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Enhanced Energy Efficiency and Adaptive Indoor Temperature Management for Residential Buildings Using an Advanced Model Predictive Control Strategy

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KEYWORDS

Model Predictive Control, HVAC Systems, Energy Efficiency, Control, Thermal Comfort.

ABSTRACT

Rising energy costs and the growing demand for occupant comfort underscore the urgent need for efficient residential heating, ventilation, and air conditioning (HVAC) systems. In response, this study presents a Model Predictive Control (MPC) strategy designed to optimize energy consumption in heating systems while ensuring thermal comfort for occupants. Developed and rigorously tested in MATLAB Simulink, the proposed MPC continuously adjusts system parameters to minimize energy usage without compromising indoor comfort.

In contrast to conventional reactive PID controllers, the proactive nature of the MPC approach delivers up to 22.7% energy savings, demonstrating its superior efficiency and adaptability. These encouraging results underscore the significant potential of MPC for smart HVAC management, where balancing energy costs, emissions, and occupant comfort is critical. The successful implementation of this control strategy in residential systems could drive substantial improvements in sustainability and occupant well-being, ultimately paving the way for greener and more energy-efficient living environments. Our findings provide valuable insights for future research and practical implementations in the evolving field of smart building technologies.

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تحسين كفاءة الطاقة وإدارة درجة الحرارة الداخلية التكيفية في المباني السكنية باستخدام استراتيجية متقدمة للتحكم التنبؤي بالنموذج

يوسف البوطاهري، بداللطيف ايت منصور، أمين تيليوا

ملخص: تؤكد تكاليف الطاقة المتزايدة والطلب المتنامي لراحة الشاغلين الحاجة الملحة لمنظومات التدفئة والتهوية وتكييف الهواء (HVAC) السكنية الفعالة. استجابة لذلك، تقدم هذه الدراسة اسراتيجية التحكم التنبؤي بالنموذج (MPC) المصممة لتحسين استهلاك الطاقة في منظومات التدفئة مع ضمان الراحة الحرارية للشاغلين. تم تطوير واختبار نظام MPC المقرح بصرامة باستخدام MATLAB Simulink، الذي يقوم باستمرار بضبط معلمات النظام لتقليل استهلاك الطاقة دون المساس بالراحة الداخلية. على عكس وحدات تحكم PID التقليدية التفاعلية، توفر الطبيعة الاستباقية لنهج MPC توفراً في الطاقة يصل إلى 7.22 %، مما يدل على كفاءتها العالية وقدرتها على التكيف. تؤكد هذه النتائج المشجعة الإمكانات الكبرة لنظام MPC في إدارة أنظمة HVAC الذكية، حيث تكون الموازنة بين تكاليف الطاقة والانبعاثات وراحة الشاغلين أمراً بالغ الأهمية. يمكن أن يؤدي التنفيذ الناجح لاسراتيجية التحكم هذه في المنظومات السكنية إلى تحسينات كبرة في الاستدامة وراحة الشاغلين، مما يمهد الطريق في النهاية لبيئات معيشية أكثر خضرة وكفاءة في استخدام الطاقة. تقدم نتائجنا رؤى قيمة للبحوث المستقبلية والتطبيقات العملية في المجال المتطور لتقنيات المباني الذكية.

الكلمات المفتاحية – التحكم التنبؤي بالنموذج، أنظمة التدفئة والتهوية وتكييف الهواء(HVAC) ، كفاءة الطاقة، الراحة الحرارية، التحكم الذكي

1. INTRODUCTION

1.1. Background

The building and construction sector accounts for a significant share of global energy consumption, representing 27% according to the International Energy Agency (IEA) report for 2022. Similarly, this industry also contributes 27% of energy-related emissions, as indicated in the same IEA report [1]. Optimizing energy consumption and improving air quality in buildings enhances occupant comfort, productivity, and health [2]. Most of the energy consumed by buildings is due to Heating, Ventilation, and Air Conditioning (HVAC) systems [3,4], making their optimization essential to reduce energy costs and environmental impact. Over the past decade, there has been increasing interest in HVAC systems for their ability to enhance energy efficiency by improving occupant comfort and reducing energy usage [5,6]. It is crucial to balance energy efficiency with thermal comfort in buildings [7].

