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Modeling and Optimization of Thermal Dynamics for MPC Models in Sustainable Building Energy Systems

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Abstract **-** This paper investigates the practical implementation of models in the energy management of buildings for complex user behavior and the use of multiple heating technologies, focusing on the development of an accurate yet efficient model. The study is exemplified by the new Institute for Hydrogen and Energy Technology building at Hof University of Applied Sciences, designed as a research platform for innovative energy solutions. We address the integration of shading strategies and the subsequent model order reduction necessary for effective Model Predictive Control application. The research involves creating a simplified resistance-capacitance model of the building's thermal zones, including its heating systems and a dual façade with solar thermal collectors. This simplified model, generated using the BRCM Toolbox and validated against a detailed EnergyPlus model, accounts for dynamic discrepancies, particularly during periods of high solar radiation. Optimization techniques are applied to the simplified model across different seasons, revealing that season-specific optimizations are more effective for long-term simulations, while a combined optimization approach is suitable for short-term and year-round MPC applications. The results underscore the potential of advanced MPC strategies to enhance energy efficiency and sustainability in complex building systems with multiple renewable energy sources.

Keywords**:** EnergyPlus, BRCM-toolbox, RC model, optimization, multiple heating systems, MPC

1. Introduction

Meeting the climate policy goals of reducing CO_2 emissions and achieving the 1.5 °C target defined in the Paris Climate Agreement is crucial for mitigating climate change. The optimization of building climate control systems and regulation strategies, especially through the integration of renewable energy sources, is an essential part of these efforts, as highlighted by the International Renewable Energy Agency (IRENA) [1]. At Hof University of Applied Sciences, the new Institute for Hydrogen and Energy Technology (iwe) serves as a research platform that embodies these principles, integrating a variety of renewable energy sources into a holistic building concept [2]. This innovative building project includes lecture halls, offices, and various laboratories related to energy systems and water. This multifunctional facility supports both academic activities and experimental research. It is equipped with solar panels on the façade and roof, which provide passive solar shading - increasing solar radiation in winter and improving solar protection in summer – while also serving as a platform for further sustainable energy solutions. The building's energy system includes photovoltaic modules, a central 150 m³ thermal stratified storage tank, micro combined heat and power units, heat pumps with ice storage systems and air absorbers. Inside, the laboratories will be equipped with test set-ups, including smaller heat pumps and burner test stands. The building's climate control strategy combines conventional HVAC systems (mainly for heating) with underfloor heating in the offices, additional radiators in the laboratories and ceiling panels in the technical areas. The aim of this work is to develop a comprehensive building model that enables efficient control, particularly in the context of Model Predictive Control (MPC). Accurate modeling is crucial, especially for capturing seasonal variations and periods of increased solar radiation in conjunction with heating demands. The approach uses a simplified resistance-capacitance (RC) model created with the Building Resistance-Capacitance Modeling (BRCM) Toolbox [3] and is validated against a detailed EnergyPlus [4] simulation model. This RC model facilitates dynamic simulations and subsequent optimization for year-round control.

This study builds on important previous work. Drgoňa et al. emphasize the comprehensive understanding required for effective MPC implementation [5]. Li et al. provide an in-depth investigation of RC models in building simulation, focusing on gray-box modeling [6]. Various simulation environments, such as FastBuildings (Modelica) [7], RC_BuildingSimulator (Python) [8] and BRCM in Matlab®/Simulink [3] provide tools for this purpose. In particular, the BRCM Toolbox supports the automatic generation of RC models, which are essential for accurate and efficient building simulations. Researchers from Cornell University published several studies [9-14] where the BRCM Toolbox was used to develop the underlying state space model. However, during periods of high solar radiation, the model cannot fully capture the thermal behavior accurately [3, 15]. Hatanaka et al. successfully optimized the model using the data generated by EnergyPlus for the thermal behavior in summer [15]. Building on these results, this paper aims to further explore different time periods, shading, and multiple heating methods within such an optimization framework. However, a complete survey of the vast literature is beyond the scope of this paper.

This article is structured as follows: First, the development of a detailed building model in EnergyPlus is described. Next, the reduction of this model is presented with the help of the BRCM Toolbox and a merging of related zones. A new optimization strategy for high solar radiation values should ensure the accuracy of the model throughout the year. The Results section compares the performance of the simplified and optimized models with that of the comprehensive EnergyPlus model and evaluates its suitability for MPC applications. The paper concludes with a summary of the main results and an outlook on future research directions in the field of MPC.

