*Avestia Publishing*
*International Journal of Environmental Pollution and Remediation (IJEPR)*
*Volume13, Year 2025*
*Journal ISSN: 1929-2732*
*DOI: 10.11159/ijepr25.003*

# Optimization of Thermal Dynamic Models for MPC-Based Sustainable Building Energy Systems

**Robin Fick[1], Julian Knopp[1], Robert Honke[1], Tobias Plessing[1]**
[1]University of Applied Sciences Hof, Institute for Hydrogen and Energy Technology,
Alfons-Goppel-Platz 1, 95028 Hof, Germany
robin.fick.2@hof-university.de; julian.knopp@hof-university.de; robert.honke@hof-university.de;
tobias.plessing@hof-university.de

***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.



*Date Received: 2024-05-29*
*Date Revised: 2024-12-13*
*Date Accepted: 2025-01-20*
*Date Published: 2025-02-04*

## 1. Introduction

Meeting the climate policy goals of reducing CO2 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. Several studies [9]-[14] demonstrate the use of the BRCM Toolbox for developing state space models in the context of building energy simulations. 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.

The article is structured as follows: Section 2 describes the development of a detailed EnergyPlus model (Subsection 2.1) and its reduction using the BRCM Toolbox (Subsection 2.2). The core of this work in Subsection 2.2 is an optimization strategy for high solar radiation to improve year-round model accuracy. Section 3 compares the simplified and optimized models to the comprehensive EnergyPlus model, evaluating their MPC suitability. Section 4 concludes with key findings and an outlook on future MPC research.

## 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 Figure 1).

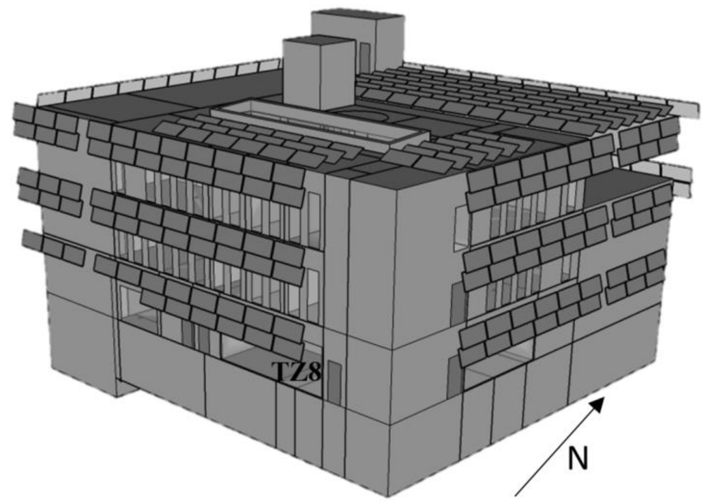


Figure 1. South-east view of the 62 zone EnergyPlus model incl. solar thermal collectors and thermal zone 8.

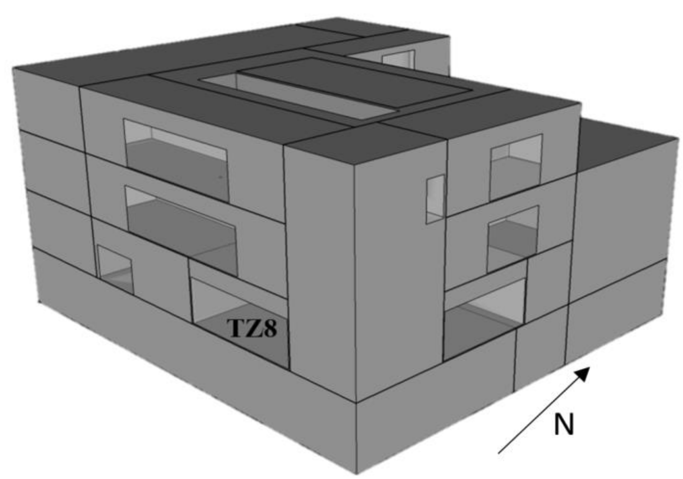


Figure 2. Reduced 19 zone model incl. thermal zone 8.

For efficiency, the detailed model was reduced to a 19-zone version by merging zones with similar thermal characteristics, such as offices or laboratories on the same floor and façade. This consolidation preserved thermal accuracy while simplifying the simulation, guided by existing literature [17]-[20]. Heating systems in the simplified model were directly adopted from the detailed EnergyPlus model for consistency. The simplified model was then applied and optimized using the BRCM Toolbox. Validation against the detailed model, based on weighted average room temperatures, confirmed its accuracy. Thermal zone 8 (TZ 8), with the largest window-to-wall ratio, located on the south façade and equipped with a ventilation unit and conventional radiators, was chosen for further validation of optimizations and simulations (see Figure 2).