HVAC systems consume a significant portion of a building's total energy. Reducing their energy demand is crucial for improving efficiency and lowering greenhouse gas emissions. Within the broader spectrum of HVAC operations, ventilation processes stand out as especially energy intensive, as they can lead to considerable heat loss in commercial, industrial, and residential settings [8]. To address these challenges, the careful commissioning of HVAC systems serves as a fundamental strategy. Commissioning not only verifies that equipment is installed and functioning as intended but also ensures that systems are fine-tuned to deliver optimal occupant comfort and energy performance [9]. This involves systematic review and calibration of system components ranging from ducts and fans to sensors and control algorithms to confirm that they achieve peak efficiency without compromising indoor thermal quality. When HVAC systems are thoroughly commissioned, buildings can realize notable benefits, including significant reductions in energy use, lower operating expenses, and healthier indoor environments. By placing special emphasis on ventilation optimization and rigorous commissioning protocols, building managers and owners can substantially shrink their energy footprint. In doing so, they align their operations with broader sustainability targets, support environmental stewardship, and respond proactively to energy and climate challenges. Recognizing the importance of these measures, current research efforts are increasingly devoted to devising advanced, data-driven control techniques that can monitor and adjust HVAC performance in real-time. These innovative control strategies aim to dynamically adapt system operations based on varying occupancy patterns, outdoor climate conditions, and evolving user preferences. Through the integration of smart sensors, predictive analytics, and automation, these advances hold considerable promise for achieving further energy savings and operational efficiency in the building sector [10,11].

1.2. Research Gap and Study Focus

However, despite these advancements, there remains a notable gap in research focused on applying these advanced control strategies specifically to residential buildings. Most studies have concentrated on commercial or industrial settings, which have different energy consumption patterns and control requirements compared to residential environments. Residential buildings present unique challenges such as varying occupancy patterns, smaller system sizes, and cost constraints, which may require tailored control approaches. This study aims to address this gap by developing and validating a Model Predictive Control (MPC) model for residential heating systems.

In this context, the adoption of Advanced Control Strategies (ASCs), rather than traditional reactive rule-based approaches, is proving to be a more effective method of saving energy in buildings. These strategies promote robust, efficient operation of HVAC systems through supervised control [12]. ASCs stand out for their ability to self-adapt, a quality that significantly improves the operational efficiency of HVAC systems and, consequently, the thermal comfort of occupants [13]. These features make ASCs particularly attractive for energy conservation in building HVAC systems. Thus, this article focuses on the study of advanced control approaches aimed at maintaining a home's temperature within a comfort zone while optimizing energy consumption.

MPC is one of the ASCs demonstrating notable effectiveness in HVAC system control, as indicated by several studies [14]. MPC uses a system model to anticipate system evolution or performance measurements over a predetermined future period. Based on the results of this prediction, optimal control variables can be determined using optimization techniques.

1.3. Previous Studies on Model Predictive Control (MPC)

MPC has emerged as a sophisticated and forward-looking approach to managing a wide range of systems, including HVAC operations in buildings. Central to MPC is the use of a mathematical representation of the system under control, which enables it to compute optimal control actions based on predefined objectives [15]. By incorporating information from a dynamic model, MPC can predict how a given environment such as a building's indoor climate will evolve over a specified time horizon, and then select the most advantageous control strategies accordingly [16]. Unlike traditional Building Automation and Control (BAC) systems that typically respond after changes have occurred, MPC's predictive capability supports proactive management. In other words, it allows the system to anticipate future environmental conditions, implement control actions in advance, and thereby optimize performance. Additionally, MPC is highly adaptable, as its objective function can be fine-tuned to achieve multiple goals, ranging from enhancing energy efficiency to improving occupant comfort [17].

Recent developments in information and communication technologies have further expanded the practical applications of MPC in building environments. Researchers and practitioners have leveraged MPC algorithms to fine-tune HVAC operations in real-time, improving both occupant thermal comfort and system efficiency [18]. Moreover, these algorithms have been deployed to strategically reduce energy expenditures [19]. For instance, Devid et al. [20] applied MPC in a commercial office building setting in the United States, successfully cutting energy consumption over a two-month period. Similarly, Freund et al. [21] implemented MPC on a large-scale building and recorded energy savings of up to 75% within three months. Another example by Bird et al. [22] demonstrated that adjusting the HVAC setpoint temperatures via MPC in a commercial building could yield significant cost savings over a two-month timeframe. Beyond individual case studies, broader reviews of MPC implementations, such as the work by H. Thieblemont et al. [23], have highlighted that when MPC is deployed in real-world building contexts, it consistently leads to improved thermal conditions and energy savings, often on the order of 10% to 30%. Collectively, these studies underscore MPC's potential as a transformative tool for building energy management. By preemptively addressing environmental variability, MPC-based control strategies contribute not only to reducing operational costs and curbing energy consumption but also to delivering healthier and more comfortable indoor environments. As technology continues to advance, the role of MPC in comprehensive, intelligent building management will likely become even more prominent.

