particularly significant in this context. Within the European Union (EU), it is responsible for approximately 40 % of total energy consumption and 36 % of greenhouse gas emissions [1,2]. Residential buildings alone account for about 27 % of the total energy consumption, while non-residential buildings, including commercial and public facilities, account for the remaining 13 %. The energy intensity of buildings varies significantly across the EU, with average annual specific consumption per square meter ranging from 47 kWh/m^2 in Malta to 300 kWh/m^2 in Romania [3]. The increasing emphasis on reducing energy consumption in buildings has resulted in the implementation of more stringent regulations aimed at improving the energy efficiency of both newly constructed and existing structures. The Energy Performance of Buildings Directive (2010/31/EU) [4] together with its subsequent amendment (2018/844/EU) [5], outlines the objective of achieving a fully decarbonised building stock within the EU by 2050. This directive further highlights the importance of fostering

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adaptable and resilient buildings, while also promoting the integration of digital technologies within energy systems. The latest amendment, Directive (EU) 2024/1275 [1], reinforces these goals and introduces measures to increase the rate of renovation, supports the digitalisation of energy systems for buildings, emphasizes enhancing the resilience of buildings to climate change impacts, and promotes the development of flexible buildings that can adapt to changing energy demands and integrate renewable energy sources more effectively.

According to the above-mentioned regulations, all buildings constructed after 2020 are mandated to comply with the Nearly Zero Emission Buildings (NZEB) standard. This standard is characterised by high energy efficiency, low energy demand, and a major reliance on renewable energy sources (RES). In 2021, a further revision was proposed, advocating for the transition from NZEB to Zero Emission Buildings (ZEB), reflecting a broader move towards a climate-neutral economy [6]. Despite these developments, a more ambitious goal is represented by Positive Energy Buildings (PEBs), which are designed not only to be energy-efficient but also to produce more energy from renewable sources than they consume over a given period. Buildings are thus positioned as active participants within broader energy networks [7].

Energy flexibility of buildings is a key component of this strategy. It contributes to reducing emissions, lowering peak loads, balancing grid energy usage, and reducing energy costs for consumers. Furthermore, energy flexibility is essential for enhancing the resilience of buildings during prolonged power outages and grid disruptions [8,9]. Energy flexibility is crucial from two interrelated perspectives. On the one hand, the increasing integration of RES into the grid results in greater intermittency in energy production, which poses challenges for grid stability and control and calls for integrated flexibility solutions. On the other hand, they offer a cost-effective solution for purchasing and utilising energy, especially in an environment of rising energy prices where consumers are increasingly focused on reducing utility bills [7,10–12].

Energy storage systems play a crucial role in enhancing energy flexibility. Xu et al. conducted extensive research on battery storage, examining various solutions such as photovoltaic storage and vehicle-to-grid technologies [13,14]. They conclude that integrating batteries can improve the energy flexibility and highlight the importance of recognising buildings as thermal energy systems. Research has also focused on borehole storage systems due to their benefits when integrated into district heating systems, especially for mitigating seasonal variations in heating patterns [15]. Chicco and Mandrone suggest that Borehole Thermal Energy Storage technologies are among the promising options for energy and economic savings, as well as for District Heating and Cooling integration, given their adaptability to various geological conditions [16].

Building energy flexibility (BEF) refers to a building's ability to manage and optimise energy demand while maintaining functionality, stability, and occupant comfort. Achieving BEF involves integrating various technologies and resources, such as building design elements, HVAC systems, electrical loads, storage systems, electric vehicles, and local weather conditions. These technologies are crucial for load-management strategies and directly impact the heating and cooling costs [12,17,18]. Askeland et al.'s work demonstrates that thermal mass flexibility can reduce peak loads and facilitate energy arbitrage, thereby lowering operational costs, though it may increase energy consumption due to preheating losses [19]. Reynders et al. developed a dynamic quantification method using size, time, and induced losses/costs as performance indicators to improve energy flexibility in residential buildings through structural thermal storage [20]. Le Dréau and Heiselberg, in their work, concluded that optimising thermal storage in Danish buildings for the benefit of the grid, while maintaining thermal comfort, relies on building control strategies influenced by the building's age, characteristics, and seasonal variations [21]. Romanchenko et al. concluded that both centralised hot water tanks and building thermal inertia are economically viable and beneficial, with the optimal choice depending on the implementation strategy and objectives [22]. Dominkovi et al. [23] investigated optimising costs in district heating networks by utilising the building's thermal mass for load shifting, while Kensby et al. [24] conducted a pilot test on a demand-side management strategy involving small variations in indoor temperature, concluding that such a strategy holds significant potential.

Another critical factor influencing the effectiveness of energy flexibility measures is the age of buildings. In Finland, approximately 43 % of buildings were constructed before the 1980s [25], and renovating them is both expensive and time-consuming. Heating control is a flexibility measure that can benefit both older and newer buildings by reducing energy costs and demand, allowing the building envelope to shift demand from high to low price hours or from peak to off-peak periods, depending on weather conditions. One way to achieve this is by activating the building's thermal mass in response to weather or signals [21,26]. Yoon et al. developed a demand response controller for a residential building in the warm climate of Texas, USA that achieved up to 10.8 % energy cost savings and 24.7 % peak load reduction [27]. In their study on a Mediterranean building, Pean et al. demonstrated that implementing a flexibility strategy based on set-point modulation according to energy prices resulted in a reduction in energy costs by approximately 20 %. [28]. Christantoni et al.'s study concluded that commercial buildings could reduce their energy demand by 14 % by using energy flexibility measures for heating and cooling [29]. In Danish climatic conditions, utilising the building's thermal mass as a flexibility measure has been found to reduce energy demand and costs, although there is a risk of overheating in new constructions [21]. In their study, Yin et al. used a living lab representing a Norwegian single-family house in Trondheim's cold climate to enhance energy flexibility through the integration of phase change materials (PCM), optimising both the PCM design and heating operation by modulating the temperature setpoint profile [30].

The EU Building Directive recognises the importance of considering local climate conditions when developing strategies to improve the energy performance and decarbonisation of buildings [1]. Energy flexibility measures in cold climate regions require further analysis, as existing research on mitigation strategies and the thermal resilience of buildings in these areas is limited. Alimohammadisagvand et al.'s work demonstrates that the implementation and price-signal-based operation of ground-source heat pumps can lead to a reduction of up to 15 % in energy costs in cold regions [31]. Kensby et al. conducted a study on five residential buildings, both lightweight and heavyweight, in Gothenburg, Sweden [24]. They used conventional feedback controllers to adjust the heating power of each building according to outdoor temperatures and observed that certain heavyweight buildings are less prone to indoor temperature variations, making them suitable for short-term thermal energy storage. Zhang et al. investigated demand-side responses during cold snap events in Kyushu, Japan, and how passive and active energy-efficiency measures in ZEBs worked when residential electricity demand varied [32]. Sheng et al. modelled and analysed an assisted living facility's thermal resilience during heat wave and cold snap, evaluating the impacts of energy efficiency measures on its thermal resilience and backup power capacity [33]. They observed that mitigation solutions effective for heat waves could potentially reduce resilience during cold events. Rehman et al. compared the energy resilience performance of a 1970s and a 2020s single-family building in Finland during blackouts, showing that while the older building failed to maintain habitability without the support of PV and battery systems, the newer building remained within habitable thresholds, highlighting the enhanced resilience of modern buildings in cold climates [34].

Understanding and predicting energy consumption through these models is only part of the equation; effectively controlling and optimising energy use within buildings is equally crucial. To achieve this, different control strategies are employed to manage energy systems in real time and ensure that buildings operate as efficiently and flexibly as possible. Among these strategies, three primary forms of controls are discussed here: PI (Proportional-Integral), RBC (Rule-Based Control) and MPC (Model Predictive Control), each offering unique benefits and challenges in the context of energy management.

A PI controller is a type of feedback control system that combines the control action of both proportional and integral controllers to maintain a steady-state value equal to the input setpoint [35]. For instance, in a building's heating system, a PI controller can be used to maintain the setpoint of the supply air [36]. In underfloor heating systems, the PI controller can be optimised to help minimise room temperature fluctuations and achieve a more efficient and stable heating system [37–39].

In an RBC system, the control actions are determined based on a set of predefined rules, typically in the form of if-then statements [40]. One of the primary advantages of RBCs lies in their inherent simplicity. In cost-based RBC systems, the rules are designed to optimise a certain cost function that could be related to metrics such as energy consumption or operational efficiency. For example, building heating systems may be programmed to operate during off-peak electricity hours to reduce costs [41–43]. RBCs have been shown to improve energy flexibility, enabling operations like delaying heat pump use during high electricity prices or adjusting the operational schedule through the use of simple heuristic algorithms [44]. However, RBCs face limitations in adapting to dynamic conditions and fluctuating external factors due to their fixed trigger parameters, which can reduce effectiveness in responding to fluctuations in grid conditions. This limitation highlights the need for more advanced control strategies capable of quickly responding to rapid changes in grid conditions and optimising operations over time.