2. Methods

This section outlines the methodology for generating a bilinear model from a detailed Energy Plus simulation model using the BRCM Toolbox [3] and its optimization for conditions with elevated solar irradiance based on the approach outlined by Hatanaka et al. [15].

2.1. Building models

To create a comprehensive foundation for analysis and optimization, a detailed building model with 62 thermal zones was developed with SketchUp as graphical editor using architectural drawings of the institute's building. This EnergyPlus model incorporates the various heating systems, enabling realistic simulations of building operations. The model considered standardized heating schedules and used 2010 reference data [16] for external conditions like solar radiation and ambient temperature. The normal vector of the north façade of the building is oriented 10° east of true north (see Fig. 1 left).

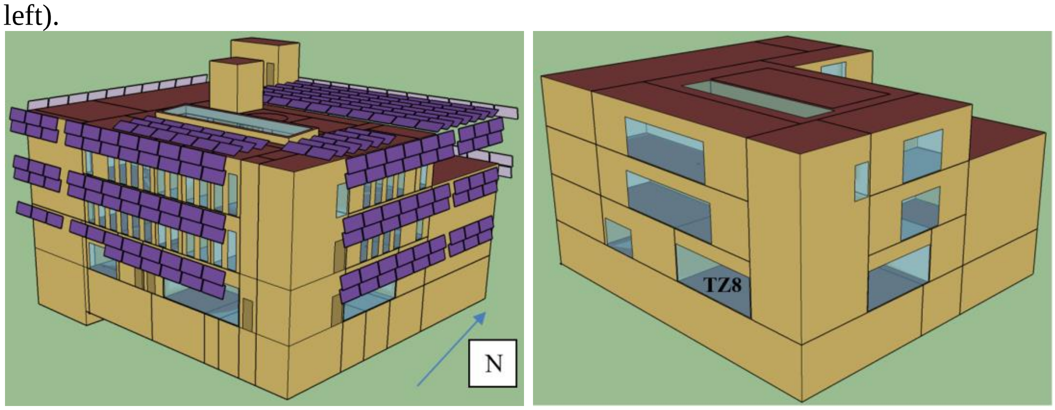

Fig. 1: Left: South-east view of the 62 zone EnergyPlus model incl. collectors, right: 19 zone model incl. thermal zone 8.

For efficiency reasons, this detailed model was reduced to a 19 zone model by merging zones with similar thermal characteristics, such as offices or laboratories on the same floor and façade. This consolidation aimed to maintain thermal accuracy while simplifying the simulation and was motivated by existing literature, ensuring fidelity to real-world building dynamics [17-20]. The different heating systems in the simplified model were adopted from those in the detailed EnergyPlus model to ensure consistency. This model was subsequently used for the application and optimization within the BRCM Toolbox. Comparisons with the detailed model, using weighted average temperatures based on room volume, validated the simplified model's accuracy. Thermal zone 8, which has the largest window-to-exterior wall ratio, is positioned on the south façade and is equipped with a ventilation unit and conventional radiators, was selected for further validation of various optimizations and simulations (see Fig. 1 right).

2.2 BRCM Toolbox and optimization/remodeling

The BRCM Toolbox is designed to create efficient and accurate building models for MPC applications. Initially, a linear thermal model is generated using the building's construction and geometry data, capturing the fundamental thermal dynamics and heat transfer properties of the building. In the second module, External Heat Flux (EHF) models are added, parameterized with additional data specific to the building's systems, such as air handling units (AHU), radiators, and underfloor heating, as well as further construction and geometry details.

In the linear model representation, the system dynamics are described using several key matrices, see first three terms of rhs. of Eq. (1). The matrix **A** represents the internal thermal dynamics of the building, capturing heat capacities of and heat fluxes through building elements. The matrix $\mathbf{B}_u$ characterizes the influence of control inputs on the system, such as heating power and blinds position, determining how these actions affect the temperature states. These different input variables are summarized in the vector **u** and contain the transient sequences determined by EnergyPlus for the simulation and comparison of the different models later. The matrix $\mathbf{B}_v$ represents the impact of external disturbances like solar radiation and ambient temperature on the system. The transient sequence of these values is combined in the vector **v**.