2. METHODS

2.1. Heating system for the home

The home heating system illustrated in Figure1, implemented using Simulink® Simscape™ blocks, consists of a heating device and a house structure comprising four main components: indoor air, house walls, windows, and the roof. In this model, the house thermally interacts with its environment through its walls, windows, and roof, where each heat transfer mode is simulated as a combination of thermal convection, thermal conduction, and thermal mass. Additionally, a temperature sensor is incorporated into the house to measure thermal variations. This model provides a clearer understanding and visualization of how heat is exchanged within the house and with its environment.

To ensure the robustness of the Simulink model, it was tested under a variety of simulated conditions, including different outdoor temperature profiles (ranging from 5°C to 15°C), occupancy patterns, and heating setpoints. The model's ability to maintain indoor temperatures within the desired comfort range while minimizing energy consumption was verified through these simulations. Additionally, the model was compared to a simplified analytical model, showing good agreement in steady-state conditions.

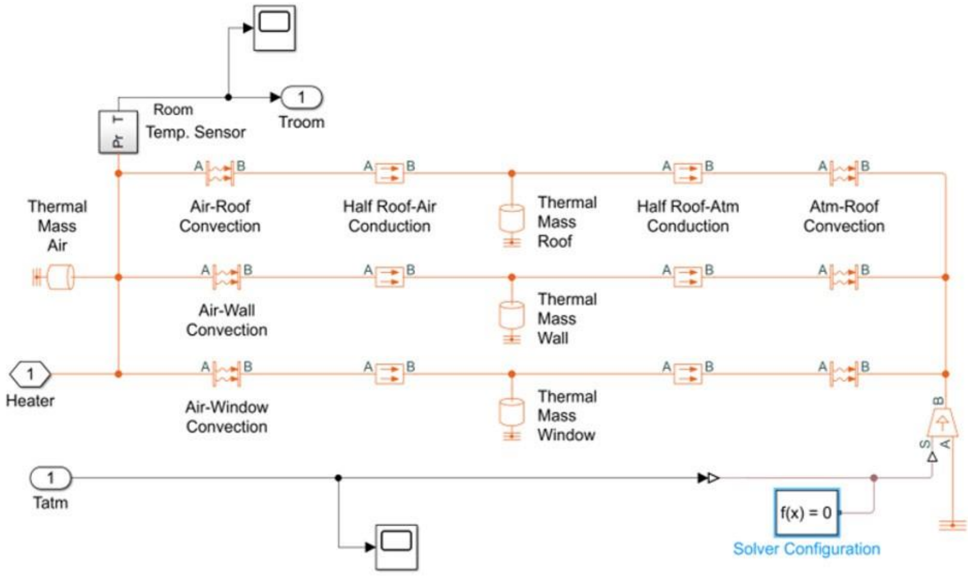

Figure 1. House Thermal Network Subsystem.

2.2. MPC Formulation

MPC represents a feedback control strategy that relies on a predictive model to anticipate forthcoming outcomes within a process. Illustrated in Figure 2, an MPC system typically comprises two core components: the plant model and the optimizer. The plant (House in this study) model serves to simulate the behavior of the environment, providing insights into its dynamics and responses. Conversely, the optimizer undertakes the critical task of generating optimal control strategies. These strategies are meticulously crafted to steer the projected outputs of the plant towards a predefined target or reference point, ensuring alignment with desired operational objectives. In essence, the optimizer acts as the brain behind the MPC framework, orchestrating control actions to effectively regulate the process and maintain desired performance levels over time.

The MPC, an ACS, endeavors to determine the optimal actions within a limited time frame by leveraging the dynamic model of the controlled object and current measurement states. This determination involves computing the future trajectory of the object's state across the optimization window period. During each sampling moment, the online MPC calculates the forthcoming sequence of control actions, implementing only the initial action from the sequence.

The inclusion of predictive information allows MPC to anticipate future conditions and incorporate them into the decision-making process, thereby enhancing system performance. In the case of HVAC applications, the MPC's objective function typically balances two key factors: the operational cost of running the HVAC equipment and the extent to which the indoor temperature deviates from a specified target setpoint. By optimizing this objective function, the resulting control strategy seeks to minimize expenses, such as energy usage or demand charges, while keeping the indoor environment as close as possible to the desired temperature level. MPC was chosen over traditional Proportional-Integral-Derivative (PID) controllers due to its ability to anticipate future conditions and optimize control actions, accordingly, leading to better energy efficiency and comfort regulation. Compared to adaptive or reinforcement learning-based controls, MPC offers a more straightforward implementation and does not require extensive historical data for training, which is advantageous in residential settings where data collection might be limited.