An MPC is a control method that uses a dynamic model to forecast the future performance of a system over a defined prediction horizon. At each time step, the controller computes the optimal sequence of future control actions through optimisation, applying only the initial control input to the system, while recalculating the sequence for subsequent timesteps [45]. In building systems, MPC often incorporates weather forecasts, future electricity prices, and thermal models to optimise energy costs, reduce energy consumption, or increase the use of renewables, all while maintaining occupant comfort [46]. Pandey et al., in their work, developed a dynamic MPC strategy to minimise the energy cost while ensuring the thermal comfort of occupants in a building in Bhubaneshwar, India [47]. The work of Morovat et al. showed a reduction of peak power demand and cost minimisation using an MPC for demand response of a school building in Montreal, Canada [48]. Yang et al.'s implementation of MPC in a single-family house with space heating integrated with a PCM water tank reduced electricity costs by 45.1 % compared to conventional controls [49]. In their study, Bamdad et al. found that MPC achieved up to 17.6 % energy savings in an office building in Sydney, nearly double the savings of RBC, when computed over three days with varying weather conditions [50]. Masy et al.'s work on the development of an economic MPC for a residential building in Belgium demonstrated a 13 % reduction in electricity costs, but it also resulted in an increase in electricity consumption (~20 %) [51].

The importance of these energy flexibility measures has become even more pronounced in the context of rising energy prices, driven by several factors in the past few years. About half of the EU's energy is imported from outside the union's borders [52]. This reliance on imports has made the energy system vulnerable to outside shocks. The European energy crisis has led to unprecedented increases in energy costs across the continent throughout 2022, with the average European price level increasing sevenfold compared to 2020 [53]. The ongoing conflict in Ukraine has significantly disrupted energy supplies, with Russia's withdrawal from the European energy market after its February 2022 invasion exacerbating the crisis, as Russia previously supplied 45 % of the EU's gas imports [54]. The marker volatility is rooted in unreliable weather conditions, the post-COVID economic recovery, mounting energy insecurity, and limited storage supplies [54,55]. Given the escalating energy costs and the pressing need for efficient energy management, accurate prediction of building energy consumption has become increasingly important. To effectively implement energy flexibility measures and optimise building performance, it is essential to predict energy use with precision. This is where building energy prediction models come into play. There are three primary types of building energy prediction models: white box, black box, and grey box [56].

In current research studies on building performance modelling, white-box modelling stands out as a robust methodology. White-box modelling uses established principles of mass, energy, and momentum conservation to simulate energy usage through detailed physical representations of building components [57,58]. Tools like TRNSYS [59–61], IDA ICE [62–64], and EnergyPlus [65–67] facilitate detailed dynamic modelling of buildings, including aspects such as building envelope, occupants, HVAC systems, and schedules in an extensive bottom-up approach. While the creation of white-box models demands numerous parameters and is time-intensive, the resulting simulations offer higher accuracy compared to other modelling methods [68]. In contrast, black-box modelling relies on data-driven approaches, using machine learning algorithms and support vector machines to link independent parameters and target variables based on historical data. However, black-box models require high-quality data, and inaccuracies, missing information, or biases can lead to suboptimal model performance. These models also sometimes lack transparency. Notably, faults within buildings can lead to substantial increases in energy consumption, potentially exceeding 100 % [68]. Although a portion of the data is reserved for validating the model during the development process, the reliability of the model for additional data remains uncertain, primarily due to unidentified key factors [56]. Their generalisability is limited due to the specific datasets they are based on, making them difficult to apply universally. Grey-box models are utilised in building energy simulations due to their ability to balance physical insights with empirical data [68]. By integrating aspects of both white-box and black-box methodologies, these models can effectively represent energy exchanges and infiltration, utilising both physical equations and measured data to improve accuracy over purely black-box approaches. There are many cases where MPC is implemented with building performance simulation software through grey-box [69–71] or black-box models [72–74]. Despite their advantages, the widespread adoption of grey-box models is hindered by challenges such as the need for more comprehensive software solutions and standardized methodologies [68,75]. Although guidelines like ASHRAE Guideline 14 and tools such as Modelica Buildings [76] provide valuable resources for calibration and model development, further advancements in these areas could increase their applicability. Few studies have been done on white box modelling of building heating systems with model predictive control [77,78]. The approach used in this study aims to address this gap by combining detailed physical modelling with advanced control strategies to optimise the energy flexibility in buildings.

This article focusses on buildings in Finland and addresses significant gaps in the study of energy flexibility in cold climates, specifically comparing older buildings from the 1970s and modern PEBs. The proposed approach involves a novel co-simulation framework, building upon the model-based control system developed by Catto Lucchino et al. [79], who applied similar techniques to double skin façades. Our research extends this concept by integrating white box models with MPC to optimise thermal comfort and energy cost. The building model is simulated in IDA ICE, while the control algorithm is implemented in Python. Data transfer between Python and IDA ICE is facilitated through a dynamic-link library, enabling real-time communication. Python sends temperature setpoints and control actions to IDA ICE, which in return provides room heating power values and indoor temperatures. This setup allows for efficient optimisation of energy flexibility in the building through automated iterations between prediction and control actions using the NSGA-II algorithm, aiming to minimize energy costs and thermal discomfort. With the focus exclusively on space heating, it assesses and compares three different control strategies – PI control, cost-based RBC, and MPC – to determine their effectiveness across varying weather conditions and energy price scenarios (steady low prices of 2015 versus fluctuating high prices of 2022). By investigating the influence of building age, design, and electricity price levels on energy flexibility, the study addresses a key gap in research on energy flexibility measures in cold climates.

In this paper, Section 1 provides an in-depth introduction and background, discussing the role of buildings as flexibility assets, reviewing relevant literature, and exploring various types of controls in building heating systems. Section 2 describes the methodology, detailing the buildings involved in the study, the weather and price data utilised, and the control and optimisation algorithms implemented. Section 3 presents the results of the study and offers a critical discussion of the findings. Finally, Section 4 concludes the paper, by summarising the key insights and implications for future research.

2. Methodology

2.1. Building description

This study examines the impact of various control strategies on the energy performance and thermal comfort of two multi-apartment buildings located in Helsinki, Finland, representative of a Nordic climate. The first building, herein referred to as ‘B1′ (Fig. 1, left), was constructed in the 1970s in compliance with the building codes of that time. It consists of three storeys, housing twenty-four units, with a total heated area of approximately 2500 m^2. B1 uses a hydronic heating system with a water radiator mounted on the wall.

The second building examined in this study referred to as ‘B2′ or ‘EXCESS Building’ henceforth (Fig. 1, right), is a modern structure constructed in 2023, featuring an envelope that exceeds current national building regulations. It has seven storeys, with fifty-one units, and a total heated area of 4000 m2, including shared areas. B2 utilises underfloor heating, which is modelled as a heating/cooling floor object in IDA ICE. Across the EU, a total of 58 PEBs have been identified, of which only five are located in the Nordic climate zone. Of these 58, eight multi-apartment residential buildings qualify as PEBs, with the ’EXCESS building’ being the only one situated in the Nordic region [80]. Consequently, this study is particularly novel, as limited research exists on multi-apartment residential PEBs in cold climates, and it provides a valuable contribution to this field.

The thermal characteristics of the two buildings, compared to the reference values of the current building codes are outlined in Table 1.

Table 1
Thermal characteristics of the two studied buildings, compared to reference values of the current building codes.

Construction	B1 Design value	B2 Design value
Floor Area of the building	2521 m^2	4542 m^2
Air tightness, m^3/(h m^2-external surface)	2.0	1.0
External wall U-value, W/(m^{2}K)	0.33	0.15
Roof U-value, W/(m^{2}K)	0.25	0.09
Floor, U-value, W/(m^{2}K)	0.40	0.16
Window U-value, W/(m^{2}K)	1.90	0.62
Exhaust air heat recovery efficiency	–	75 %

The table highlights significant differences in insulation levels and airtightness, with B1 displaying higher air leakage compared to B2.

2.2. Weather data and energy prices

The coldest days of winter in Helsinki, located in the coastal regions of Southern Finland, typically occur at the beginning of February [81]. Due to the computationally intensive and time-consuming nature of this co-simulation, the simulation was conducted for the first week of February (February 1 – February 7) for the years 2015 and 2022. In 2015, the minimum recorded temperature was −14 °C, whereas in 2022, it reached −18.2 °C. The weather data for the years 2015 and 2022 are depicted in Fig. 2 and were obtained from the meteorological records of the Helsinki Kumpula station [80]. This timeframe is a critical temporal marker for the study, as it allows us to capture and analyse the extreme cold weather conditions in Southern Finland, thereby improving the relevance of the findings. The corresponding hourly electricity prices of 2015 and 2022 were obtained from ENTSO-E [83,84].

The rationale for selecting these specific years is that 2015 represents a period of normal electricity prices, while 2022 corresponds to a period characterised by an energy shock, as can be seen from the hourly price curve (Fig. 3) and price-duration curve (Fig. 4). As it can be observed from Fig. 5, the prices for the first week of February in 2015 were low and stable, whereas in 2022, the prices were high and fluctuating. The reasoning behind this was discussed in Section 1. The price levels corresponding to the year 2015 shall hereinafter be denoted as ‘P2015′, while those associated with the year 2022 shall be referred to as ‘P2022′.

