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Implementation of a Forecast-Based Predictive Controller in a Residential Building

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1 ABSTRACT

To support the European Union's decarbonization pathway for buildings – phasing out fossil heating and cooling by 2040 and achieving zero-emission standards by 2050, this work presents a forecast-based model predictive control (MPC) for thermally activated building components (TAB). TAB provides large-area, low-temperature heat transfer and substantial thermal storage, enabling the controller to use environmental inputs such as solar irradiation to maintain comfort. The proposed MPC reduces complexity by embedding a lightweight, physics-based building model directly in the controller source code and avoiding heavy machine learning pipelines. A 48-hour forecast horizon with hourly updates leverages weather data (temperature, wind, cloudiness) and on-sitebuilding measurements to compute additional heating/cooling actions. Optimization is formulated first via least-squares error minimization for temperature tracking, then extended to a cost-based objective that includes dynamic tariffs, local renewables, CO2 price signals, and a season-dependent comfort band to enable short-term load shifting. Demonstrations in residential buildings in Vienna and Lower Austria show feasibility, high thermal comfort, and improved operability for non-expert users. The results indicate that a complexity-reduced MPC can deliver cost-aware, climate-aligned control with practical implementation effort, supporting broader adoption in the residential sector.

Keywords: Forecast-based controller, model predictive control, load shifting, urban resilience, urban planning

2 INTRODUCTION

In order to slow climate change, the European Union has set a guideline to decarbonize the building stock. The guideline has two distinct milestones on how to achieve that. Until 2040, fossil fuels for heating and cooling have to be phased out and replaced by renewable energies. In the year 2050, the building stock has to reach the standard of a zero-emission building(Europäische Union, 2024).

Thermal component activation is an important basis for sustainable and climate-friendly new buildings. It enables heating energy to be transferred over a large area to the respective residential units at a low flow temperature. This system turns the activated building mass into a large heat storage unit that can absorb and release a large amount of heat energy without causing significant fluctuations in the temperature of the concrete core(Heidenthaler et al., 2021). Based on this system, a controller has been developed that is capable of recording environmental influences such as solar radiation for a period in the future and, based on this forecast, controlling the heat input into the component activation in such a way that the desired target temperature is not significantly exceeded or undershot. For example, solar radiation is actively used to maintain the temperature. Additional functions, such as the inclusion of peak wind power,can be integrated into the forecast-based predictive control (MPC) through extensions and boundary conditions.

3 FORECAST-BASED PREDICTIVE CONTROLLER

Model predictive control (MPC) is a constrained optimal control approach that uses a predictive model to compute control actions over a finite horizon, updating the plan as new data arrive in a receding-horizon manner. It relies on a building model together with current measurements, state estimates, and forecasts of disturbances such as weather to predict and optimize future behavior. A state estimator provides the controller with the best available estimate of the building's internal state for decision making. The controller then manipulates actuators such as heat flows, valve openings, and pump powers to reduce energy use while maintaining occupant comfort within specified bounds. MPC can be formulated as linear, nonlinear, or hybrid, with the choice driven by modeling fidelity and computational considerations. MPCs enable short-term load shifting by using forecast data toshift required heat and cold production into favorable times(Drgoňa et al., 2020).

Yu et. al. estimate, that an MPC can save up to 26,9% in monthly electricity costs, when compared to a basic rule based controller with the same constraints (Yu et al., 2025). This depends of course on more than one factor. Electricity prices, climate and the properties of the residential building are some of the decisive properties when it comes to measuring the cost savings of an MPC.

3.1 Complexity of MPCs

Model predictive controllers for multi-party residential buildings in the literature can be found in a variety of types. Some models use complex machine learning algorithms to filter noise or adapt to new system behaviour. Machine learning can also be applied to certain sub-tasks for example to rework weather forecast data. Different models have varying complexity when it comes to training, implementation and maintenance. Zong et al. give an overview of the advantages and disadvantages of complex MPC models driven by machine learning and sophisticated algorithms:

Pro	Cons
Factors in stochastic properties of disturbance variables (e.g. weather forecast, occupancy profiles)	Highly complex for regular users, as the required background knowledge for active interaction can be high.
Can react to variable energy prices and other influential variables	Time-consuming data analysis and modelling
Can realize short-term load shifting	MPC strategies require higher investments which may not be compensated by additional savings in a short time
Can be formulated in a distributed manner. Computational load can be split among several solvers.	