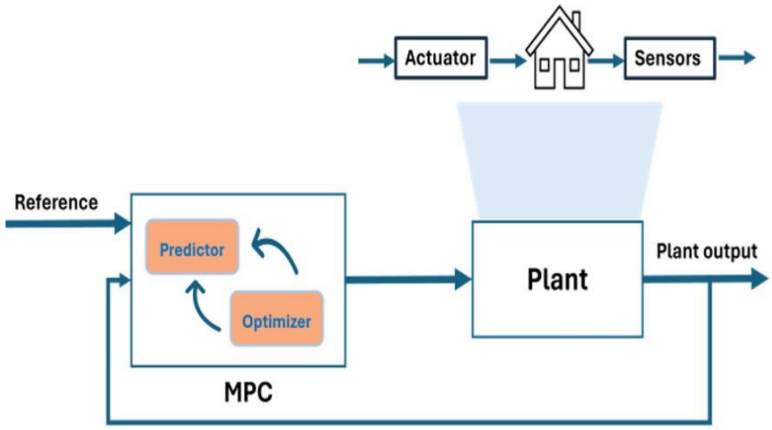

Figure 2. Diagram illustrating the MPC controller.

A general mathematical formulation of an MPC problem is often expressed as follows:

$$J = min \sum_{\{k=n\}}^{\{n+m-1\}} Obj(\tilde{y}^k, u^k) \tag{1}$$

$$\tilde{y}^{\{\ddot{u}+1\}} = f(\tilde{y}, u), k = n, n+1, \dots, n+m-1 \tag{2}$$

$$\tilde{y}^n = y^n_{initial} \tag{3}$$

$$u^k \in U, k = n, n+1, \dots, n+m-1 \tag{4}$$

$$\tilde{y}^k \in X, k = n, n+D, \dots, n+m-1 \tag{5}$$

Here, $\tilde{y}^k$ represents the predicted state variable (e.g., indoor temperature) at the discrete time step k, and u^k denotes the associated control inputs (control signals for heating). The objective function, shown in Eq. (1), encapsulates the trade-off between maintaining thermal comfort and minimizing energy use over a specified prediction horizon (from time step n to n+m-1). The model's dynamics are defined in Eq. (2), mapping current states and control inputs to the next state. This set of equations accounts for various thermal factors, including changes in indoor temperature as influenced by heating or cooling actions, as well as evolving outdoor conditions. Eq. (3) sets the initial conditions for the MPC algorithm, ensuring that the optimization problem starts from the current known state of the building environment. The method used to select or estimate $y^n_{initial}$ also influences the classification and design of the overall MPC approach. Different initialization techniques may lead to variations in how the controller responds to disturbances or uncertainties. Finally, Eqs. (4) and (5) impose constraints on both control inputs and state variables. For example, $u^k \in U$ ensures that all control actions remain within the allowable range of actuator capabilities, while $\tilde{y}^k \in X$ enforces physical or operational limits on system states, such as maximum or minimum allowable temperatures.

In summary, these mathematical relationships define how MPC leverages future predictions, sets comfort and cost objectives, and apply system constraints to yield an optimal, forward-looking control strategy for HVAC operation.

2.3. MPC design

To efficiently design the MPC, it is essential to identify key parameters such as controller sampling time, prediction and control horizons, and associated weights and constraints. Figure 3 illustrates these parameters. These parameters play a vital role in influencing the complexity of the control algorithm and determining its overall performance. It is important to note that these parameters are indispensable when implementing MPC.