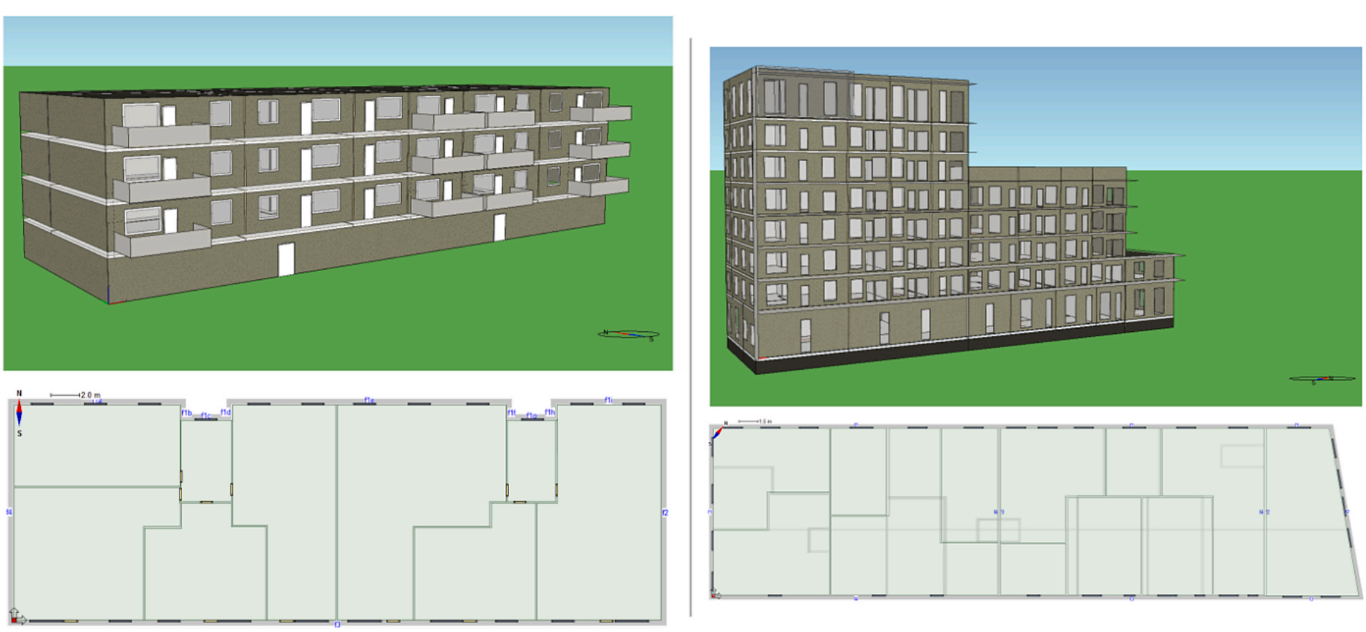

Fig. 1. The 1970s-era, poorly insulated building B1 (left) and the modern PEB B2 (right) in Helsinki modelled using IDA ICE.

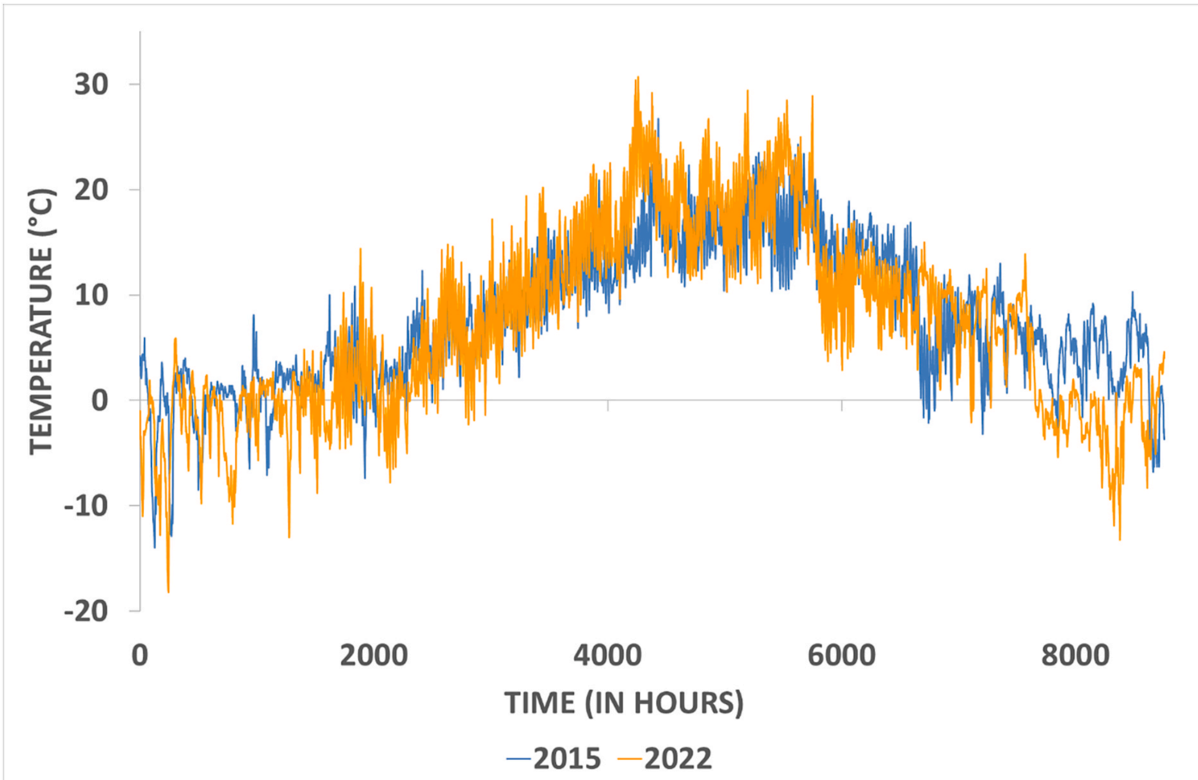

Fig. 2. The weather data for the years 2015 and 2022, as observed at Helsinki Kumpula station [82].

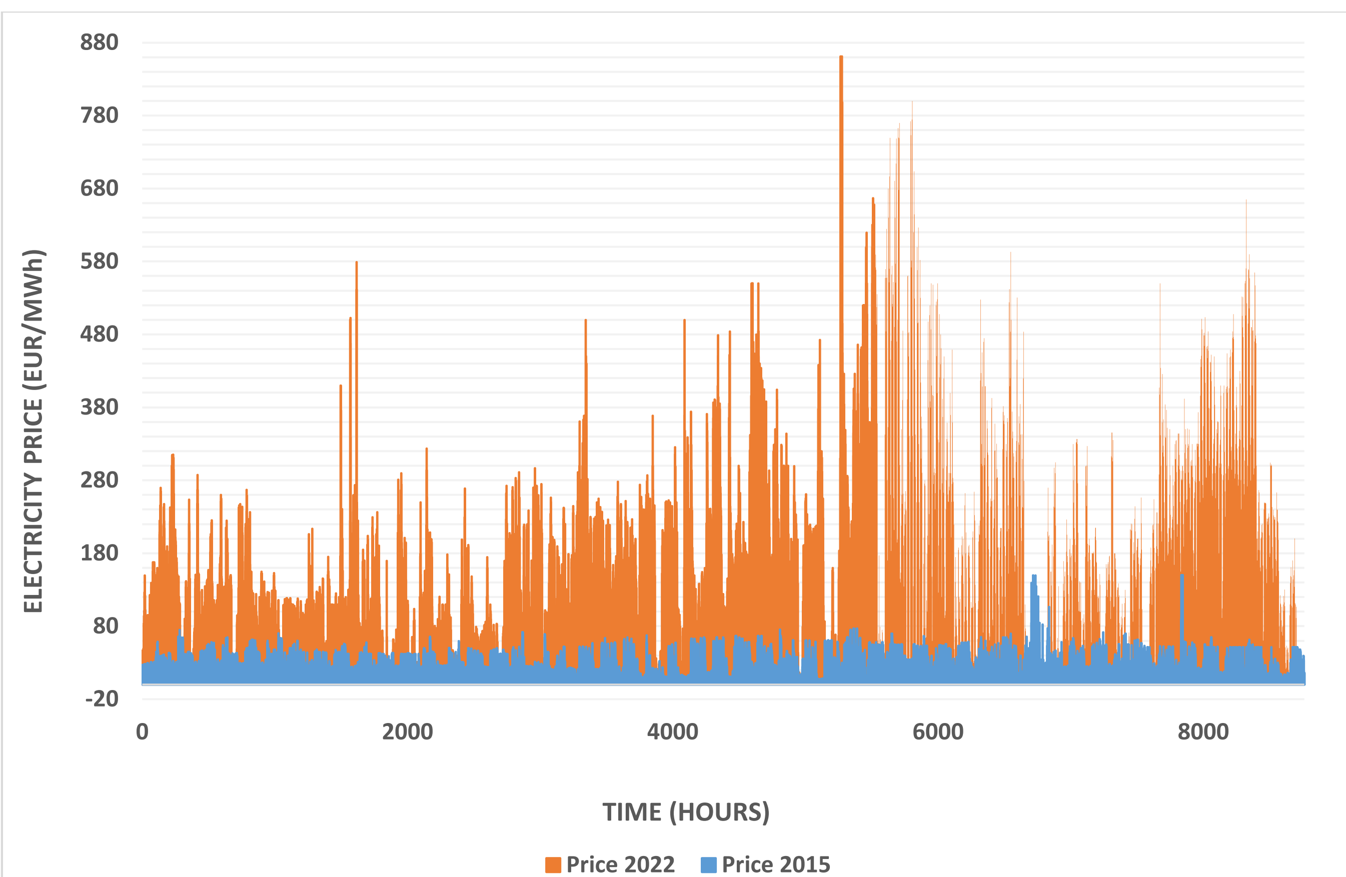

Fig. 3. The hourly electricity price curve for the simulated years, 2015 and 2022 [83,84].