## 2. 2. BRCM Toolbox and optimization

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. The combination of these submodels encapsulates the system's dynamics and is formally represented in Eq. (1)

$$\mathrm{x}_{\mathrm{k+1}} = \mathrm{Ax}_{\mathrm{k}} + B_u u_k + B_v v_k + \sum_{i=1}^{n_u} ( B_{vu,i} v_k + B_{xu,i} x_k ) u_{k,i} \tag{1}$$

In this representation, the dynamics are structured through key matrices that describe the building's thermal behavior and interactions, as detailed in the first three terms on the rhs. of Eq. (1). Matrix *A* captures the building's internal thermal dynamics, including heat capacities and fluxes through building elements. Matrix *Bu* represents the influence of control inputs, such as heating power and blinds position, on the temperature states. These inputs are summarized in vector *u*, containing transient sequences derived from EnergyPlus for later simulation and model comparisons. Matrix *Bv* accounts for external disturbances, including solar radiation and ambient temperature, summarized in 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 *Bvu* captures the interaction between external disturbances and control inputs, such as the combined effect of solar irradiation and blinds position on heat fluxes. The matrix *Bxu* 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 modeling step is the discretization of the combined model, converting continuous equations into a form suitable for numerical optimization with fixed time steps, here one-hour intervals. This ensures accurate and efficient predictions of the building's thermal behavior under various conditions, making the model robust and practical for real-world applications [3].

The initial comparison between the simplified 19-zone toolbox model and the detailed EnergyPlus model revealed notable discrepancies, particularly during periods of high solar radiation. These issues, as also noted in previous studies [3], [15], primarily affect the heat flow representation through windows and highlight the need for focused optimization. By refining the *Bvu* matrix to better capture solar influences and the dual façade's shading effects, the optimization process aims to align the simplified model more closely with the detailed EnergyPlus results. The next paragraph outlines the specific optimization steps taken to address these issues and enhance predictive accuracy under varying solar conditions.

The optimization process utilized a nonlinear least-squares solver (lsqnonlin of Matlab®) [21], [22] to refine the *Bvu* matrix in the bilinear part of the model. Constraints were applied to ensure physically sensible solutions by strongly limiting deviations from the original entries. Only entries related to solar irradiation intensities in the *Bvu* matrix were optimized. The effectiveness of the refined Bvu matrix was evaluated under various criteria, including optimization duration, solar irradiance levels, and the passive shading effects of the dual façade. Seasonal performance evaluations (winter, spring, and summer) provided insights into the robustness and adaptability of the optimized matrix, capturing the thermal dynamics of the modeled environment.

Three optimization variants were carried out. The first, referred to as summer optimization, follows the method of Hatanaka et al. [15] and focuses on the first week of July, refining the *Bvu* matrix to better account for high solar irradiance and passive shading effects typical of summer. This ensures more accurate simulations under peak solar loads. The second, winter optimization, focuses on the first week of January, adjusting the *Bvu* matrix to represent thermal dynamics during lower solar irradiance and increased heating demands. The third, combined optimization (January-July), uses a dataset combining the first two weeks of January and July to create a holistic model capable of capturing thermal dynamics across both seasons.

The performance of these models was further assessed outside the optimization periods, starting in the third week of January, March, and July. This evaluation validated the ability of each optimized matrix to handle thermal dynamics across 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 Figures 3 to 5. Initial temperatures of inner wall layers, which are part of the state vector $x$, could not be retrieved from EnergyPlus. For the simulation, we simply used the temperature of the adjacent room as an approximation. Subsequently, a detailed examination of different optimization methods is conducted, evaluating their suitability for simulating the building with associated thermal zones.

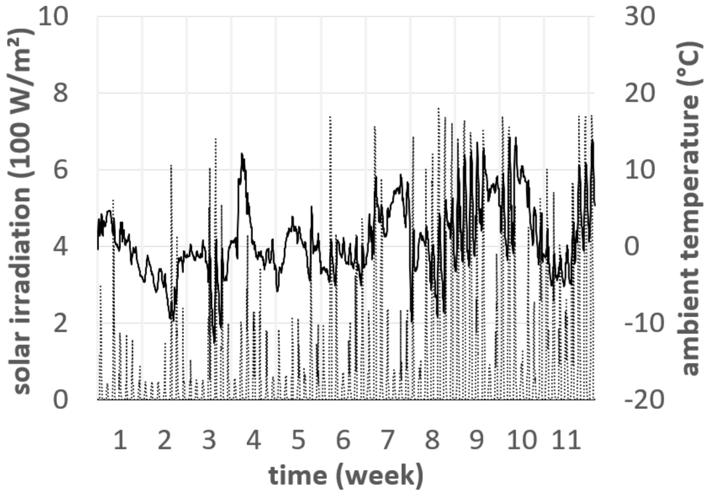


Figure 3. Solar irradiation on south façade (dotted) and ambient temperature (solid) in winter.

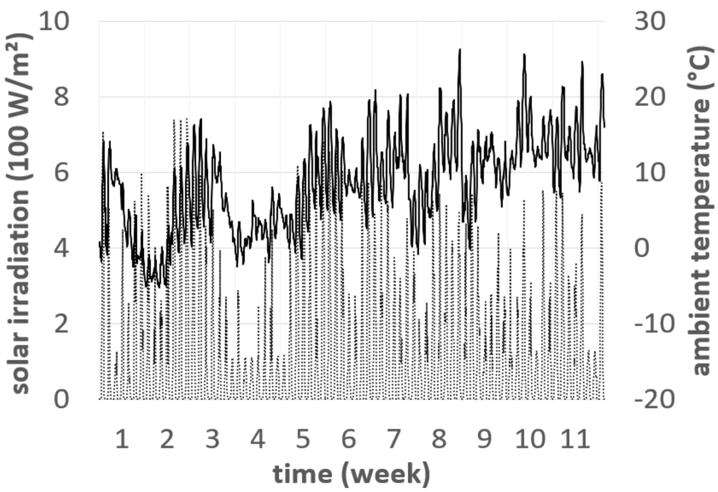


Figure 4. Solar irradiation on south façade (dotted) and ambient temperature (solid) in spring.