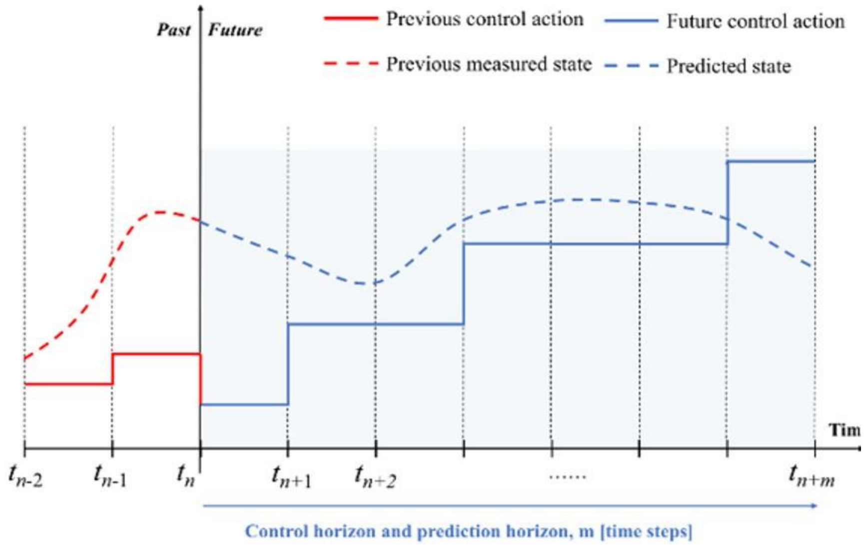

Figure 3. Diagram illustrating the MPC.

A sensitivity analysis was conducted to evaluate the impact of key MPC parameters on system performance. The prediction horizon varied from 10 to 20 steps, and the sampling time was adjusted between 1 and 5 minutes. Results showed that a longer prediction horizon generally led to better energy savings but increased computational time. A sampling time of 1 minute provided a good balance between control responsiveness and computational feasibility. The weights in the objective function were also tuned to prioritize either energy savings or temperature regulation, depending on the specific requirements.

In terms of real-time implementation, the MPC algorithm was designed to run efficiently on standard computing hardware. The computational time for each optimization step was found to be approximately 0.2 seconds on a typical PC (DELL XPS 15 9500), which is well within acceptable limits for real-time control applications.

The primary purpose of the MPC controller described in this work is to determine optimal control inputs that minimize an objective function over a specified prediction horizon. The underlying mathematical model of the house is employed to assess its present thermal state, while integrated weather forecasts inform predictions of future conditions. By combining current measurements with anticipated changes, the MPC aims to fine-tune the system's control parameters, ensuring that both near-term and long-term performance objectives are met efficiently.

In practice, the MPC continuously forecasts how the indoor temperature will evolve within the chosen prediction window. At each decision point, it calculates the best possible heating strategy to keep the actual indoor climate as close as possible to the target temperature, all while reducing heating-related energy costs. To accomplish this, the controller simulates various scenarios adjusting heating inputs and evaluating their impact on future temperatures to identify the sequence of control actions that achieve the optimal balance. This process is repeated at every time step, leveraging updated information about outdoor weather conditions, current indoor states, and occupant comfort requirements. Over time, this iterative optimization approach ensures that thermal comfort and energy efficiency are maintained, adapting dynamically to changing environments and operational constraints.

3. RESULTS AND DISCUSSION

To accurately evaluate the effectiveness of the MPC-based control strategies developed in this study, their outcomes were systematically compared against those obtained from a conventional PID controller. By examining both approaches under similar conditions, it was possible to conduct a comprehensive assessment of the proposed MPC system's advantages over standard control methods.

From an indoor environmental quality perspective, the degree to which the controller maintained the setpoint temperature served as a key metric. This indicator provided direct insight into the thermal comfort levels experienced by occupants. In this study, thermal comfort was operationally defined as maintaining the indoor temperature within a tolerance of ±1°C around the target setpoint of 22°C, in accordance with the criteria outlined in the ASHRAE Standards [24]. In parallel, the energy performance of the heating system was scrutinized by analyzing its specific energy consumption. By doing so, the study could ascertain not only whether the MPC approach improved comfort, but also how effectively it reduced energy use relative to a conventional controller.

All these performance evaluations were facilitated through simulations carried out in the MATLAB Simulink Simscape environment. This platform allowed for a detailed representation of the building's thermal behavior, the heating system's response, and the controllers' actions. Figure 4 illustrates the model's architectural layout, offering a clear visual guide to how each component of the system fits into the overall control framework. Through this integrative modeling and analysis, the study could thoroughly validate the potential benefits of MPC for enhancing both comfort and energy efficiency in building heating applications.

The initial step involved configuring the MPC controller based on the mathematical model introduced in Section 2. During this phase, parameters such as sampling intervals, prediction horizons, and related control settings were carefully tuned to ensure that the MPC output would be optimal. By making these adjustments, it was possible to refine how the controller interprets real-time data, anticipates future states, and selects control actions accordingly.