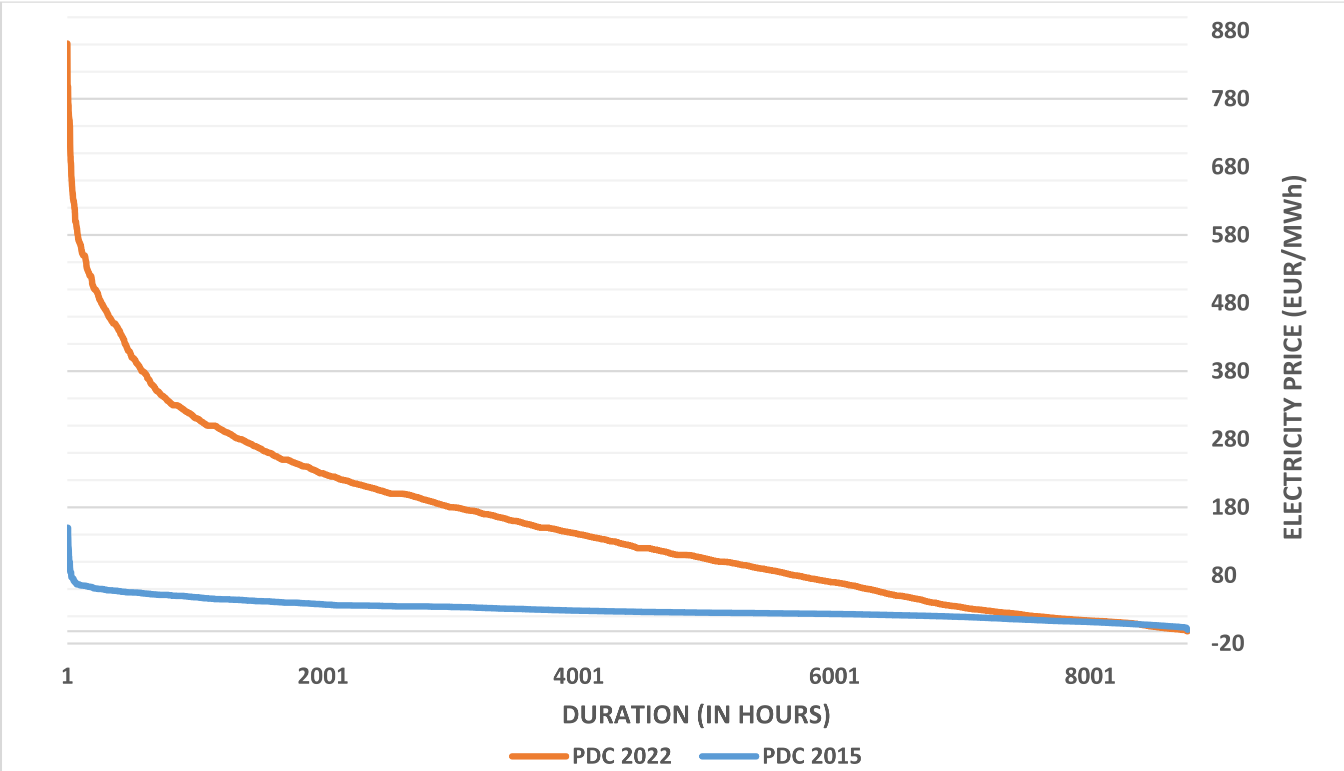

Fig. 4. The price-duration curve illustrating low and stable price levels in 2015 versus the high and fluctuating price levels in 2022.

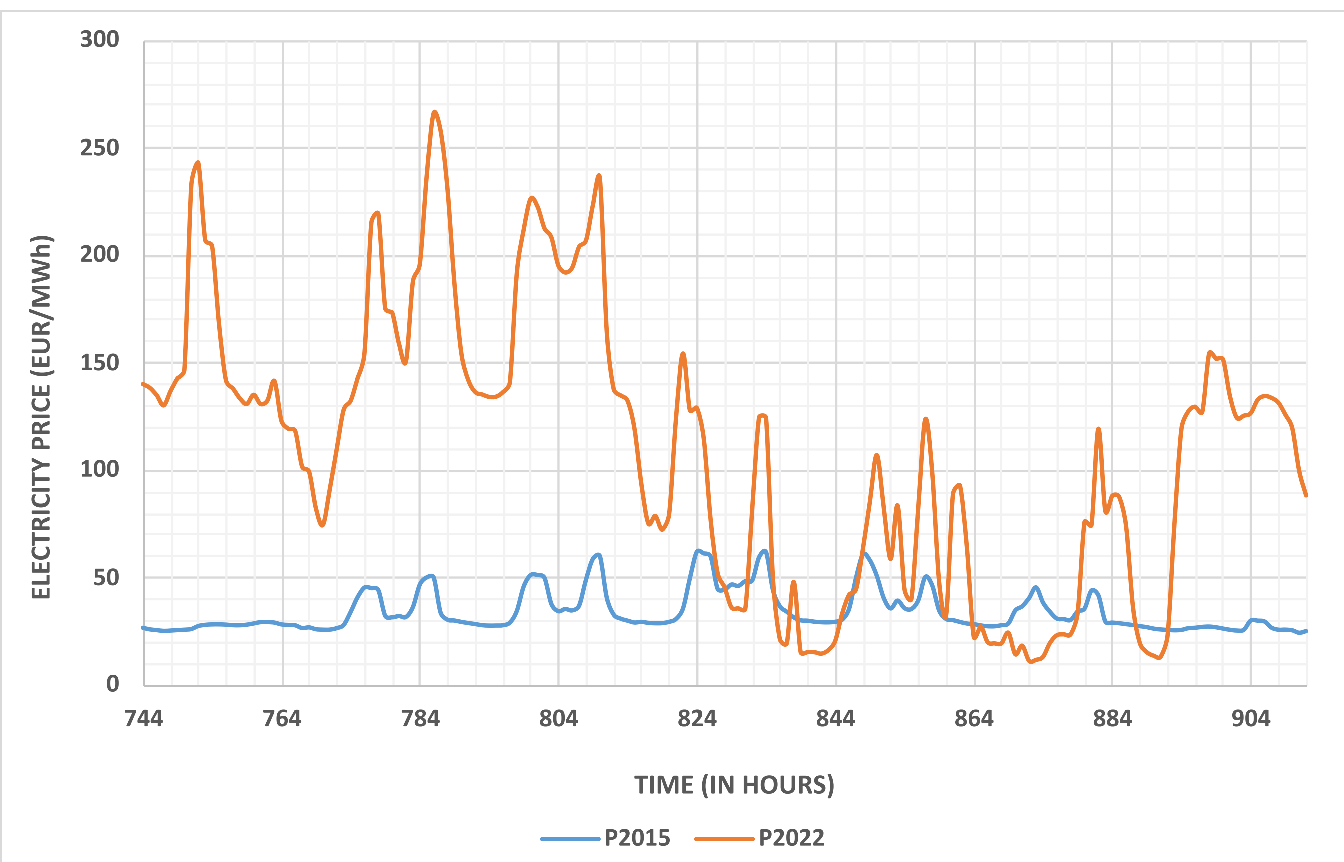

Fig. 5. The electricity price during the simulated period; the first week of February in 2015 and 2022 – obtained from ENTSO-E [83,84].

2.3. Building energy simulation and co-simulation with Python

The IDA ICE (Indoor Climate and Energy) building performance simulation software was used for the analysis. This tool, designed for precise modelling and simulation of detailed, dynamic multi-zone models, is used to investigate the thermal indoor climate and energy consumption of the building. IDA ICE has been extensively validated in previous research, ensuring the accuracy and reliability of the findings [62,85–87].