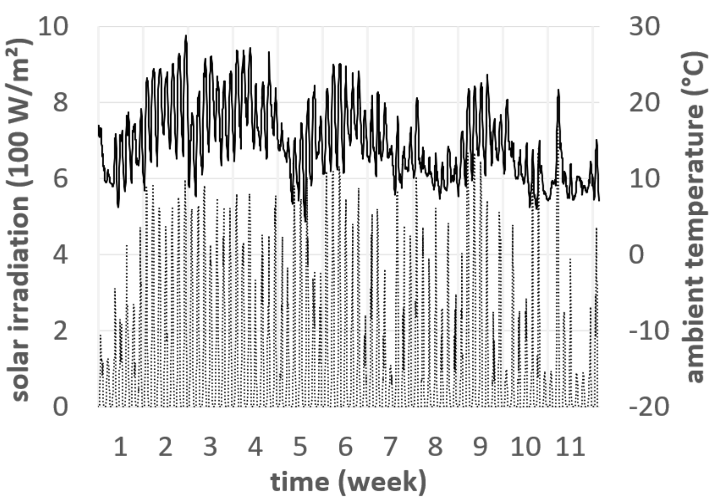


Figure 5. Solar irradiation on south façade (dotted) and ambient temperature (solid) in summer.

We start with discussing the performance of the initial toolbox model with reference to Figures 6 to 8. It is important to note that the observed 'drop' in the toolbox results, specifically the indoor temperature of TZ 8 on the first day of each simulation series, can be attributed to the preselected room temperature conditions – extracted from EnergyPlus – imposed on the individual wall layers No initialization simulation was performed to begin the computation in a 'steady-state' condition. Consequently, the temperature profile across the wall layers may not accurately reflect realistic conditions at the simulation start. No initialization simulation was performed to ensure consistent initial conditions for the computation. Consequently, the temperature profile across the wall layers may not accurately reflect realistic conditions at the simulation start.

During the first week of the winter observation period, the toolbox model produced its most accurate results, with discrepancies of approximately 1 °C emerging after a few days. By the end of the second week, however, substantial deviations of several degrees Celsius became apparent. These divergences were initially less pronounced during the first 12 days, partly due to the steadily declining ambient temperature (from approximately 3°C to -8.6°C) and the simulation period beginning with a weekend, during which no active heating occurred. The high window-to-wall ratio combined with the low sun angle in winter and minimal shading provided by the dual façade, contributes significantly to these deviations from the EnergyPlus data. These discrepancies persist throughout the observation period due to consistently high and even increasing solar irradiation levels. Furthermore, the active heating calculated by EnergyPlus during at least the first six weeks also contributes to higher indoor temperatures compared to the toolbox model results.

In the spring period, the model exhibits even more significant deviations. These discrepancies can be partially attributed to the initial conditions and to the high solar radiation (see Figure 4). In the first one-and-a-half weeks, poor weather with lower solar gains and lower ambient temperatures limited indoor temperature discrepancies. As ambient temperatures rose and sunny conditions prevailed, the indoor temperature deviations increased markedly. For instance, in week four, low ambient temperatures combined with heavy cloud cover required additional heating, which is reflected in the plateau observed in EnergyPlus temperature data (see Figure 7). After this period, additional heating was no longer needed, and the toolbox model continued to diverge from the EnergyPlus reference as solar gains intensified.

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. Over the first four weeks, the indoor temperature in TZ 8 rises steadily, interrupted only by a brief decline caused by a temporary drop in ambient temperature. For the remainder of the simulation period, the model shows a strong dependency on ambient temperature and solar gains. The large window area in TZ 8 amplifies its sensitivity to solar radiation, resulting in pronounced deviations. In contrast, zones with smaller window-to-wall ratios exhibit smaller discrepancies, underscoring the critical influence of solar gains on model accuracy. These deviations highlight the need for optimization, particularly for periods with higher solar radiation.

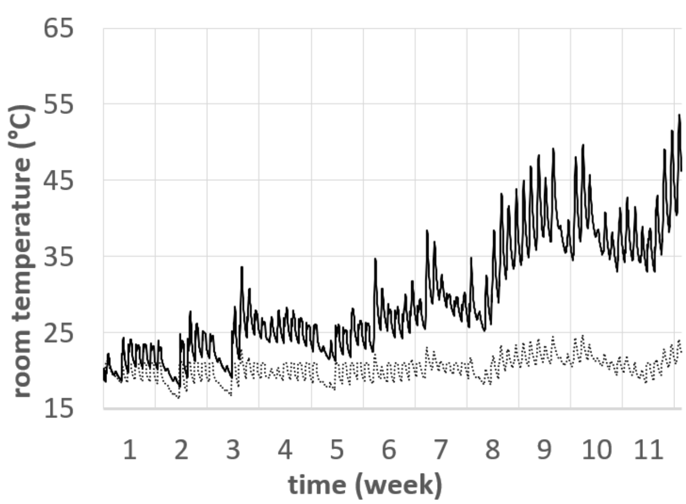

Figure 6. Evaluation of the room temperature for the Initial Toolbox Model (solid), EnergyPlus (dotted) in winter.