A crucial aspect of the combined model is the inclusion of bilinear terms in Eq. (1), representing the interactions between temperatures (states **x**), control inputs (**u**), and external disturbances (**v**). These bilinear terms are essential for modeling complex thermal behaviors. The matrix $\mathbf{B}_{vu}$ captures the interaction between external disturbances and control inputs, e.g. modeling how solar irradiation combined with the position of blinds affects heat fluxes. The matrix $\mathbf{B}_{xu}$ describes the interaction between the system states (temperatures) and control inputs, e.g. capturing how the current temperature within building zones influences the effectiveness of heating actions.

The final step in the modeling process is the discretization of the combined model, transforming the continuous equations into a suitable form for numerical optimization with specified fixed time steps, in this case with one-hour steps. This approach ensures that the model can predict the building's thermal behavior accurately and efficiently under various conditions, making it robust and applicable in practical scenarios [3].

$$\mathbf{x}_{k+1} = \mathbf{A}\,\mathbf{x}_k + \mathbf{B}_u\,\mathbf{u}_k + \mathbf{B}_v\,\mathbf{v}_k + \sum_{\mathbf{i=1}}^{\mathbf{n_u}} \left(\mathbf{B}_{vu,i}\,\mathbf{v}_k + \mathbf{B}_{xu,i}\,\mathbf{x}_k\right)\mathbf{u}_{k,i} \tag{1}$$

However, it became clear that the model had difficulties in accurately simulating and representing summer scenarios with periods of increased level of solar irradiation. This limitation has also been noted by other sources [3, 15] and justifies optimization using the methodology proposed by Hatanaka et al. [15]. This detailed optimization process will be examined more closely in the next section, outlining the specific steps taken to address this issue and enhance the model's performance under varying solar radiation conditions.

The comparison between the simplified 19 zone toolbox model and the detailed EnergyPlus model also highlighted disparities, particularly during sunny periods. To address this, focused optimization efforts aimed to enhance the model's performance. The primary objective was to improve the accuracy of heat flow representation, especially through windows, crucial for capturing solar influences, reflected in the $\mathbf{B}_{vu}$ matrix. By refining this matrix and optimizing the model's response to external factors, the aim was to enhance predictive accuracy. This optimization process was pivotal for aligning the simplified model's behavior with the comprehensive EnergyPlus model, thereby enhancing its overall fidelity in representing the building's thermal dynamics, including shading effects of the dual façade.

The optimization process focused on utilizing a nonlinear least-squares solver (lsqnonlin of Matlab®) [21, 22], to refine the $\mathbf{B}_{vu}$ matrix in the bilinear part of the model. In order to ensure physically sensible solutions, constraints in lsqnonlin were defined in such a way that the alternations in relation to the original entries were strongly limited. It is important to note that only the entries corresponding to the intensities of solar irradiation were subjected to optimization in the $\mathbf{B}_{vu}$ matrix. The effectiveness of the optimized $\mathbf{B}_{vu}$ matrix was assessed under diverse criteria, optimization durations, levels of solar irradiance and passive shading by the dual façade. By systematically evaluating the performance of the models in winter, spring and summer, insights were gained into the robustness and adaptability of the optimized matrix. These evaluations helped to capture the details of the thermal dynamics within the modeled environment. Alongside a comparison of the EnergyPlus data based on the weighted 62 zones with the initial toolbox model and three optimizations were carried out below.

The first optimization variant, referred to below as summer optimization, follows the method of Hatanaka et al. [15] and focuses on the first week of July. In this optimization the $\mathbf{B}_{vu}$ matrix is adapted so that high solar irradiance and passive shading effects typical of summer are more accurately taken into account and a more accurate simulation of thermal conditions under peak solar loads is ensured. The second variant, winter optimization, addresses the thermal behavior during the first week of January. In this approach the $\mathbf{B}_{vu}$ matrix is adjusted to accurately represent thermal dynamics under typical winter conditions, which are characterized by lower solar irradiance and increased heating demands. The third variant is the combined (January-July) optimization. This method uses a continuous dataset that includes the first two weeks of January followed by the first two weeks of July. The purpose is to determine a $\mathbf{B}_{vu}$ matrix that can accurately adjust to thermal dynamics in both winter and summer, providing a holistic model that considers the seasonal influences of dual façade shading and partial heating. The performance of the different models was assessed outside these optimization periods, starting in the third week of January, March and July. This approach validates whether each optimized model can robustly handle the thermal dynamics throughout the year.