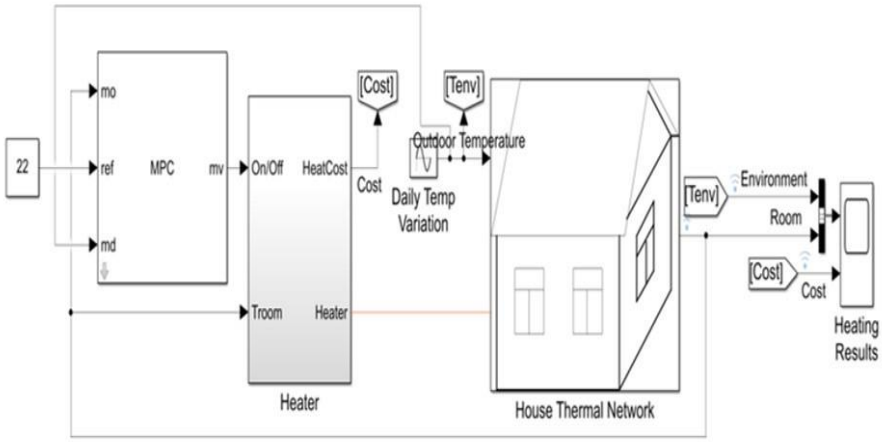

Figure 4. A model that depicts the structure of MPC in a block format.

Figure 5 presents the optimal input and output responses of the MPC, thereby illustrating how various parameter choices influence the controller's overall effectiveness. Analyzing these graphical results enhances our understanding of how adjustments to the MPC parameters shape system behavior, helping to identify the most favorable configuration for stable, efficient, and responsive control under the given operating conditions.

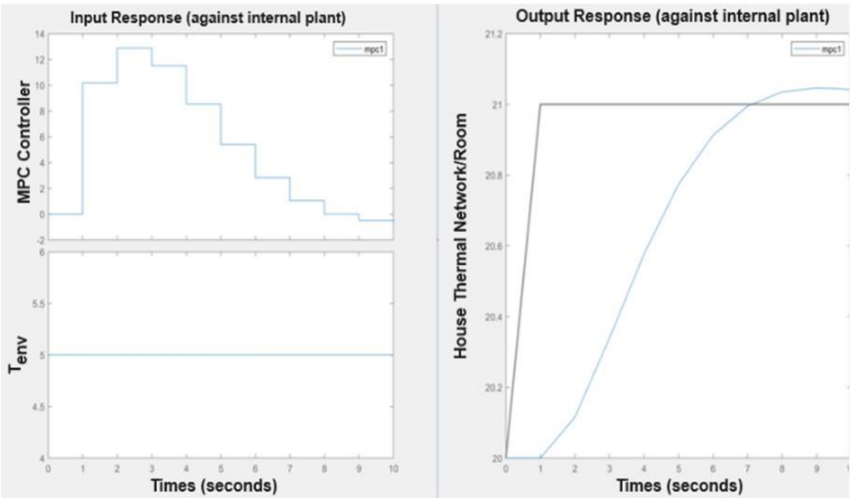

Figure 5. MPC Configuration.

From a thermal comfort perspective, the proposed MPC-based approach regulates indoor temperature over a 50-hour measurement period. During this timeframe, the controller targets an indoor temperature of 22°C, utilizing a heating system managed by the MPC. To assess the effectiveness of the proposed method, its performance is evaluated based on its capability to maintain stable indoor temperature conditions over the observation window. Throughout the experiment, the MPC consistently and reliably met its objectives, keeping the indoor environment comfortably within the designated setpoint range. Notably, this stability was achieved even when outdoor temperatures fell below the target level, underscoring the controller's robust ability to preserve occupant comfort. Figure 6 provides a visual representation of the indoor temperature trajectories managed by the MPC, offering a clearer insight into how the controller navigates changing conditions to uphold the desired comfort parameters.

When comparing these results to those obtained from a traditional PID controller, it is evident that both methods can sustain the room temperature within the specified comfort zone. By dynamically adjusting their control actions, both controllers succeed in aligning the indoor climate with the established performance criteria.

To facilitate this comparison, Figure 7 illustrates the room temperature fluctuations as regulated by the PID and MPC controllers. By examining these graphs, readers can thoroughly analyze the strengths and weaknesses of the proposed MPC approach in relation to the conventional PID solution. Such an evaluation not only sheds light on the effectiveness of the MPC but also informs future improvements and refinements in building climate control strategies.

In addition to ensuring thermal comfort, the study also examined the energy efficiency aspect of the developed MPC controller, focusing on its capacity to reduce the heating system's overall energy consumption. Over a 50-hour evaluation period, the energy usage and associated operating costs of the heating system under MPC control were monitored and recorded. These results were then compared with those obtained using a conventional PID controller to determine if the MPC approach yielded measurable improvements.