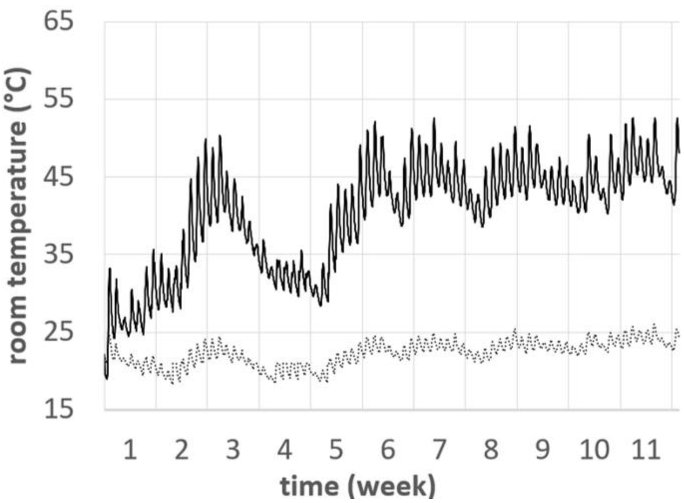

Figure 7. Evaluation of the room temperature for the Initial Toolbox Model (solid), EnergyPlus (dotted) in spring.

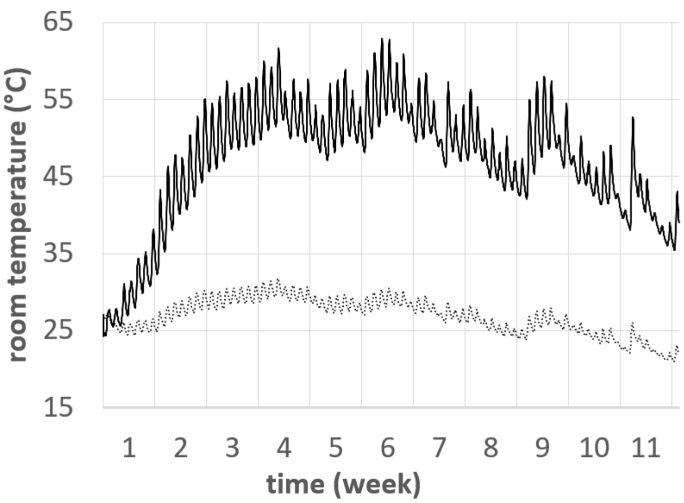

Figure 8. Evaluation of the room temperature for the Initial Toolbox Model (solid), EnergyPlus (dotted) in summer.

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 Figures 9 to 11). The objective of this optimization was to adapt the *Bvu* matrix to take into account the increased solar irradiance and passive shading effects without active heating. As in previous analyses, the initial decline in room temperature caused by the initialization assumptions is again noticeable. However, this optimized model provides an improved representation of thermal dynamics, particularly under high solar irradiation, delaying the impact of extreme weather conditions on room temperature. Consequently, the initial undercooling persists slightly longer in this optimized version. This effect is most pronounced in winter, due to the lack of heating gains over weekends, and in summer, following early cold spells with low solar gains (see Figures 5, 9, and 11). In spring, this effect is minimal and short-lived due to higher solar irradiation present from the start.

The summer-optimized model shows good agreement with the EnergyPlus model during summer and spring, successfully integrating seasonal shading effects provided by the dual façade design. Notably, it also performs well during a temporary heating period in the fourth week of spring, accurately representing heating loads under low solar irradiation conditions, despite the optimization not being explicitly tailored for such heating scenarios.

In contrast, significant discrepancies arise in winter, where the model fails to maintain minimum room temperatures even with integrated heating systems, highlighting limitations for year-round simulations. This issue would lead to overestimated heating gains in an MPC application, resulting in inefficient building operation. Furthermore, during the early weeks of the winter simulation, a slight overshoot in room temperature, typically less than 1 °C is observed at the beginning of each heating cycle. This behavior is attributed to the optimization of the *Bvu* matrix, which incorporates interactions between external factors and internal climate control systems. However, the quality of the model results decreases over longer simulation periods, such as winter, leading to significant deviations during prolonged heating periods.

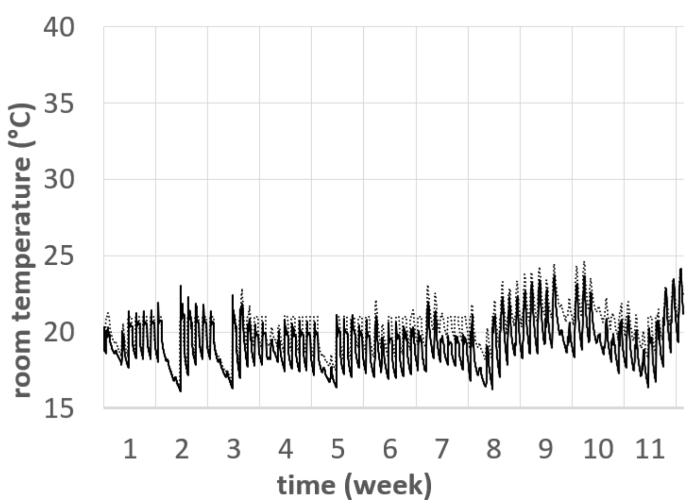

Figure 9. Evaluation of the room temperature for the summer-optimized model (solid), EnergyPlus (dotted) in winter.

