



Comparison of time-invariant and adaptive linear grey-box models for model predictive control of residential buildings

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ABSTRACT

Model predictive control (MPC) is a promising optimal control technique for activating building energy flexibility using its thermal mass. The performance of the MPC controller is directly related to the accuracy of the model prediction. Grey-box models, based on physical laws and calibrated on measurement data, are commonly used to represent the building thermal dynamics in MPC. Most research works use Linear Time-Invariant (LTI) grey-box models even though weather conditions vary significantly throughout the heating season. This is critical as inaccurate model prediction can lead to a lower performance of the MPC controller. This study introduces two adaptive MPC schemes to overcome this limitation of LTI models. The first one, called the Partially Adaptive MPC, only updates the effective window area of the prediction model. The second one, called the Fully Adaptive MPC, updates all the parameters of the grey-box model. The adaptive MPC performance is compared with MPC using LTI models in two different tests. The simulation-based results show that MPC based on LTI performs well if the control model is trained during a period with similar weather conditions as the period when the MPC will be applied. The Partially Adaptive MPC is unable to deliver satisfactory prediction performance due to the limited number of parameters that are updated. The Fully Adaptive MPC has the best performance compared to the other MPCs, especially as it avoids thermal comfort violations.

1. Introduction

The penetration of renewable energy sources (RES) in the energy system is increasing fast. However, RES is weather-dependent and uncertain, which brings challenges to the grid when balancing supply and demand. Therefore, more flexible energy solutions are needed for the future energy system. Demand response (DR) is considered a solution on the demand side to balance the volatility of electricity generation [1,2]. The definition of building energy flexibility given by the IEA EBC Annex 67 is closely related to DR, which is the ability of a building to manage its demand and generation according to local climate conditions, user needs and grid requirements [3]. A significant proportion (20–40%) of the final energy consumption is consumed by buildings in developed countries [4]. The large thermal mass of a building can be used as short-term heat storage, making it a suitable candidate to perform DR.

To store heat, the indoor temperature fluctuates between appropriate temperature limits that preserve the occupant's thermal comfort. Model predictive control (MPC) is a promising technique for performing DR in buildings. Numerous studies have addressed the potential of MPC to provide flexibility to the grid from the building thermal mass, see e.g. Refs. [5–11]. As the quality of the prediction model has a considerable impact on the control performance, developing an appropriate prediction model is the prerequisite for MPC deployment.

According to the availability of explicit models, the mathematical modeling of a dynamic system has three main categories, namely white-box, black-box, and grey-box models. White-box models are based on physical laws and have high prediction accuracy. However, white-box models have high mathematical complexity, and their calibration is time-consuming. Black-box models are purely data-driven based on time-series measurements from a system. Both a sufficient amount and quality of training data are needed to ensure the quality of the model.

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Nomenclature

RES	Renewable Energy Sources
DR	Demand Response
MPC	Model Predictive Control
BPS	Building Performance Simulation
RC	Resistance and Capacitance
LTI	Linear Time-Invariant
PID	Proportional Integral Derivative
PSO	Particle Swarm Optimization
ACS	Anti-Causal Shift
PLR	Part Load Ratio
HTC	Heat Transfer Coefficient
PRBS	Pseudo-Random Binary Signal

Grey-box models are a combination of white-box and black-box models. The model structure of grey-box models is constructed with the dominant physical processes of the system and measurement data are used to calibrate the model parameters. In the building automation field, lumped resistance and capacitance models (RC networks) are commonly used to represent the heat dynamics of a building. Grey-box models have better extrapolation properties than black-box models [12,13] and require less experimental data in most cases [14].

Existing research has demonstrated that linear time-invariant (LTI) models can approximate the heat dynamics of buildings with sufficient accuracy for MPC [15–19]. However, it remains unclear whether an LTI grey-box model trained from one period is able to provide decent prediction in another period due to time-varying weather conditions throughout the year. The performance of the MPC controller cannot be guaranteed when using an LTI model over a long period of time. Consequently, two approaches can be followed.

- An adaptive MPC controller that updates the parameters during operation becomes a potential solution. Adaptive MPC has been widely applied in engineering in general, but it has surprisingly been rarely investigated in building energy control [20]. Yang et al. [21] developed an adaptive robust model predictive control for indoor climate optimization, the model is based on a detailed grey-box model and updates the parameters every 24 h. Yang et al. [22] also introduced an adaptive machine-learning-based model for building control based on an artificial neural network (ANN). Fux et al. [23] used an extended Kalman filter-based self-adaptive thermal model for passive house demand prediction with the model updating the parameters at each time step. Choi et al. [24] used an adaptive neural network model to perform the optimal control for a data center. Maree et al. [25] proposed an adaptive control for heating demand-response in buildings that incorporates a reinforcement learning (RL) strategy. Zhang et al. [26] proposed a time-dependent solar aperture estimation method based on B-splines, which could be considered an adaptive grey-box model of buildings. Merema et al. [27] and Wolisz et al. [28] also applied adaptive control strategies for long period control, which updates the coefficients of ARX models during operation.
- The alternative approach is to train the LTI model over a specific period of the year which leads to a model that generalizes well over the entire space-heating season. This is the approach followed by Broholt et al. [29] suggesting that the end of the heating season is the most robust month to train the model for the climate of Denmark. However, they have not tested the impact of the model prediction accuracy in MPC.