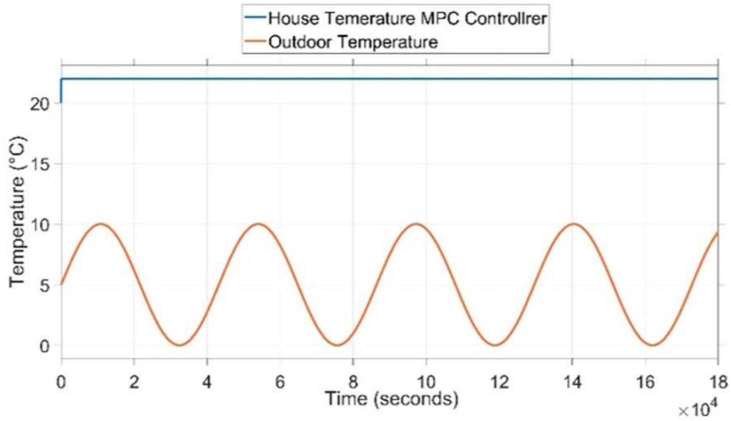

Figure 6. Indoor and outdoor environment temperature for MPC controller.

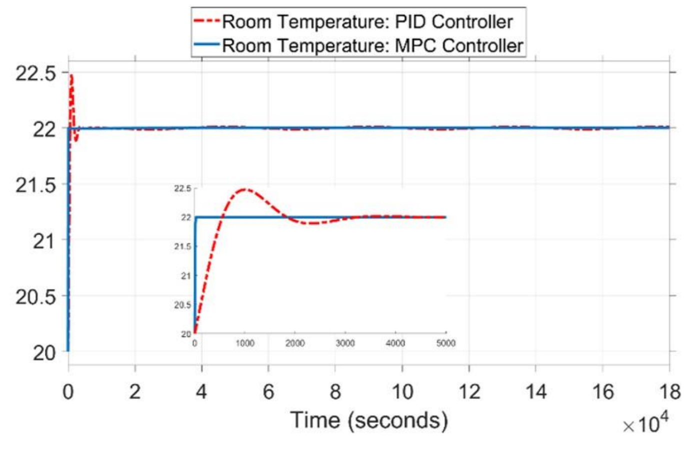

Figure 7. Energy consumption for MPC and PID controllers.

The findings clearly indicate that the MPC controller provides substantial energy savings. Specifically, over a 50-hour period, the MPC controller achieved energy savings of 22.7% compared to the PID controller. This result was consistent across multiple simulation runs, with an average savings of 22.7% and a standard deviation of 1.5%, indicating reliable performance improvement. By intelligently forecasting future conditions and optimally adjusting the heating input, the MPC consistently outperforms the PID controller in terms of energy consumption. Figure 8 presents a side-by-side visualization of the operating costs associated with both controllers, offering a clear indication of the enhanced energy efficiency achieved by the MPC.

These results underscore one of the MPC's key advantages: its ability to intelligently balance energy usage and comfort levels. By lowering energy costs while maintaining occupant satisfaction, the MPC approach positions itself as a more sustainable and cost-effective solution when compared to traditional control methods.

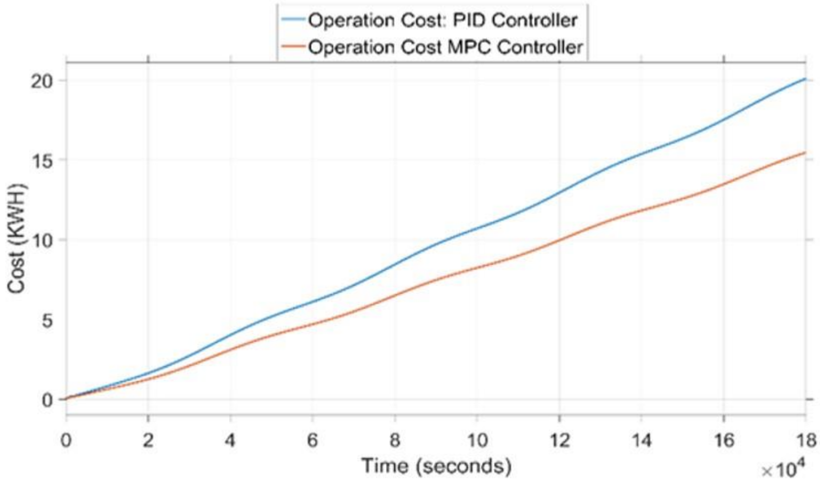

Figure 8 : Indoor environment temperature for MPC and PID controllers.