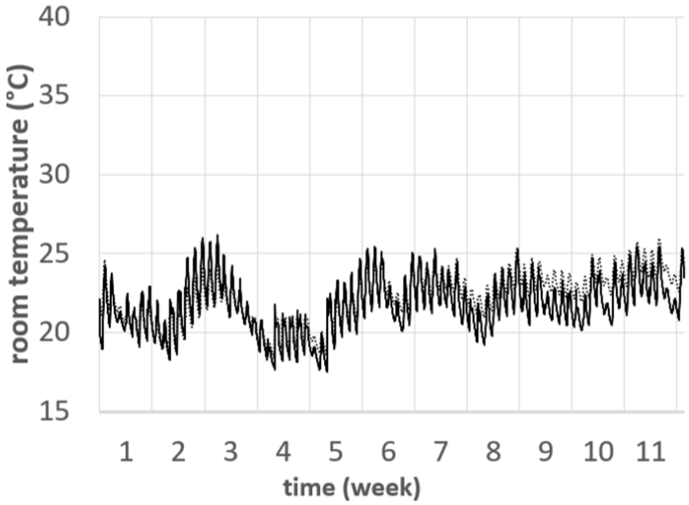

Figure 10. Evaluation of the room temperature for the summer-optimized model (solid), EnergyPlus (dotted) in spring.

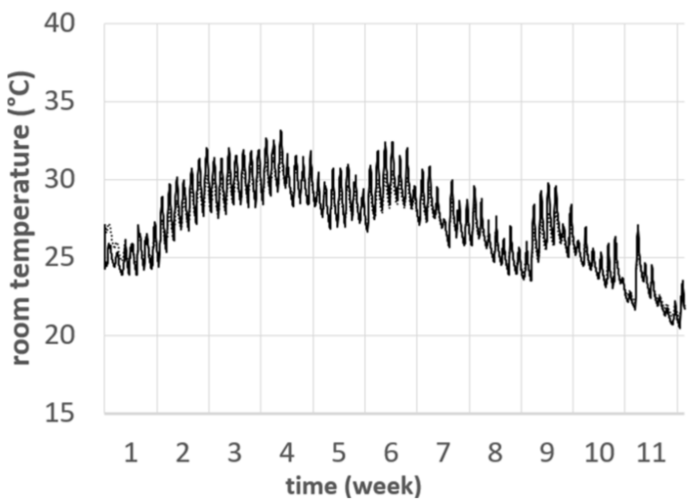

Figure 11. Evaluation of the room temperature for the summer-optimized model (solid), EnergyPlus (dotted) in summer.

The second optimization focuses on the winter period, in particular the first week of January (see Figures 12 to 14). This optimization attempts to modify the *Bvu* 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 winter-optimized model performs well in January and February, but discrepancies occur again in March as soon as solar irradiation level increases (see Figures 3 and 12). Temperature spreads of over 20 °C are successfully captured with this optimization and show no significant deviations from the reference model, even during weekends when no heating gains are present. Although the early morning peaks described above persist, the subsequent hourly temperature values align closely with the EnergyPlus reference.

Significant deviations are also observed in summer, indicating the model's unsuitability for year-round simulations (see Figure 14). After an initially undercooled phase, external influences cause internal temperatures to rise excessively. Within approximately one week, the model's simulated temperatures exceed the EnergyPlus reference once again. Nevertheless, the winter-optimized model achieves notably lower maximum temperatures compared to the unoptimized version, reducing the peak from over 60°C to just under 40°C.

A similar improvement is observed in the spring period, where the maximum temperatures are reduced from 52°C in the unoptimized model to 34°C in the winter-optimized version (see Figure 13). At the beginning of spring, the winter-optimized model aligns relatively well with the EnergyPlus reference due to low solar irradiation and declining ambient temperatures. However, during the transition from week 2 to 3, short periods of higher solar irradiation lead to noticeable deviations.

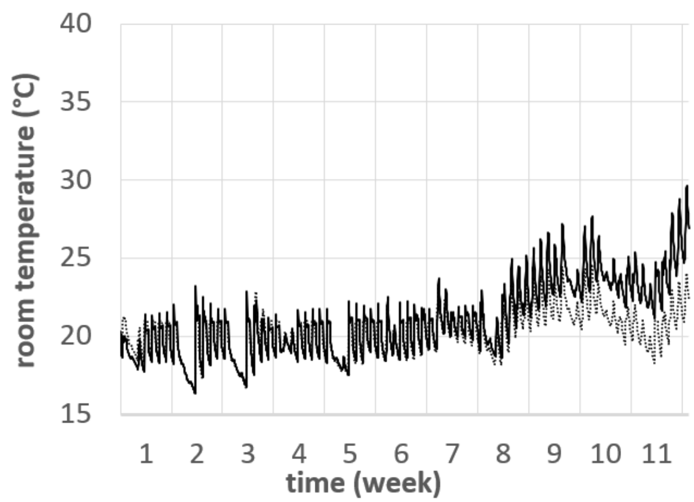

Figure 12. Evaluation of the room temperature for the winter-optimized model (solid), EnergyPlus (dotted) in winter.