3. Results

For a representative analysis, the thermal zone 8 from the 19 zone toolbox model was selected as already described in the building models' section. Specifically, it is expected to exhibit the behavior highlighted by Hatanaka et al. [15] and Sturzenegger et al. [3], wherein the toolbox-generated model tends to noticeable deviations when simulating the dynamics of building temperatures during summer months with higher solar irradiation. To demonstrate this also for the models used here, initially, however, a comparison is drawn between the results obtained from the elaborated EnergyPlus model with 62 zones and the initial model generated by the BRCM Toolbox with 19 zones, focusing on winter, spring, and summer months. The corresponding outdoor temperatures and solar irradiation, exemplified on the south façade, are shown in Fig. 2. The room temperatures for the adjacent walls were used to define the temperature data that cannot be determined from EnergyPlus, such as the individual wall layers, which must also be specified in the vector $\mathbf{x}$ as initial condition for the simulation. Subsequently, a detailed examination of different optimization methods is conducted, evaluating their suitability for simulating the building with associated thermal zones.

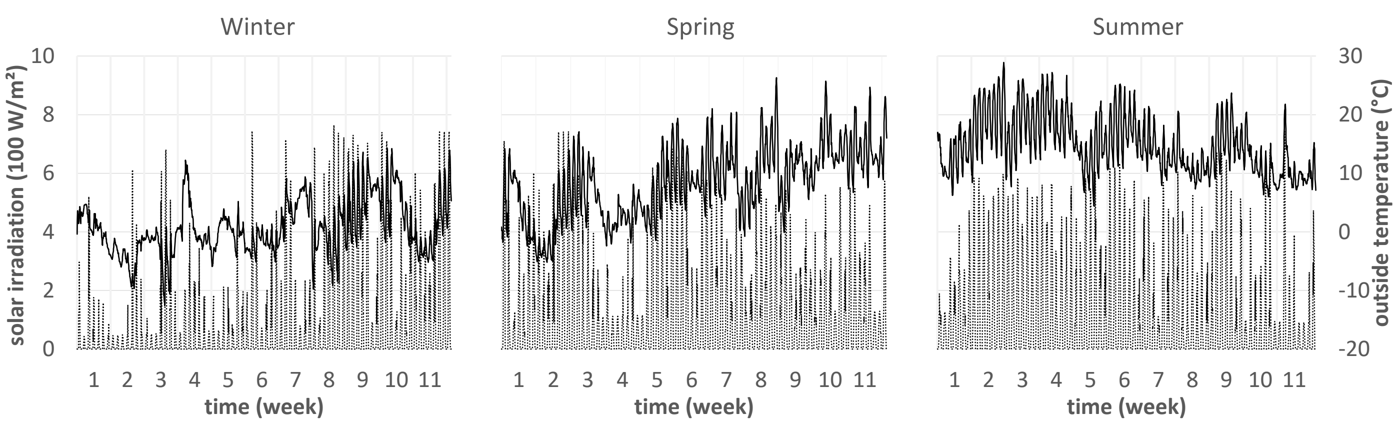

Fig. 2: Solar irradiation on south façade (dotted) and outside temperature (solid).

We start with discussing the performance of the initial toolbox model with reference to Fig. 3. In the first week of the winter observation period, accurate results are obtained. However, by the end of the second week, obviously discrepancies emerge. The high window-to-wall ratio combined with low sun angle in winter, resulting in minimal shading, leads to significant deviations from the EnergyPlus data after a few days. This issue persists throughout the entire observation period due to constantly high irradiation levels. In the spring period, the model exhibits even more significant deviations. These discrepancies can be partially attributed to the initial conditions, where wall temperatures were set to room temperature for all layers, and to the high solar radiation (see Fig. 2). The negative trend continues, with the deviations remaining large or even increasing. In the first two days of the summer season, the model performs comparatively well due to low irradiation levels. However, as soon as the irradiation increases after a few days, significant deviations in the model's accuracy become apparent. Other thermal zones with smaller window areas exhibited smaller differences, highlighting the sensitivity of thermal zone 8 to solar gains. These deviations underscore the need for optimization, particularly for periods with higher solar radiation.