Due to the computational intensity of the simulations, which often require hours or even days to complete, the process was streamlined by focusing on the "worst" zone. In IDA ICE, the "worst" zone is defined as the zone with the most significant deviation from optimal thermal comfort conditions, i.e., highest percentage of people dissatisfied (PPD). Another common method of quantifying thermal discomfort is analysing how many unmet hours occurred when the mean air temperature fell below or above the heating/cooling setpoint Specifically, a 2-room apartment with a kitchenette (2 h + kk) on the top floor in B1 (PPD: 16.83 %, 523 unmet hours during the simulated period, where the mean air temperature fell below the heating setpoint) and a 2 h + kk apartment on the fourth floor in B2 (PPD: 12.15 %, 72 unmet hours) were identified as particularly challenging in terms of maintaining thermal comfort with the existing controllers. For simulation efficiency, these zones were replicated using the 'cloning' functionality in IDA ICE. Cloning facilitates the replication of building bodies or thermal zones within a simulation model, streamlining the creation and management of complex models by allowing the duplication of similar objects. The cloned zones were then integrated into control simulations performed using a co-simulation framework between Python and IDA ICE. The final model used in the co-simulator was the one with the replicated zones, ensuring consistency and efficiency in the simulation process.

In addition to its detailed modelling capabilities, IDA ICE facilitates seamless co-simulation with external programs, such as Python, via a dynamic-link library (idaapi2.dll), which allows socket communication interaction by providing a library API function accessible with Python [88]. This research builds upon the co-simulation framework developed by Catto Lucchino et al. [79], who developed a model-based control system for double skin façades. This research aims to develop an advanced model predictive controller. Given the extensive number of iterations between prediction and control actions, automation of the process is essential, as it is not inherently supported within IDA ICE and thus, co-simulation is important.

In this case study, the building model was simulated using IDA ICE 5.0, and the optimisation algorithm was implemented in Python 3.11 (64-bit), which acts as the master. A framework was also developed for this purpose. Through API function calls, a pre-existing model is loaded into IDA ICE, and control actions are executed through Python scripts utilising the ctypes library. This communication between IDA ICE and Python is facilitated through the IDA Message Broker Service. The API further enables commands such as opening the model in IDA ICE, accessing the objects and their values (e.g., room temperature), and saving the model. Python 3.11 was utilised not only to automate the process but also for the optimisation algorithm and post-processing of the extracted results.

The structure of the data transferred between Python and IDA ICE involves several elements that facilitate the co-simulation process. Python sends temperature setpoints and control actions derived from the optimisation algorithm to IDA ICE. These setpoints and actions are used to adjust the building's HVAC system to maintain thermal comfort and minimize energy costs. In return, IDA ICE provides room heating power values and indoor room air temperatures over the prediction horizon, which are crucial for calculating the total energy cost and assessing thermal discomfort. Additionally, IDA ICE sends the current state of the building. This information helps update the optimisation model and refine control strategies. Furthermore, simulation start and end times are managed by Python and communicated to IDA ICE to ensure that simulations run for the correct periods. These data exchanges can be summarized in Table 2.

The developed code aims to optimise the heating temperature setpoints by minimising the total energy cost and thermal discomfort experienced by the occupants. A multi-objective Non-dominated Sorting Genetic Algorithm II (NSGA-II), called from the pymoo Python library, is used to perform the optimisation. Within IDA ICE, the "Advanced level" simulation is used for model simulation, and the results of each simulation run are directly extracted. Room heating power and the room temperature data were read from .PRN files that were generated during the IDA ICE simulations over the prediction and control horizon.

2.4. Control strategies and optimisation algorithm

In this study, three control strategies—PI control, RBC, and MPC—are implemented for the heating systems in both buildings.

The PI controller was directly implemented in IDA ICE, where it was used to maintain the room air temperature at the designated heating setpoint. This setpoint is determined per the Finnish D3 Assuinkerrostalo (building code) regulations [89]. In accordance with these regulations, the stipulated heating setpoint for residential buildings in Finland is approximately 21 °C, while the cooling setpoint is generally established at 25 °C.

The Rule-Based Control (RBC) strategy implemented in this study considers energy prices from the preceding and succeeding 12-hour periods. The energy price at the current time step is classified as either 'high' or 'low' based on varying percentiles (50th, 60th, 70th, and 80th). This percentile-based classification is more responsive to price fluctuations, and the 12-hour window provides ample data for the controller to process before implementing flexibility measures [90]. Control actions are then implemented according to this classification. Building upon the authors' previous work [26], the optimal strategy for cost savings was identified. The most significant cost savings were achieved by setting the building's heating setpoint to 21.5 °C during low-price periods and reducing it to 19 °C during high-price periods. Consequently, this approach was adopted as the RBC strategy for the current study. The workflow for the RBC integrated with IDA ICE is illustrated in in Fig. 6.

In this work, an economic model predictive control approach was also developed with the objective functions defined as energy cost and thermal discomfort. These objective functions are commonly utilised in MPC applications for buildings and energy systems [91–93]. The MPC minimizes these objective functions within hard constraints, which include maintaining indoor temperatures between 19 °C and 23 °C and limiting the heater's power output to its maximum design capacity of 3200 W. The resolution of the temperature control is 0.1 °C, as is the case with the EXCESS building discussed in this study, as well as with newer buildings in Finland.

The simulation begins with a 2-week warm-up period (December 15–31 of the previous year) to initialize the building's state. For the

Table 2
Summary of parameters exchanged between IDA ICE and Python during co-simulation.

Data	Source	Description
Heating Temperature Setpoints	Python	Optimised setpoints for each zone
Control Actions	Python	Control actions derived from the optimisation algorithm
Simulation Start/End Times	Python	Start and end times for each simulation run
Room Heating Power	IDA ICE	Heating power consumptions for each zone
Room Temperature Data	IDA ICE	Indoor air temperature values for each zone
State of the Building	IDA ICE	Current state of the building

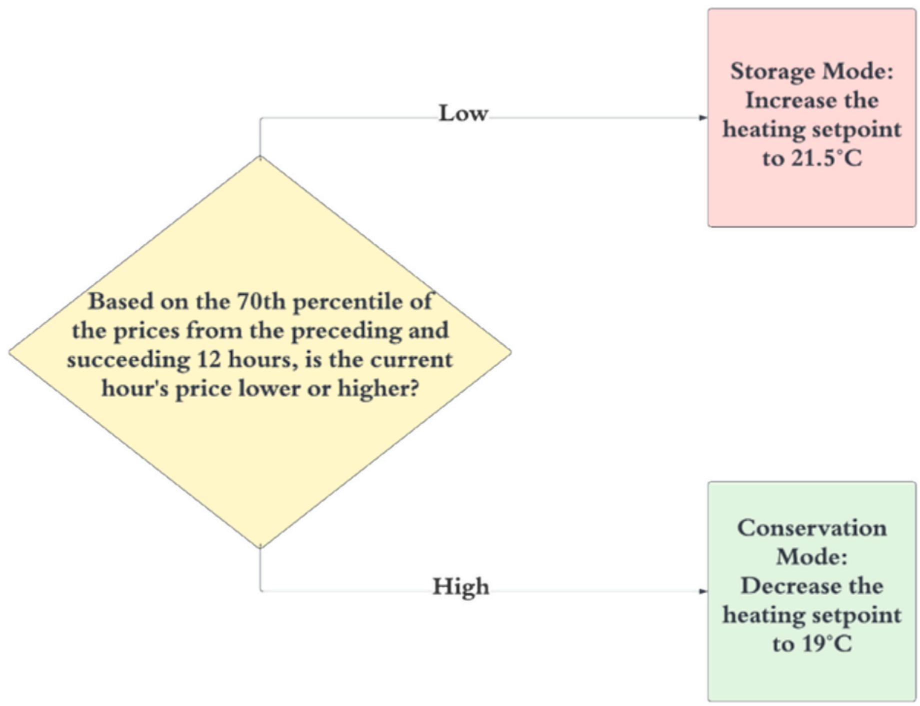

Fig. 6. The workflow for the RBC strategy utilised in this work.

developed MPC, a prediction horizon of 6 h and a control horizon of 1 h were selected. This selection was made to improve the accuracy of the forecast and to allow for finer time steps in the control action [50,94]. The optimisation algorithm iterates to minimize both energy cost and thermal discomfort and generates a sequence of setpoints over prediction horizon (6 values) and give them to IDA ICE model to run simulation for six hours. The optimal setpoints for the next 6 h by evaluating all Pareto-optimal solutions and identifying the best trade-off solution based on the Euclidean distance in the objective space, where equal weights are assigned to both objective functions. The first value of the setpoints within the prediction horizon is then implemented in the real building to operate the heating system. After one hour of operation with the optimal setpoint, the building's state is extracted and stored. This study makes use of the "hot start" feature in IDA ICE, which allows