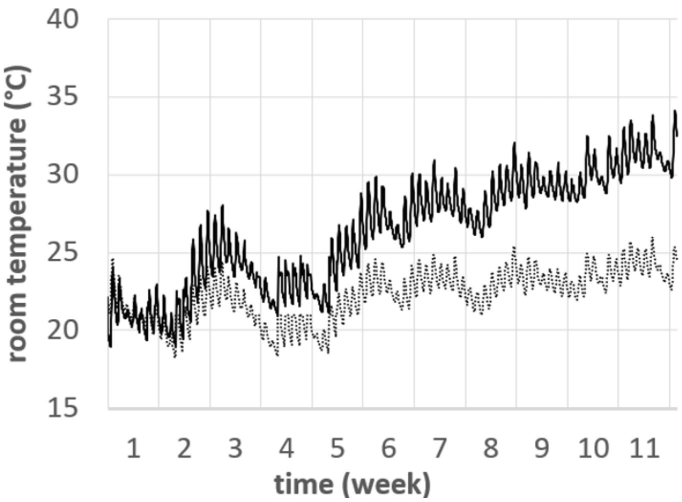

Figure 13. Evaluation of the room temperature for the winter-optimized model (solid), EnergyPlus (dotted) in spring.

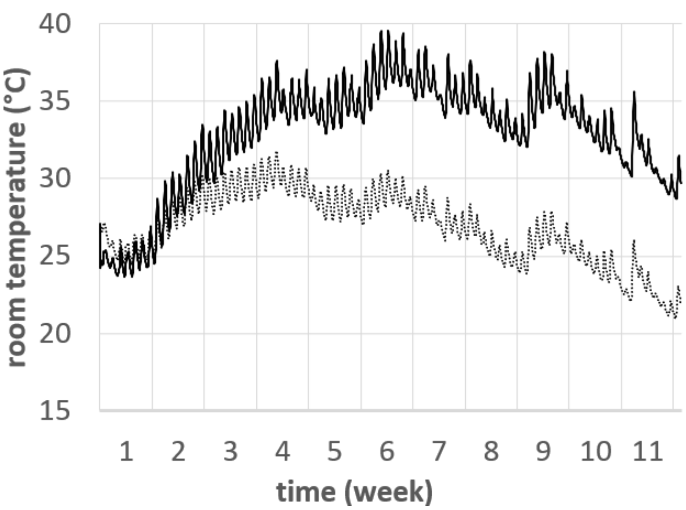

Figure 14. Evaluation of the room temperature for the winter-optimized model (solid), EnergyPlus (dotted) in summer.

The third optimization approach combines data from the first two weeks of January and July to create a more versatile *Bvu* matrix capable of managing thermal dynamics across both, winter and summer periods. This optimization accounts for heating activities, varying solar angles and the dual façade concept (see Figures 15 to 17). As observed in previous scenarios, initial deviations were present in both the winter and summer simulations due to the chosen initialization assumptions.

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. While temperature peaks at the beginning of each day could not be entirely eliminated, the remaining hourly values aligned closely with the EnergyPlus reference. Only after week 8, when solar irradiation increased significantly, the model displayed slightly elevated temperatures, with maximum deviations of approximately 2 °C.

In the first week of spring, 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. After a noticeable deviation between weeks 2 and 3, the temperature gradually realigned with the reference values as solar gains decreased. A similar pattern was observed around week 7, followed by a return to better agreement with the EnergyPlus data in subsequent 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 the first week. However, values slightly began to diverge again afterward. After two weeks of simulation, the deviation remained within approximately 1 °C. With declining solar irradiation, the calculated temperature consistently remained slightly above the reference values. This behavior may indicate limitations in the model's ability to accurately represent building heat losses during prolonged periods.

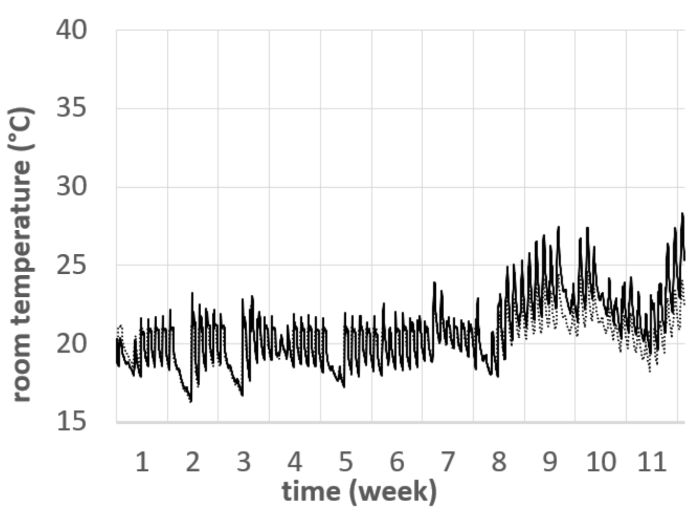

Figure 15. Evaluation of the room temperature for the combined January/July-optimized model (solid), EnergyPlus (dotted) in winter.