Existing research on the robustness of Model Predictive Control (MPC) using Linear Time-Invariant (LTI) models predominantly focuses

on scenarios with stable weather conditions, overlooking the complexity related to variable weather. This gap is critical, as it raises questions about the performance of LTI models under changing environmental conditions. Our study directly addresses this knowledge gap by comparing the performance of conventional MPC based on LTI models with adaptive MPC strategies in a simulated environment (i.e., co-simulation). We introduce two adaptive MPC approaches, the Partially Adaptive MPC and the Fully Adaptive MPC, and evaluate their effectiveness in managing the thermal dynamics of buildings under variable weather conditions. This comparison provides novel insights into the adaptability and resilience of these control strategies based on linear grey-box models, contributing significantly to the field of building energy optimization and demand response in the face of renewable energy integration.

Two candidates for adaptive MPC controllers are designed. The first one, called the *Partially Adaptive MPC*, only updates the effective window area of the grey-box model when the prediction error is higher than a specific threshold during operation. The effective window area is a model parameter which is the ratio between the solar gains injected in a node of the RC model and the total solar irradiation measured on a horizontal plane (I_{so}). The main reason to focus on the effective window area is that solar gains are highly non-linear [30] and a dominant factor that influences the model accuracy. Due to cloud cover, changing altitude and zenith angles of the sun, the effective window area is expected to change significantly during the space-heating season, especially for high latitudes. The second one, called the *Fully Adaptive MPC*, updates all the parameters when the prediction error exceeds a specific threshold during operation. It means that the parameters related to the thermal dynamics of the building envelope are also calibrated during operation, even though the physics is less non-linear than the solar gains [30]. It gives more degrees of freedom as more parameters can be calibrated compared to the other adaptive MPC. However, the Fully Adaptive MPC theoretically takes more time to converge when it updates the model parameters. Furthermore, there is a risk of obtaining a set of unphysical parameters due to insufficient training data (meaning that the model is practically non-identifiable).

IDA ICE is a building performance simulation (BPS) software that performs detailed dynamic multi-zone simulations. It is used to mimic the thermal dynamics of a residential building in a realistic way, which is the emulator of the virtual experiments. Firstly, the model identification uses the data generated from IDA ICE where the building has been heated using different excitation signals during the space-heating season to train the parameters of the grey-box model. Secondly, the obtained grey-box models are then used as the LTI model of the MPC controller or as the initial model for the adaptive MPC controller. The controller is written in MATLAB and coupled with IDA ICE with a co-simulation function provided by a company called EQUA.

The remainder of the paper is structured as follows. Section 2 describes the virtual co-simulation experiment setup, which includes the IDA ICE building information, the excitation signals, the boundary conditions, and the co-simulation routine. Section 3 describes the methodology of this study, including the grey-box model structure and the algorithm to identify the grey-box model parameters, followed by the optimal control problem setup and the algorithm of the adaptive grey-box model. Section 4 presents the results, which compare the control performance of the MPC controllers based on the two control objectives. Finally, a discussion is given in Section 5 followed by conclusions in Section 6.

2. Description of virtual experiments setup

Virtual experiments are conducted using co-simulation, where the IDA ICE model is used as the emulator. The IDA ICE model was developed in a previous study [31]. The appearance of the building model in IDA ICE is shown in Fig. 1. It is a two-story detached house located in Oslo. The house has a floor area of 160 m² and is constructed of wood.

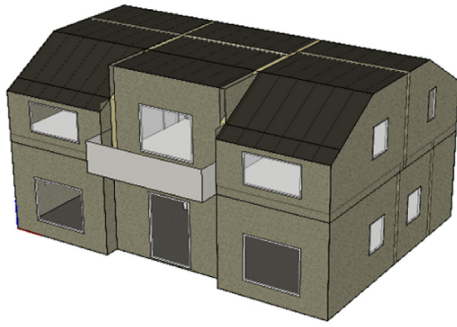


Fig. 1. Virtual 3D geometry of the building model in IDA ICE (showing the southwest facade).