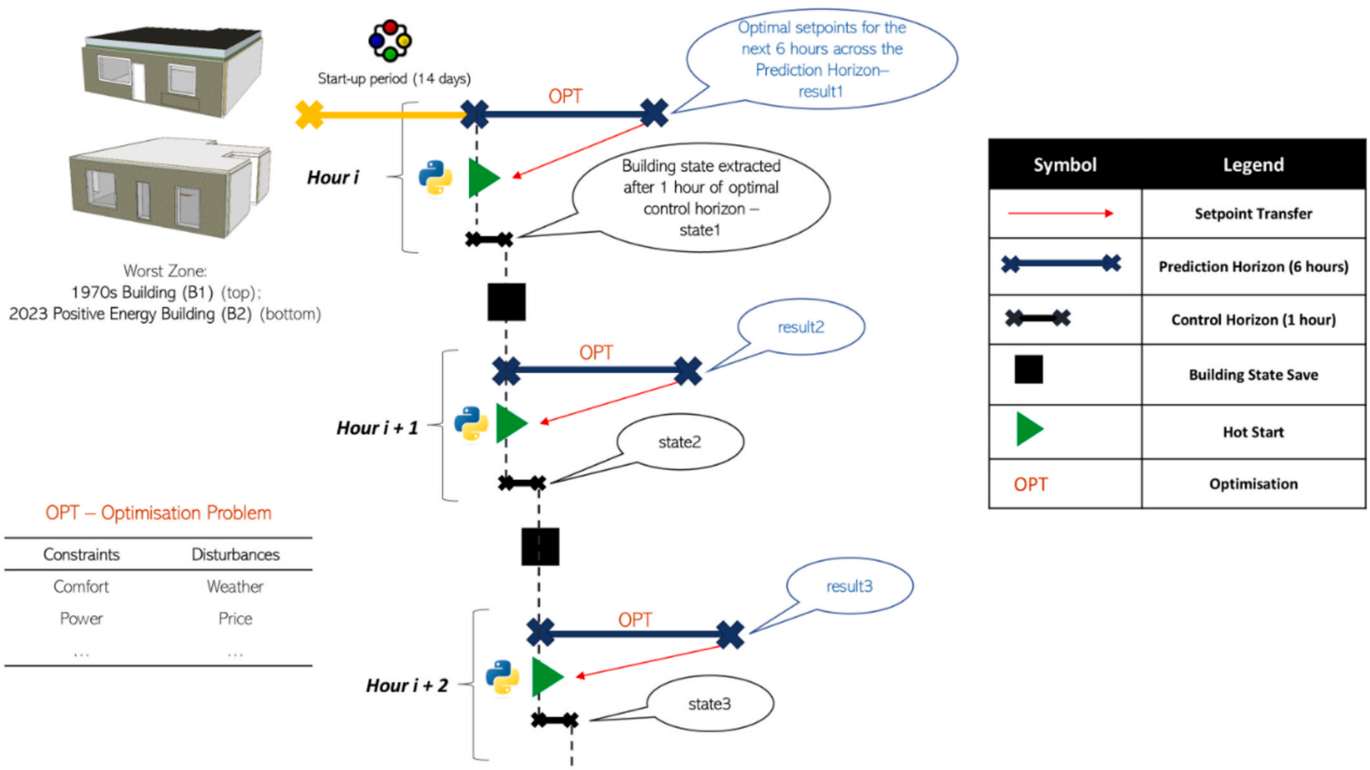

Fig. 7. The workflow for implementing the MPC used in this work, in co-simulation with IDA ICE.

simulations to commence from a predefined state rather than from initial conditions [call_ida_api_function(ida_lib.runIDAScript, building,"(:call run-special [@]:hot T:no-lin T)".encode('utf-8'))]. The simulation time is then advanced by 1 h, and the iterative process continues until the end of the simulation period. The workflow for integrating the MPC with IDA ICE is depicted in Fig. 7.

The NSGA-II is an extensively used evolutionary algorithm for solving multi-objective optimisation problems [95] showing high performance compared to other evolutionary algorithms [96]. Space Heating control in buildings often requires balancing multiple, often conflicting, objectives, such as minimising energy costs while concurrently minimising thermal discomfort, all within specified temperature setpoint constraints [97,98]. NSGA-II manages such scenarios by generating a Pareto front of optimal solutions, and unlike traditional optimisation methods that may converge to local optima, it is aimed at achieving global optima. In this study, a population size of 25 offsprings and 50 sets of generations were selected for the NSGA-II implementation.

3. Results and discussions

This section interprets and analyses the case study results, evaluating the effectiveness and limitations of the proposed RBC and MPC approach in achieving predefined control objectives. These control strategies were evaluated for their effectiveness in reducing energy costs and maintaining thermal comfort in the 'worst zone' of two different building typologies: an apartment building built in the 1970 s (B1) and a modern PEB (B2). The analysis was conducted for two different price scenarios: the low, stable price levels of 2015 and the high, fluctuating price levels of 2022.

Initially, when the three control strategies were implemented in B1 for 2015 price levels for the first week of February, the results were as follows: As evidenced by Fig. 9, the baseline PI control strategy exhibited the lowest cost-effectiveness, with an energy cost of about 957 euro cents. Conversely, the MPC strategy proved to be the most economical, with an energy cost reduction of approximately 743 euro cents, which translates to savings of 214 euro cents, or 22.3 % savings compared to PI. The RBC strategy followed suit, with savings of 91 euro cents, corresponding to 9.5 % of savings as compared to PI.

The operational behaviour of the heating system in the building can be observed in the heating power versus time graph presented in Fig. 8. The PI control maintains a relatively constant heating power. In contrast, the RBC strategy leads to fluctuations in heating power, with periods of high heating power and intervals of little to no heating, often resulting in increased power consumption to reach the set point. On the other hand, the MPC strategy demonstrates a more dynamic response, adjusting based on the fluctuating energy prices, making it the most economical option overall.

Subsequently, when the same controls were applied on the same building for the high and fluctuating price conditions of 2022, a similar trend was observed, with the MPC resulting in the most cost savings. As it can be seen from Fig. 9, the RBC approach yielded savings of approximately 552 euro cents (17.2 %), while MPC achieved savings of approximately 958 euro cents (29.9 %). Fig. 9 illustrates the combined impact of the three control strategies on operational costs and savings for building B1, comparing the price levels of 2015 and 2022. The combined figure allows for a clearer comparison of the strategies' performance across different years.

Similarly, when the controls were applied to the modern B2 under 2015 price conditions, it was observed that the RBC resulted in cost savings of approximately 10 euro cents (4.6 %) as compared to base case PI. On the other hand, the MPC demonstrated the highest cost savings of around 22 euro cents (10.1 %). The effect of the PI, RBC and MPC on B2 for 2015 price levels could be obtained from Fig. 10.

Now, when the same controls were applied on the building for the high and fluctuating 2022 price levels, a similar trend was observed, with the MPC resulting in the most cost savings. As it can be seen from Fig. 10, with the RBC there was a savings of around 78 euro cents (7.9 %), whereas, with an MPC, there was a savings of ∼ 147 euro cents

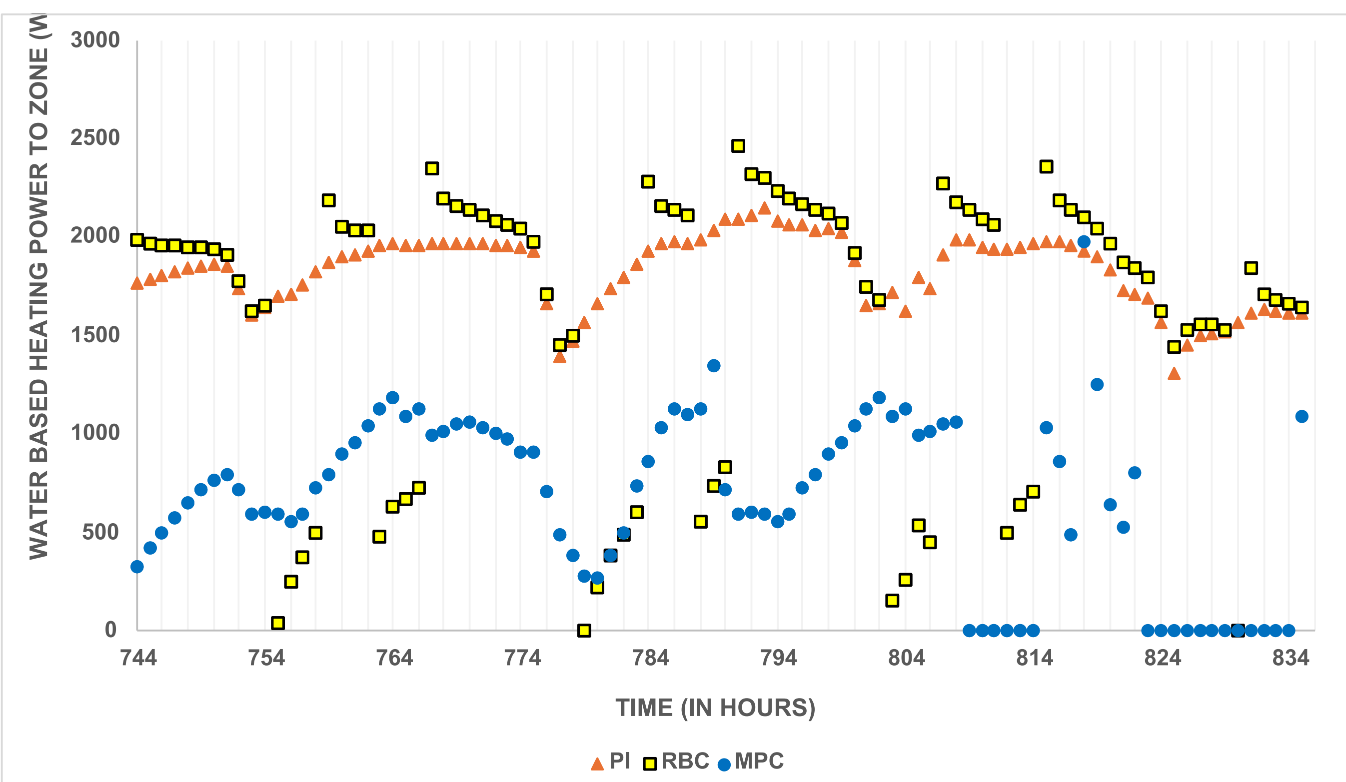

Fig. 8. Operational behaviour of the heating system in building B1 versus time for the three control strategies.