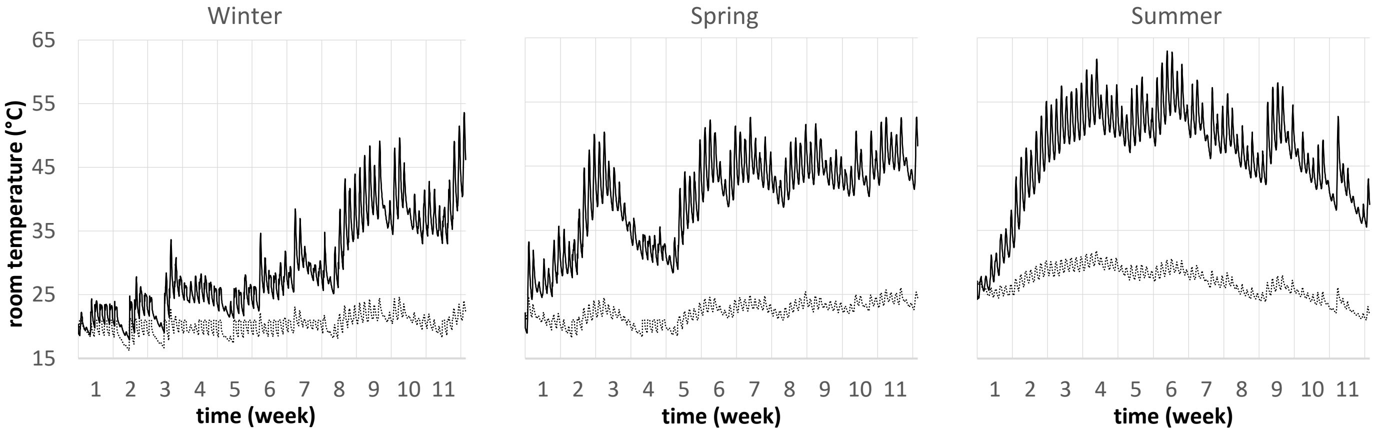

Fig. 3: Evaluation of the room temperature for the Initial Toolbox Model (solid), EnergyPlus (dotted).

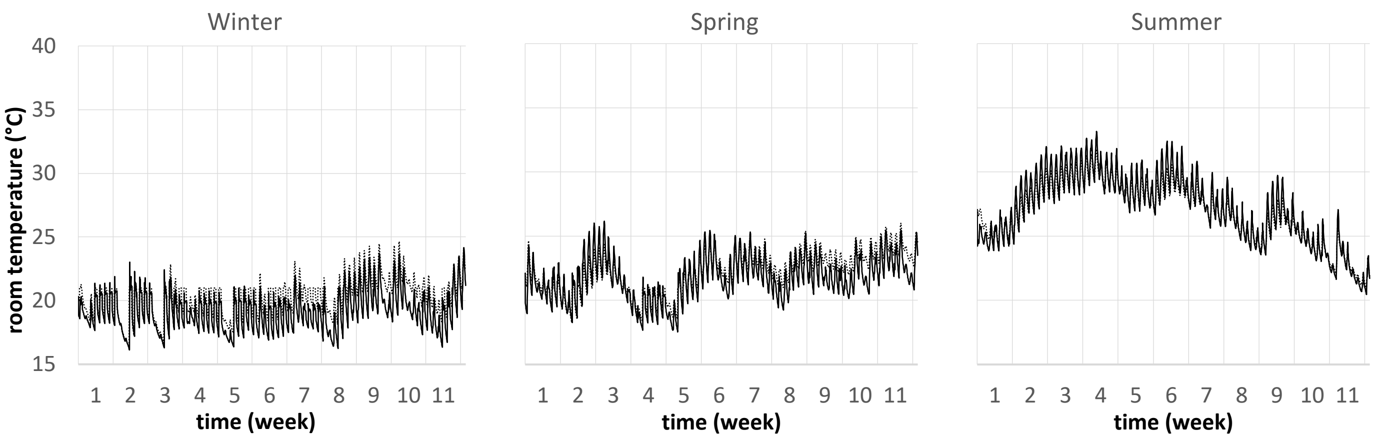

Fig. 4: Evaluation of the room temperature for the summer-optimized model (solid), EnergyPlus (dotted).