Table 1: Advantages and disadvantages of MPCs in the residential building sector (Krz et al., 2019)

Zong et al. explain, that an MPC can improve on the concept of a regular outdoor temperature-based controller by factoring in stochastic properties of disturbance variables like weather pattern, occupant related disturbances like airing or cooking and dynamic electricity prices. An MPC is able to include a number of variables and decide the best time for energy distribution in it´s set boundries and time limits, making short time load shifting possible. On the contrast, MPCs elevate the complexity of control. This leads to challenges and boundaries that can hinder the implementation and operation of MPCs. When designing MPCs, machine learning often is at the center of the approach. Reliable models need a lot of training time and data to work sufficiently enough. A building model is also needed, as well as a processing unit where all the data is connected and applied to the building model. A complex MPC needs more attention in the implementation phase when compared to regular controllers and are mostly handled by the developers due to higher complexity. This also applies to data analysis and adjustments in operation. Higher complexity and solutions outside the norm, like an MPC lead to higher investment costs and therefore longer payback periods, when compared to widespread controllers. Another boundry is set by the users. Many MPC concepts fail, because regular users are not able to operate the controller in the right way. While the complexity for the MPC can be high, the interface for the user is required to be straight foreward and easy to use and understand(Krz et al., 2019),(Georges, 2019),(Kamthe and Deisenroth, 2018),(Yang et al., 2020).

3.2 Reduction of Complexity

Reducing the complexity of an MPC addresses the disadvantages of these controllers and can lead to a better outcome when it comes to implemented projects and user acceptance. An MPC in its core is an optimizer. To reduce the complex machine learning models, a different approach is suggested by Wolf et al., 2020. By using easier models that do not rely on sophisticated artificial neural networks, several advantages can be shown. Most MPCs for residential buildings use a highly sophisticated building model in a specialized simulation program like TRNSYS, MATLAB or EnergyPlus. The core idea is to map the energy balance of the set boundaries with given input variables. The output of this can be used in the further optimization. While highly accurate, the computational effort and possible interface issues can restrict the choice of the MPC´s hardware platforms. Building a basic building model that is capable of portraying the energy balances, masses and window areas has a sufficient quality for control operations and can be implemented in the source code of the MPC, making it lightweight. Depending on the aim of the MPC, the optimization can be streamlined as well. If the goal is to meet a certain setpoint, a simple minimization of the sum of squares error between room temperature and setpoint temperature can achieve these results and can be embedded into the source code (Wolf et al., 2020).

4 STRUCTURE OF AN MPC WITH REDUCED COMPLEXITY

As presented before, building an MPC controller with reduced complexity is possible. To better understand its workings the following diagram describes the structure of the proposed MPC:

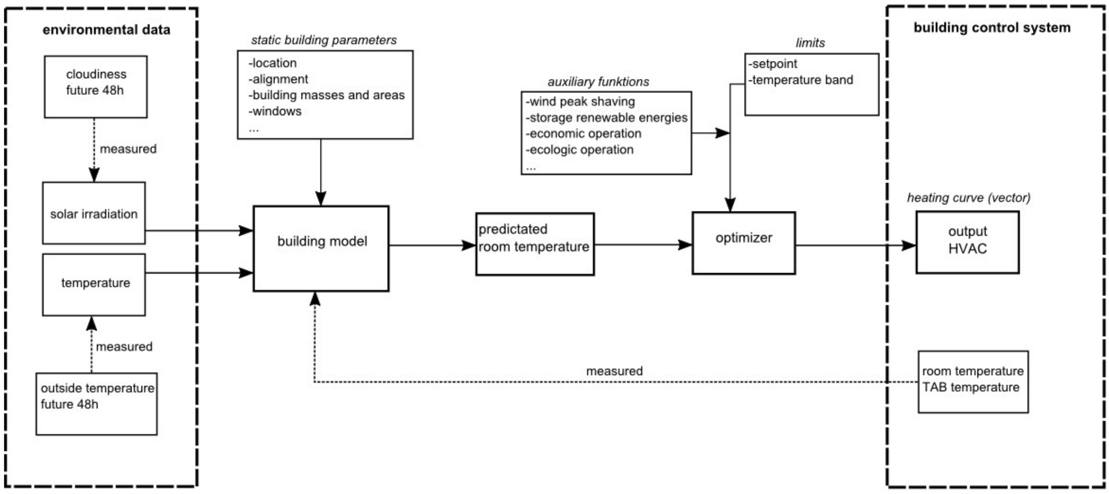

Figure 1: Structure of an MPC with reduced complexity

The outlined structure is based on MPC controllers that are already in active use in residential buildings in Vienna and Lower Austria, Austria. In the following part, the individual components will be described.