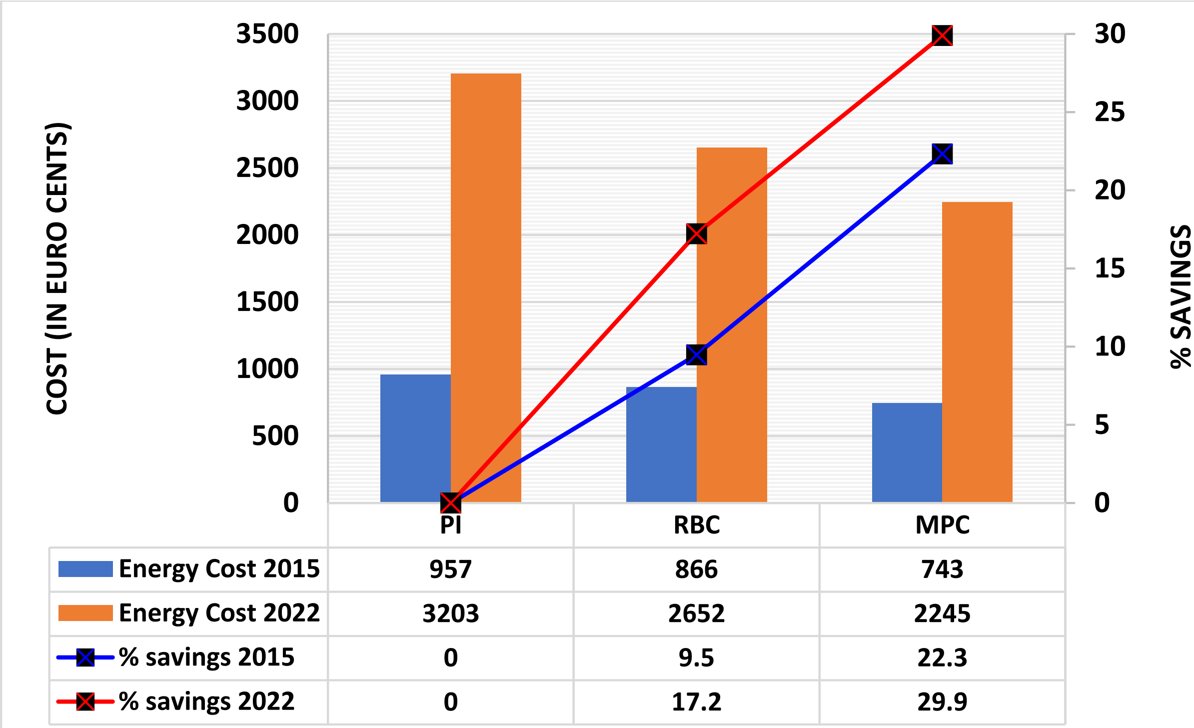

Fig. 9. Combined Effect of the Three Control Strategies on B1 for 2015 and 2022 Price Levels.

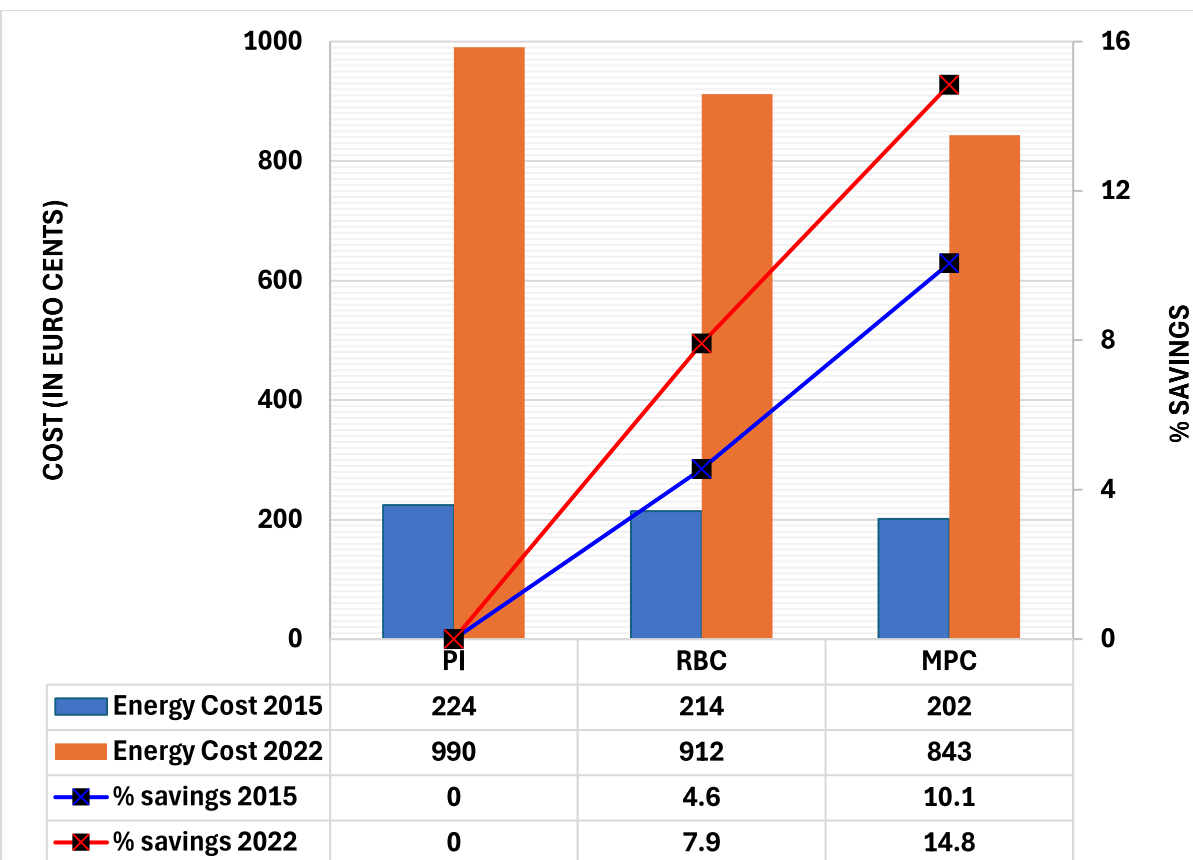

Fig. 10. Combined Effect of the Three Control Strategies on B2 for 2015 and 2022 Price Levels.

(14.8 %). Fig. 10 shows the impact of the three control strategies on operational costs and savings for building B2, comparing the price levels of 2015 and 2022.

Fig. 11 compares and contrasts the cost savings in terms of % as compared to base case PI control. The results indicate that the MPC strategy consistently outperforms both the PI and RBC strategies in terms of cost savings, particularly under conditions of high and fluctuating energy prices in 2022. This is attributed to the MPC's ability to dynamically adjust to real-time conditions, thereby optimising energy usage more effectively than the static rules of RBC or the reactive approach of PI control.

Compared to other energy storage systems, the storage potential of a building's thermal mass is influenced by numerous factors, including the building's insulation level, heating system, and other architectural features. Leaky buildings with poor insulation levels exhibit a smaller thermal time constant, while passive houses and modern PEBs, characterised by their high insulation levels, maintain a longer thermal time constant. These factors necessitate different control strategies to effectively balance energy flexibility, overall energy consumption, and occupant thermal comfort.

It is also observed that the potential for cost savings is greater in older buildings with poor insulation, as they start from a lower baseline of energy efficiency. Implementing advanced controls, such as RBC and MPC, results in greater cost savings in older buildings compared to newer, more energy-efficient structures. With around 43 % of Finnish building stock constructed before the 1980s, the potential for cost reduction through energy flexibility is especially notable. In poorly insulated buildings, such as B1 in this study, even minor improvements can lead to significant reductions in energy consumption and costs. Smart controls can optimise heating schedules, minimise unnecessary heating, and address specific inefficiencies. Consequently, the initial investment in smart control systems and insulation improvements yields a higher return in older buildings, where the disparity between the current and optimised states is more substantial. The inferences presented, along with the findings summarised in Table 2, are supported by the results of previous studies [99–102]. These earlier works provide additional evidence that aligns with the trends and conclusions in this study. Table 3 summarises the impact of factors such as building age and price levels on energy flexibility and associated costs.