The first optimization, which follows the methodology of Hatanaka et al. [15], focuses on the summer period, in specific the first week of July (see Fig. 4). The objective of this optimization was to adapt the $\mathbf{B}_{vu}$ matrix to take into account the increased solar irradiance and passive shading effects without active heating. The summer-optimized model shows good agreement with the EnergyPlus model during summer and spring. However, significant discrepancies are observed in winter, as the model failed to maintain minimum room temperatures even with integrated heating systems, indicating its limitations for year-round simulations. The model performs well during a temporary heating period in the fourth week of spring, accurately representing heating loads in combination with low solar irradiation. However, the quality of the model results decreases over longer simulation periods, such as winter, leading to significant deviations during prolonged heating periods.

The second optimization focuses on the winter period, in particular the first week of January (see Fig. 5). This optimization attempts to modify the $\mathbf{B}_{vu}$ matrix to more accurately capture the thermal dynamics typical of winter, including heating operations and reduced shading due to the lower sun angle combined with the dual façade concept. This model performs well in January and February, but discrepancies occur again in March as soon as solar irradiation level increases. Significant deviations are also observed in summer, indicating the model's unsuitability for year-round simulations. These issues were particularly evident during the transition from week 2 to 3 in spring correlating with a short period of higher solar irradiation.

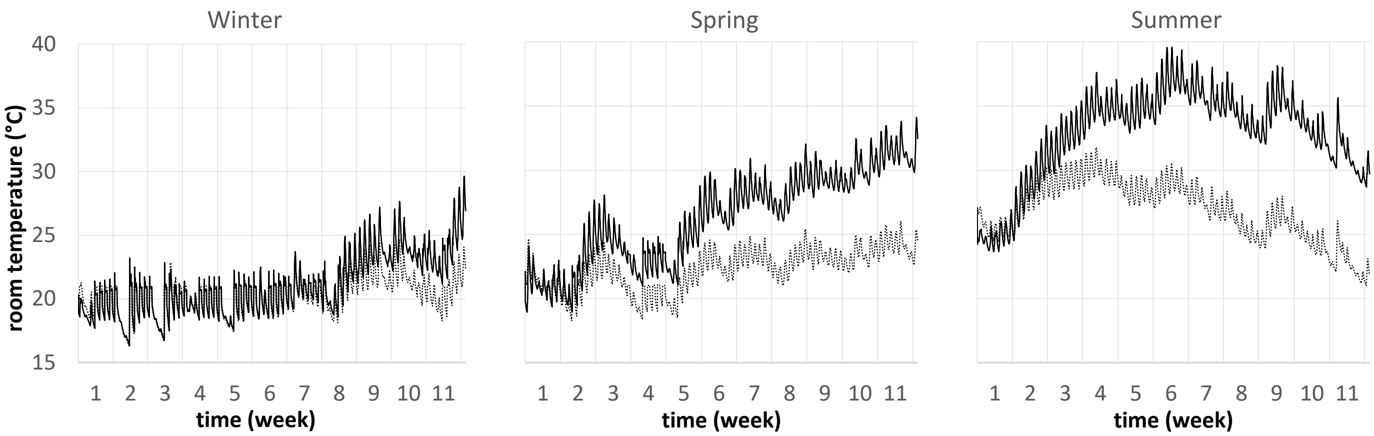

Fig. 5: Evaluation of the room temperature for the winter-optimized model (solid), EnergyPlus (dotted).