4.1 Sensor and Forecast data

The proposed MPC has a forecast horizon of 48 hours. For this purpose, local weather forecast data for the next 48 hours is retrieved. The data consists of outside temperature, wind speeds and cloudiness. The cloudiness in percent of blocked sunlight in combination with the solar irradiation and the course of the sun's position for the given location make it possible to approximate the solar irradiation.

For the calculations, live data from the building is needed. The room air temperature, temperature of thermally activated building components (TAB), outside temperature and energy meters have to be integrated into the MPC to deliver data of the state of the system for each new calculation (Wolf et al., 2020).

4.2 Building model

The building model is the central component of the MPC. For new buildings, the structure of the walls and the building materials used are known. This makes it possible to calculate the thermal storage mass Cp,R of the building. The thermal storage capacity of the thermally activated building components Cp,TAB must be taken into particular consideration. The solar inputs QSolardepend on the orientation and size of the windows, as well as the solar irradiation, which is influenced by cloud cover, time of day and season. Convection and ventilation losses QConv represent the heat losses of the building during the heating period. These heat quantities can be easily calculated for ventilation systems. The model ignores disturbance variables that are difficult to calculate QDist. For example, variables such as internal gains from electrical appliances or heat losses through ventilation via windows or doors are not considered in the model.

To understand how much energy have been put into the considered zone, an energy meter is used. In the schematic the energy meter is implemented using a temperature sensor to measure the temperatures on supply flow and return flow and a flow meter on the returnflow instead of the proposed single unit device. To control the heat flow into the zone in the heating period, a three-way valve is used, mixing the returnflow with the supply flow to establish the desired resulting flow temperature that is specified by the MPC(Wolf et al., 2020).

Editors: M. Schrenk, C. Beyer, T. Popovich, J. Ryser, D. Mawlood
ISBN 978-3-9504945-5-6

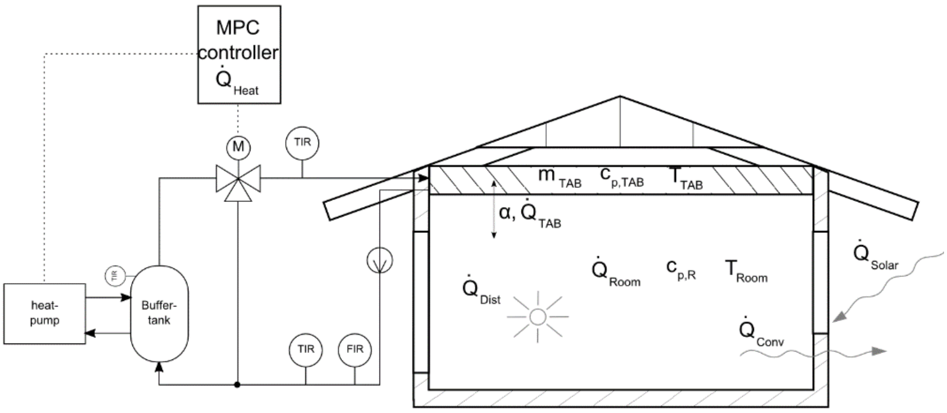

Figure 2: Schematic structure of the building model(Wolf et al., 2020)

This building model is implemented into the complexity reduced MPC via the coding language C, directly in the source code. The properties of the building like mass, alignment, window area and room dimensions are transferred into a static building model. Dynamic variables like outside temperature, room temperature and solar irradiation are projected onto this model.

4.3 Optimization

To optimize the temperature comfort, the setpoint temperature of the user has to be met with high precision. For this, the MPC can use the forecast data to mitigate the effects of environmental impacts on the room temperature.