4. Conclusion

This paper presents a comparative study on the effectiveness of MPC in optimising energy flexibility for buildings in cold climates, comparing it with PI and Rule-based control methods. The implementation of MPC in building energy management emerges as a promising strategy for achieving substantial cost savings and enhancing energy flexibility. By dynamically adjusting the heating setpoint to changing environmental conditions and occupant behaviours, this control strategy shows significant potential for optimising the energy performance of buildings, as supported by the findings.

The results show that the MPC delivered the greatest cost savings, especially under conditions of high and fluctuating prices. In the 1970s building (B1), MPC achieved up to 29.9 % cost savings compared to PI control. In the modern building (B2), MPC resulted in up to 14.8 % cost savings. The findings demonstrate that the potential for cost reduction through energy flexibility is significantly greater in older, poorly insulated buildings due to their higher energy consumption, highlighting that the benefits of implementing strategies like MPC are more pronounced where energy inefficiencies present greater opportunities for optimisation. With nearly half of Finland's building stock dating back to before the 1980s, the potential for cost reduction through energy flexibility is particularly significant.

The method and framework developed in this study are designed to

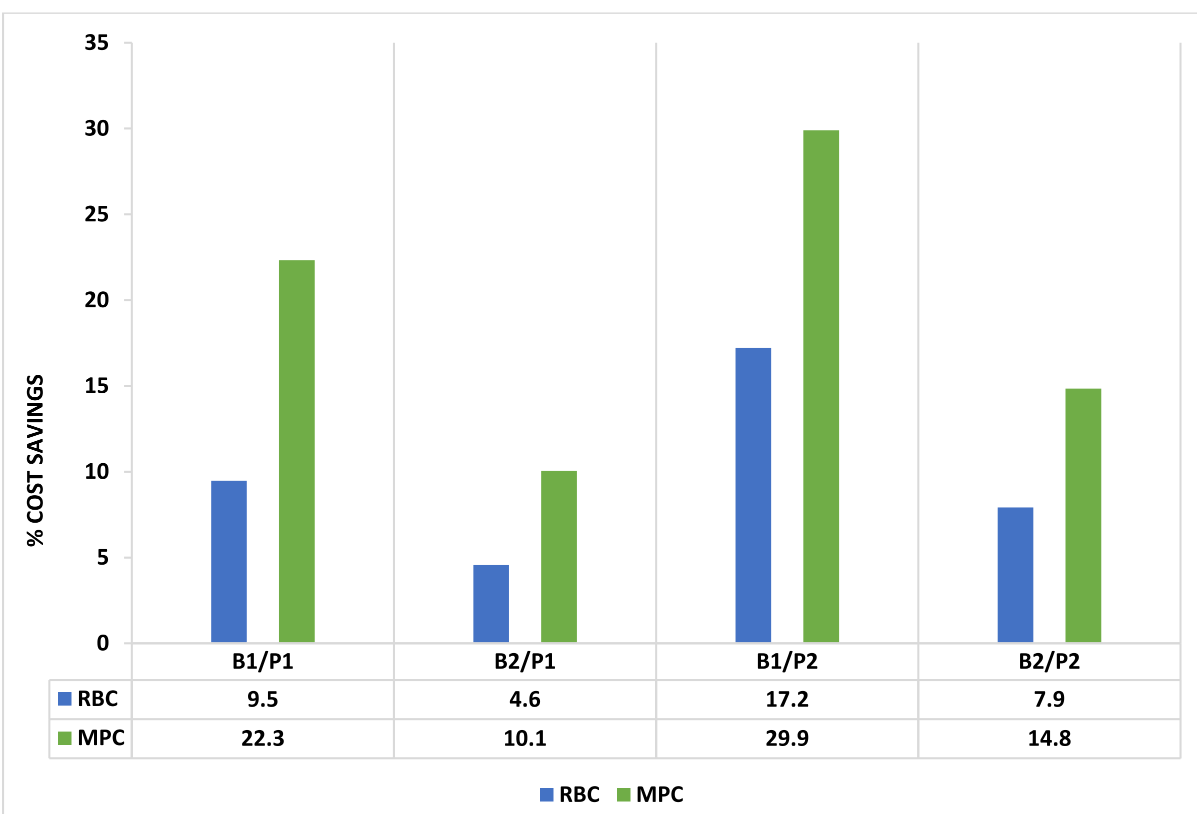

Fig. 11. Total Cost savings in % (as compared to PI control) when the RBC and MPC are implemented for the two buildings (B1, B2) for the two electricity price levels (P1, P2).

Table 3
Discussion: influence of building age, design, and electricity price levels on energy flexibility.

Influence of building age and design	Older buildings, such as the 1970s structure examined in this study (B1), exhibit greater potential for cost savings when implementing advanced control strategies due to their lower baseline efficiency. This enables more significant improvements through advanced control strategies (RBC, MPC). In contrast, modern buildings like the EXCESS building (B2), with already high levels of energy efficiency, demonstrate smaller absolute savings; however, they still benefit from the application of advanced control strategies.
Impact of Price Levels	The effectiveness of advanced control strategies is more pronounced under high and volatile energy price conditions, as observed in the 2022 scenario (P2022). The MPC strategy's dynamic ability to anticipate and respond to price fluctuations results in significant cost savings, highlighting its importance in environments characterised by dynamic energy pricing. When energy prices are low and stable, the potential for savings is limited since the baseline costs are already low, and there's less incentive to adjust usage dynamically.
Implications for retrofitting older buildings vs. designing new ones	The findings emphasise the value of retrofitting older buildings with advanced control systems to enhance energy efficiency and reduce operational costs. Given the substantial stock of ageing buildings in Finland, retrofitting represents a practical and cost-effective approach to improving energy performance. For new constructions, integrating smart control systems from the outset can further enhance building resilience and operational efficiency.

be highly adaptable across various climates and building types. While the focus is on specific case studies in Helsinki, Finland, the same methodology can be tailored to different building models and climates. This flexibility allows for the substitution of the building model without significant modifications, accommodating diverse building types and geographical locations. By using local weather data and adjusting the parameters accordingly, the methodology ensures effective control strategies in different climatic conditions. While this study uses a white box model, the MPC approach is equally viable with grey or black box models. Once the real case building is equipped with a building management system and sensors, the MPC can be effectively used to reduce energy costs. A stochastic MPC would be developed to mitigate the uncertainties in the weather forecast. The real-time data from the sensors can be integrated into the MPC framework to facilitate dynamic adjustment of the control strategies, ensuring optimal performance. To facilitate reproducibility – the modelling assumptions, parameter selection, and details about the formulation of MPC (objective functions, constraints, etc.) are clearly outlined.

A key contribution of this work is the novel application of white box modelling and co-simulation techniques for MPC, offering a more accurate representation of building dynamics. However, despite its advantages, the white box modelling approach used in this study is computationally demanding, requiring substantial resources for accurate simulation and optimisation. Future research will focus on validating these findings with real-world data by implementing the proposed control strategies in operational buildings and monitoring their performance. Such validation would provide more robust evidence of the approach's effectiveness and scalability. However, it is also important to consider that while the potential for cost savings is higher, the absolute energy consumption in an old building may still be greater than in a new, well-insulated building, even after improvements. Additionally, integrating MPC with renewable energy sources, such as solar panels and wind turbines, or other energy storage systems, could further enhance a building's energy flexibility and improve its resiliency. Future work will also include comparing the speed and accuracy of MPC implementations using black and grey box models, as well as evaluating the control strategies across different building types.

The study also points towards the potential role of MPC in improving building resilience, particularly in cold climates such as Helsinki. By integrating energy flexibility with resilience strategies, MPCs could potentially optimise energy usage and contribute to maintaining indoor temperatures during short-term planned grid disruptions. For instance, MPC systems could pre-heat buildings before a scheduled blackout, thereby improving the survivability and comfort of occupants during the outage. This proactive approach allows buildings to store and manage energy more effectively, enhancing occupant safety and operational continuity during extreme weather events or brief energy supply instability. Future research could explore adapting this MPC framework to optimise not only energy flexibility but also potential savings in energy consumption and emissions. Additionally, investigating longer forecasting and control horizons could help address the challenges of maintaining indoor temperatures during prolonged grid disturbances. If implemented on a large scale across the building stock in Finland, such a system could play a significant role in improving overall energy efficiency, reducing environmental impact, and contributing to national energy goals.

CRediT authorship contribution statement

Rakesh Ramesh: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hassam Ur Rehman:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Ala Hasan:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization. **Leena Eerolainen:** Writing – review & editing, Writing – original draft, Conceptualization. **Hang Yin:** Writing – review & editing, Software, Methodology, Investigation, Conceptualization. **Mohamed Hamdy:** Writing – review & editing, Supervision, Resources, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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