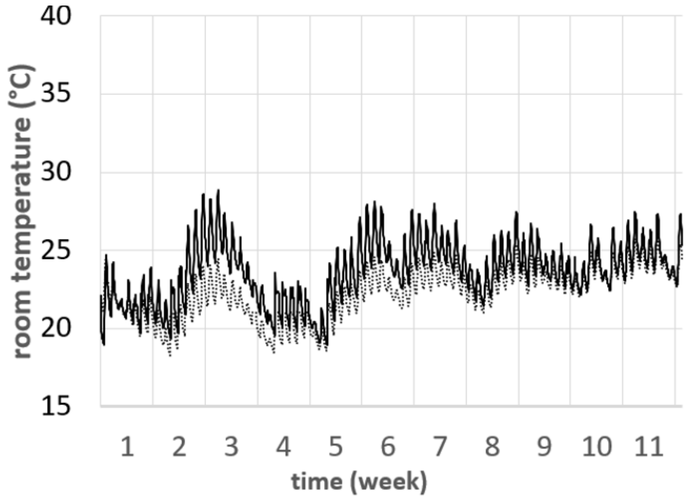


Figure 16. Evaluation of the room temperature for the combined January/July-optimized model (solid), EnergyPlus (dotted) in spring.

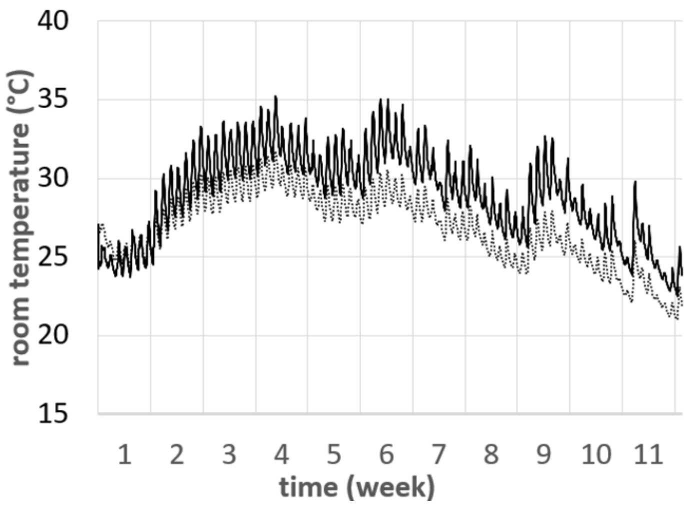


Figure 17. Evaluation of the room temperature for the combined January/July-optimized model (solid), EnergyPlus (dotted) in summer.

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.

Regarding possible errors, inaccuracies can generally arise due to the simplification of the physical model by the BRCM toolbox. These effects could be amplified by the reduction of the geometric model, which combines similar rooms, potentially leading to accuracy issues when considering internal heat flows between thermal zones. Despite these factors, the temperature results – also for other thermal zones within the building – remain realistic, and the trends influenced by external factors such as the ambient temperature or solar radiation, align with expected physical behavior, as confirmed by the EnergyPlus reference data. This program, which was used to determine the reference data sets, also offers extensive configuration options for almost all aspects and subsystems of an energetic building model. For the basic configuration of the white model and the internal system technology, the default values were used as far as possible. Further refinement and optimization of these parameters could increase the accuracy of the reference data used for future optimization.

Additionally, changes in building furnishings or modification to specific rooms may influence the internal thermal behavior. For instance, increased solar radiation entering through windows might affect not only the observed zone but also neighbouring rooms in a modified way. Similarly, future additions to the building, such as equipment or systems, could impact the simulation results and control precision due to further internal gains. However, since the building is still under construction and real measurement data will soon be available for further validation, these risks are expected to diminish in the medium to long term, supporting robust building regulation.

To further improve the reliability and accuracy of the validation simulations presented here, future studies could also include initialization simulations. This should enable a more precise representation of temperature distributions across various wall layers and their associated heat losses or gains, simulating a consistent state before the actual simulation or validation.

Greater accuracy in the model optimization could be achieved by using localized weather data directly measured at the exposed site, and integrating it into the

EnergyPlus simulation. Additionally, employing longer optimizations datasets would enhance the precision of the optimized model. While only one of the five system matrices was optimized in this study, the fundamental thermal and physical behavior of the building will largely remain intact. This flexibility ensures that the model can realistically adapt to specific conditions outside the currently optimized data sets. With these improvements, the accuracy of the predicted values could be further increased, which would lead to the development of more precise models and thus to higher efficiency levels in future buildings.

## 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 model reduction techniques 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.

## 5. Acknowledgements

The authors gratefully acknowledge financial support from the German Federal Ministry for Economic Affairs and Climate Action (BMWK) under the 7th Energy Research Program with the funded project OUR-E (grant number 03EN6023A).

**References**

[1] IRENA, "World Energy Transitions Outlook 2023: 1.5°C Pathway," International Renewable Energy Agency, 2023.