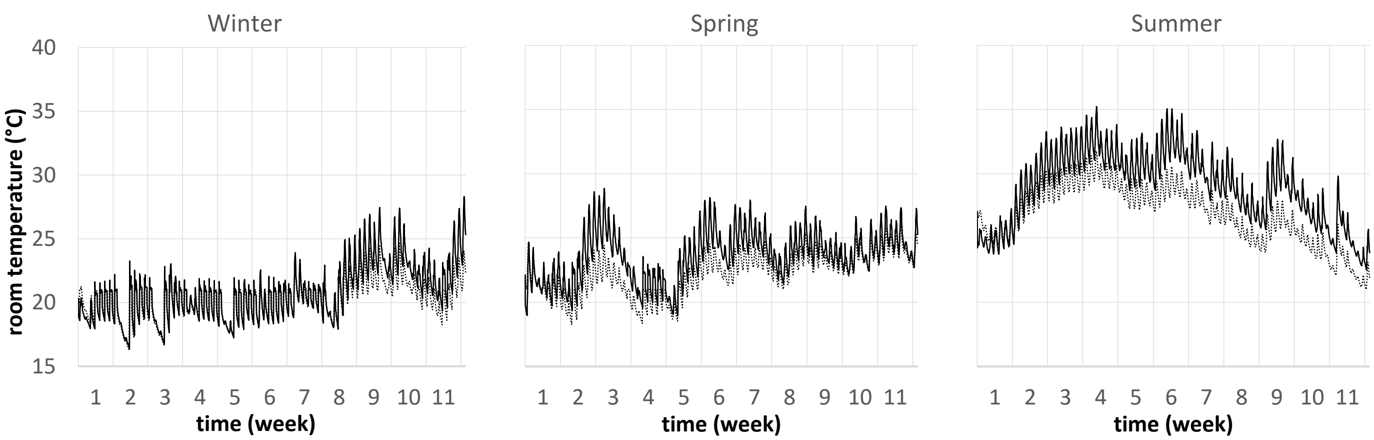

Fig. 6: Evaluation of the room temperature for the combined January/July-optimized model (solid), EnergyPlus (dotted).

The third optimization approach combining data from the first two weeks of January and the first two weeks of July aimed to create a more versatile $\mathbf{B}_{vu}$ matrix capable of managing thermal dynamics across both winter and summer periods, including heating activities and varying solar angles, taking into account the dual façade concept. During the winter simulation, this optimization was capable of maintaining room temperature in heating periods over a longer duration, resulting in minor deviations from the EnergyPlus model. This outperforms all other scenarios, including the purely winter-optimized model, from January to May. In the first spring week, this combined optimization also performed well compared to other optimizations. Although it did not match the quality of the summer optimization results, it better maintained room temperature over a longer period than the winter optimization and the initial model. This improvement is likely due to better incorporation of solar altitude and the increased passive shading effects of the dual façade concept in later periods. Future optimizations might benefit from including periods with medium solar elevations, such as in spring or autumn. In the summer simulation, good values were achieved within one week. However, values began to diverge again afterward.

As the previous assessment focused on only one of the 19 thermal zones, an analogous assessment was also carried out for each of the remaining 18 zones. Across all seasons, the combined optimized model showed the best performance for short durations. For longer dynamic simulations, it is recommended to use models optimized specifically for each time period. Therefore, selecting between summer and winter optimizations is sufficient for model selection. The optimization data, based on the EnergyPlus model, include the integrated shading concept of the dual façade, which affects the building's thermal balance across different seasons and solar elevations. Moreover, the optimized model accounts for internal factors and various HVAC systems such as the AHUs, radiators, and underfloor heating, particularly during winter months. For the main focus on MPC, the combined optimized model consistently delivers good results across all relevant thermal zones, especially for shorter periods (less than two weeks), making it suitable for implementation within a MPC framework.

4. Conclusion

The primary focus of this investigation was the practical modeling of a building and its thermal zones, including multiple heating technologies and shading using a dual façade concept. The focus was on the ability to accurately map the dynamic behavior, particularly for the future implementation of a predictive building control system. A detailed EnergyPlus model served initially as a reference and data basis, which was then converted into a reduced model by simplification of the building and room properties of individual zones using the BRCM Toolbox. Deviations from the reference model, particularly in the summer months with higher solar irradiation, were adjusted using various optimization strategies over different time frames. The optimizations were carried out for the summer and winter periods, and also combined for January and July. It has been shown that for longer-term simulations of the building, it is advisable to use models that are optimized for the respective time period or season, as they are capable of providing good-quality results over a longer period. The combined optimization for summer and winter periods provided favorable outcomes for different seasons and external conditions within short time frames, making it still suitable for further use within MPC for the building.

In terms of model accuracy, future optimizations can be made to further refine the models. This could include extending optimization periods for seasonal models and expanding the dataset for the development or refinement of combined-season models. Furthermore, incorporating additional state variables, such as the external temperatures of the façade layers, into the optimization process beyond the use of only thermal zone values from EnergyPlus could provide even more precise insights into the shading effects of the dual façade concept on internal temperatures, even if at the expense of optimization time. The research focus should now shift towards the implementation of MPC utilizing Singular Value Decomposition methods to streamline the complexity of the current model. This will enable more efficient and effective control strategies to be implemented. Future efforts will also include a rigorous validation of the presented models with real data from the institute and its complex thermal zones after completion. This validation aims to ensure the practicality and reliability of such models in real-world scenarios, improving their applicability and effectiveness in optimizing the building energy management.

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