For this, the dynamic forecast data (outside temperature, solar irradiation) is projected onto the static building model. The actual room temperature (T_{real}) gives the system a starting point for calculations. A predictive room temperature vector for the next 48 hours is calculated from this building model via the energy balance. The first task of the optimizer, which represents the next step, is to compare this predictive room temperature with the target room temperature set by the user and to specify a heating or cooling load for the heating system. In the basic version of the MPC, the deviation from the optimum comfort level (setpoint temperature of the user) is determined by minimizing the error sum of squares (LSE) (Klepicet al., 2023).

$$f(\vec{x}) = \sum_{i=0}^{47} \left(T_{SP,i}(\vec{x}) - T_{real,i}\right)^2 \rightarrow min \tag{1}$$

As described in (1), the aim of the basic optimization function is to minimize the offset of the room temperature (T_{real}) from the setpoint temperature (T_{SP}). The result of the optimization is a heating/cooling vector for the next 48 hours. The first element of this vector is transferred to the heating and cooling generator system and represents the energy demand for the following hour. This calculation is repeated every hour. (Klepic et al., 2024)

To take this approach a step further, the target function is converted into a cost optimization. This consists mainly of three parts as described in equation (2)

$$f(\vec{x}) = \sum_{i=0}^{47} \left(C_{Comfort,i}(\vec{x}) + C_{Cost,i}(\vec{x}) - B_{preheat,i}(\vec{x})\right) \rightarrow min \tag{2}$$

The optimization consists of three parts.

$C_{Comfort,\ i}(\overline{x})$ represent costs for not reaching the desired temperature levels. To increase the flexibility, a temperature band around the setpoint is introduced. It gives the MPC the ability to shift load into favorable time spans. For summer and winter this temperature band looks different, as shown in Table 2.

The temperature band is different for heating and cooling seasons. The reason is that in the heating season, overheating requires energy and therefore gives the system the flexibility to store more heating energy into the TAB when the conditions are favorable. This stored heating energy can be used to keep the room temperature levels into set limits during unfavorable production times. For cooling this principle is the exact opposite.

	Upper band	Lower band
Cooling season	T_{SP} + 1K	T_{SP} -3K
Heating season	T_{SP} + 4K	T_{SP} – 0,5K

Table 2: Amplitude of the temperature band for heating and cooling

$C_{Cost,\ i}(\overline{x})$ are the actual costs for the energy required to produce the heating or cooling energy required to reach the targeted room temperature levels. For these costs, locally produced renewable energy systems, like photovoltaic or wind can be implemented. Flexible energy tariffs and costs for CO_2 can also be included to give a more holistic approach to costs of energy use (Wolf *et al.*, 2020; Klepic *et al.*, 2024).

$B_{preheat,\ i}(\overline{x})$ describe a bonus for preheating or precooling. Energy use is to be moved into hours with favorable costs, which reduces the costs for heat production in the observed forecast horizon.

5 CONCLUSION AND OUTLOOK

The presented work aligns with the European Union's pathway toward decarbonizing the building stock by 2040 and achieving zero-emission performance by 2050. By leveraging thermal component activation (TAB) as a distributed storage and low-temperature heat transfer system, and combining it with a forecast-based model predictive control (MPC), the approach enables efficient, comfort-oriented operation that actively uses environmental inputs such as solar irradiation and variable energy costs.

A central contribution is the reduction of MPC complexity. By embedding a lightweight, physics-based building model directly into the controller source code, avoiding heavy machine learning pipelines, and adopting streamlined optimization objectives, the proposed MPC maintains the core benefits of predictive control – load shifting, cost-aware operation, and comfort assurance – while reducing implementation effort, computational burden, and user-side complexity. The integration of a temperature band around the setpoint provides the flexibility required for shifting energy use to favorable time windows, with asymmetric bounds tailored to heating and cooling seasons to exploit TAB storage effectively. The cost-oriented formulation allows inclusion of local renewable generation, dynamic tariffs, and CO2 price signals, thereby supporting both operational savings and climate targets.

The proposed MPC is currently in the demonstration phase in 3 projects. One project is already operational in Purkersdorf, Austria. It consists of 2 residential units in a two-family home and is controlled by an MPC with comfort optimization. The second demonstration project is called "ZQ3Demo" and consists of 15 residential units in a housing estate in Donaustadt, Vienna. Here a mixture of MPCs with comfort optimization and cost function optimization is tested. Four residential units with rule-based controllers are monitored as well to compare the results of the MPCs to conventional controllers. Another project with 3 residential units controlled by an MPC is currently providing data in Wolkersdorf, Austria. This project called "Zukunftshaus Wolkersdorf" consists of 3 comfort optimization MPCs.

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Editors: M. Schrenk, C. Beyer, T. Popovich, J. Ryser, D. Mawlood
ISBN 978-3-9504945-5-6

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