[2] R. Fick, O. Stark, R. Honke and T. Plessing, "Innovatives Versorgungskonzept zur multiplen Nutzung erneuerbarer Energiequellen des Instituts für Wasser- und Energiemanagement," in *Proceedings of RET.Con, Nordhausen*, 2022, pp. 82-93.

[3] D. Sturzenegger, D. Gyalistras, V. Semeraro, M. Morari and R. S. Smith, "BRCM Matlab Toolbox: Model generation for model predictive building control," in *2014 American Control Conference*, Portland, OR, 2014, pp. 1063-1069.

[4] U.S. Department of Energy’s (DOE) Building Technologies Office. (2024, February 10). "EnergyPlus™ (Software) | OSTI.GOV," 30 September 2017. [Online]. Available: https://www.osti.gov/biblio/1395882.

[5] J. Drgoňa, J. Arroyo, I. C. Figueroa, D. Blum, K. Arendt, D. Kim, E. P. Ollé, J. Oravec, M. Wetter, D. L. Vrabie and L. Helsen, "All you need to know about model predictive control for buildings," *Annual Reviews in Control*, vol. 50, pp. 190-232, 2020.

[6] Y. Li, Z. O'Neill, L. Zhang, J. Chen, P. Im and J. DeGraw, "Grey-box modeling and application for building energy simulations - A critical review," *Renewable and Sustainable Energy Reviews*, vol. 146, p. 111174, 2021.

[7] R. De Coninck, F. Magnusson, J. Åkesson and L. Helsen, "Toolbox for development and validation of grey-box building models for forecasting and control," *Journal of Building Performance Simulation*, vol. 9, no. 3, p. 288–303, 2016.
[8] P. Jayathissa, M. Luzzatto, J. Schmidli, J. Hofer, Z. Nagy and A. Schlueter, "Optimising building net energy demand with dynamic BIPV shading," *Applied Energy*, vol. 202, pp. 726-735, 2017.
[9] A. Ajagekar and F. You, "Deep Reinforcement Learning Based Automatic Control in Semi-Closed Greenhouse Systems," *IFAC-PapersOnLine*, vol. 55, no. 7, pp. 406-411, 2022.
[10] W.-H. Chen and F. You, "An Energy Optimization Model for Commercial Buildings with Renewable Energy Systems via Nonlinear MPC," *Chemical Engineering Transactions*, vol. 94, pp. 505-510, 2022.
[11] G. Hu and F. You, "Hybrid Physics-based and Data-driven Model Predictive Control for Multi-Zone Building's Thermal Comfort Under Disjunctive Uncertainty," *IFAC-PapersOnLine*, vol. 55, no. 7, pp. 352-357, 2022.
[12] S. Yang, H. O. Gao and F. You, "Building electrification and carbon emissions: Integrated energy management considering the dynamics of the electricity mix and pricing," *Advances in Applied Energy*, vol. 10, p. 100141, 2023.
[13] S. Yang, H. O. Gao and F. You, "Model predictive control in phase-change-material-wallboard-enhanced building energy management considering electricity price dynamics," *Applied Energy*, vol. 326, p. 120023, 2022.
[14] T. Xiao and F. You, "Building thermal modeling and model predictive control with physically consistent deep learning for decarbonization and energy optimization," *Applied Energy*, vol. 342, p. 121165, 2023.
[15] T. Hatanaka, T. Ikawa and D. Okamoto, "Remodeling of RC Circuit Building Thermodynamics Model with Solar Radiation Based on A Regularization-like Technique," in *12th Asian Control Conference (ASCC)*, Kitakyushu, pp. 7-12, 2019.
[16] Climate.OneBuilding.Org, "2024, February 10," [Online]. Available: https://climate.onebuilding.org/WMO_Region_6_Europe/DEU_Germany/BY_Bayern/DEU_BY_Hof_106850_TRY2010_10_Jahr_BBSR.zip.
[17] Q. Hu, F. Oldewurtel, M. Balandat, E. Vrettos and C. J. Tomlin, "Building model identification during regular operation - empirical results and challenges," in *2016 American Control Conference (ACC)*, Boston, MA, pp. 605-610, 2016.
[18] Y. Sun, F. Haghighat and B. C. Fung, "Fairness-aware data-driven-based model predictive controller: A study on thermal energy storage in a residential building," *Journal of Energy Storage*, vol. 87, p. 111402, 2024.
[19] T. Wietzke, J. Gall and K. Graichen, "Occupancy prediction for building energy systems with latent force models," *Energy and Buildings*, vol. 307, p. 113968, 2024.
[20] Y. Chen, J. Gao, J. Yang, U. Berardi and G. Cui, "An hour-ahead predictive control strategy for maximizing natural ventilation in passive buildings based on weather forecasting," *Applied Energy*, vol. 333, p. 120613, 2023.
[21] T. F. Coleman and Y. Li, "An Interior Trust Region Approach for Nonlinear Minimization Subject to Bounds," *SIAM Journal on Optimization*, vol. 6, no. 2, pp. 418-445, 1996.
[22] T. F. Coleman and Y. Li, "On the convergence of interior-reflective Newton methods for nonlinear minimization subject to bounds," *Mathematical Programming*, vol. 67, pp. 189-224, 1994.