This significant difference highlights the superior energy-saving capabilities of our MPC approach, optimizing up to 22.7% of the heating system's operating costs. As shown in Figure9, the operating cost is 15.47 KWH for the MPC controller compared to 20.1 KWH for the PID controller.

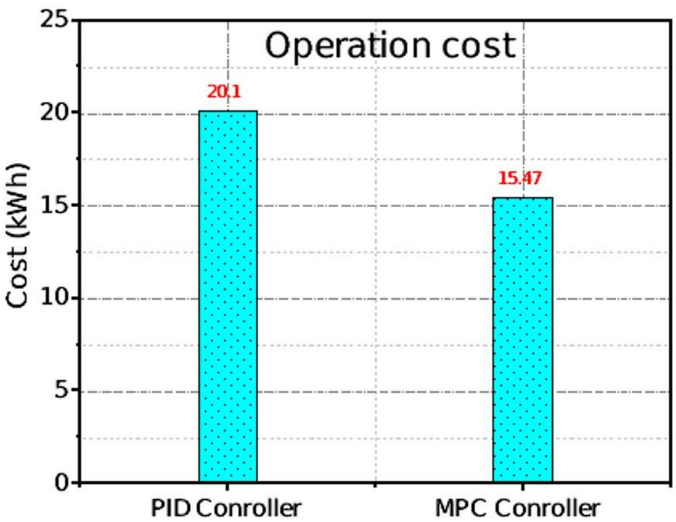

Figure 9. Operating cost for both MPC and PID controllers.

4. MPC IN HEATING SYSTEMS: BENEFITS, CHALLENGES, AND PROSPECTS.

The findings of this study demonstrate that the MPC controller not only effectively regulates indoor temperature but also minimizes the energy consumption of heating systems. By leveraging its adaptive control capabilities, the MPC system emerges as a cost-effective and sustainable solution for indoor thermal management, delivering significant energy savings, enhanced occupant comfort, and improved environmental sustainability. These promising results lay a solid foundation for future research aimed at exploring the practical implementation of MPC technology in real-world scenarios and across diverse heating system contexts. While the benefits of MPC are evident, several practical aspects warrant careful consideration. One critical factor is the computational requirement; the MPC algorithm necessitates solving optimization problems at each time step, indicating that real-time implementation is feasible with current computing hardware. Another important consideration is the initial setup cost associated with installing sensors and integrating the control system, which may pose a barrier in smaller residential settings or those with budget constraints. Future investigations should focus on developing simplified MPC algorithms and cost-effective implementation strategies to broaden its accessibility. Moreover, since our simulations were conducted under controlled conditions, field testing and continuous monitoring are essential to accommodate variations due to unpredictable occupant behavior, fluctuating weather patterns, and system aging. Despite these challenges, the substantial potential of MPC in achieving energy efficiency and maintaining thermal comfort positions as a promising technology for modern building management systems, particularly in the evolving landscape of smart buildings.

5. CONCLUSION

This study presents a significant advancement in the field of HVAC control strategies for residential buildings through the implementation of a Model Predictive Control (MPC) approach. The results demonstrate that MPC effectively balances occupant comfort and energy efficiency, achieving up to 22.7% energy savings compared to traditional PID controllers while maintaining desired indoor temperatures, with a reliable standard deviation of 1.5% across simulations. Both controllers successfully sustained thermal comfort, defined as maintaining indoor temperatures within ±1°C of the 22°C setpoint, but MPC's proactive nature provides superior energy management by anticipating and adapting to changing conditions. This highlights the potential of MPC as a leading-edge solution for intelligent and sustainable residential HVAC systems.

Looking ahead, practical deployment of MPC in real-world residential settings is recommended to validate its performance under diverse conditions. Future research should focus on:

- Integrating advanced weather forecasting to enhance prediction accuracy.
- Exploring scalability to different building types and sizes, including multi-zone or hybrid systems, to broaden applicability.
- Investigating integration with renewable energy sources to maximize sustainability.
- Addressing integration challenges, such as retrofitting existing HVAC systems or ensuring compatibility with diverse building designs, which may require significant investment and technical expertise.

- Considering economic feasibility and user acceptance, including developing user-friendly interfaces to enhance occupant engagement and adoption, given the computational and cost barriers identified.

By tackling these areas, MPC can be further optimized to meet the evolving needs of energy efficient and comfortable living environments, contributing to global sustainability efforts.

Authors contribution: Youssef Boutahri: Conceptualization, Model Development, Methodology, Simulation, Writing – Original Draft. Abdellatif Ait Mansour: Visualization, Data Analysis, Review & Editing. Amine Tilioua: Validation, Supervision.

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