This building has a lightweight construction and complies with the Norwegian passive house standard (NS 3700 [32]). The building floor plan is presented in Fig. 2. The residential building is equipped with balanced mechanical ventilation with a heat recovery unit. This heat exchanger is modelled with constant effectiveness of 85% without bypass (like a plate heat exchanger), which gives better linearity to the IDA ICE model. The dominant heat dynamics to be modelled is the envelope, which has relatively good linear properties. Therefore, it is reasonable to use a linear grey-box model as the prediction model for the MPC controller. The IDA ICE model is multi-zone, but all the internal doors of the building are set to be open. The embedded ventilation network model inside IDA ICE can account for the large bidirectional airflow due to open doorways. The air temperature inside the building in the simulation is thus relatively uniform due to large convective heat transfer between rooms. Therefore, it is reasonable to use a mono-zone grey-box model as the prediction model in this study. This also decreases the computational time of the MPC optimization significantly. The volume-averaged air temperature of all the thermal zones is taken to represent the indoor air temperature of the grey-box model. The space-heating system in the IDA ICE model is electric radiators which are the most common for Norwegian residential buildings [33]. The thermal capacity of electric radiators is neglected as it is small compared to the envelope. The profile for internal gains and occupancy is based on the Norwegian technical standard TS3031:2016 [34]. These daily profiles with 1-h resolution do not vary during the space-heating season.

The heat dynamics of the building need to be excited to collect information-rich input-output data to train the model parameters. The Pseudo-Random Binary Sequence (PRBS) is considered to be an ideal excitation signal since it approximates white noise properties, which can excite the dynamic system in a large spectrum of frequencies [35,36]. The PRBS signal is applied to the only controllable input of the system (i.

e., electric radiators) to collect the training data. However, applying a PRBS signal to the space-heating system is not always feasible as a PRBS signal may cause large indoor temperature variations, which can be experienced as uncomfortable for occupants. Thus, the data collected under conventional operations are also taken as training data. To this end, intermittent heating with changing temperature setpoints between daytime and nighttime (i.e., a night setback) is applied. The local controller of the radiator is an on-off control that is representative of electric radiators. In this study, the model trained from the PRBS signal is only used for the MPC based on an LTI control model. The historical weather data of Oslo is taken from Shiny Weather Data [37]. Some characteristics of the weather conditions and the period of the PRBS signal excitation experiments are given in Table 1. The model trained using the full winter intermittent heating with changing temperature setpoints is used for the MPC based on an LTI model and as the initial model for both candidates of the adaptive MPC.

The co-simulation virtual experiment lasted for 61 days (from November 1st to December 31st). The time step in the co-simulation is set to 15 min. At each step, IDA ICE first sends the calculated volume-averaged indoor temperature (T_i) of the building to MATLAB. The MPC controller then takes the prediction of the weather data and the internal heat gains into the MPC optimization. It generates the optimal control sequence (i.e., the optimal heating power, Q_h) over the prediction horizon. Only the first time step of the control sequence is sent to IDA ICE to be executed during one time step. After the first time step is completed, the new state of volume-averaged indoor temperature is sent back to MATLAB again and a new round starts. The process keeps iterating within the co-simulation framework until the predetermined simulation period is completed. A sketch of the co-simulation process is presented in Fig. 3. Khatibi et al. [38] have used a similar co-simulation setup in IDA ICE in their study to investigate the flexibility of the air heating and ventilation system. IDA ICE requires an initialization period before the temperature difference between the zones is realistic. Therefore, a PID control is taken at the beginning of the co-simulation before starting the MPC. The length of this initialization of the virtual experiment is set to be a half-day before switching to MPC.

In the MPC, the minimum indoor temperature limit is set to be 20 °C and the maximum limit is set to be 24 °C. There is a night setback for the minimum temperature limit decreasing from 20 °C to 16 °C from 11 p.m.

Table 1

Weather conditions during PRBS experiments.

Type	Mean outdoor temperature	Sky	Starting date	Duration
Cold	0 °C	Overcast	12/24/2019	One week
Mild	5 °C	Overcast	11/23/2019	One week

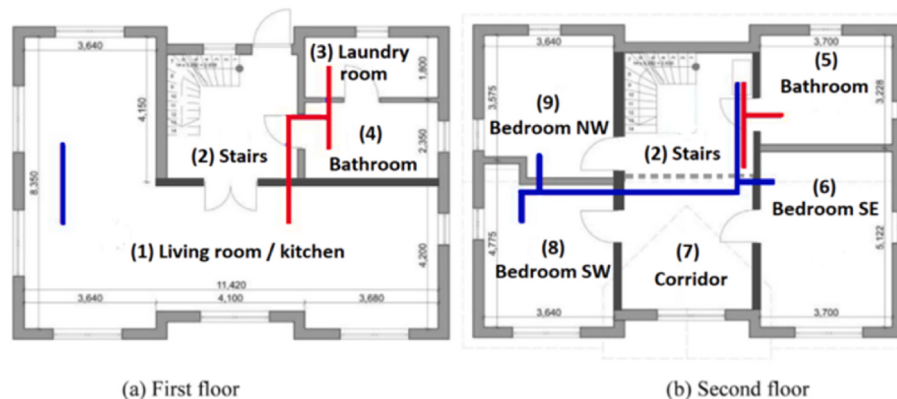


Fig. 2. Floor plan of the test building (ducts for the supply air are in blue and in red for extraction). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

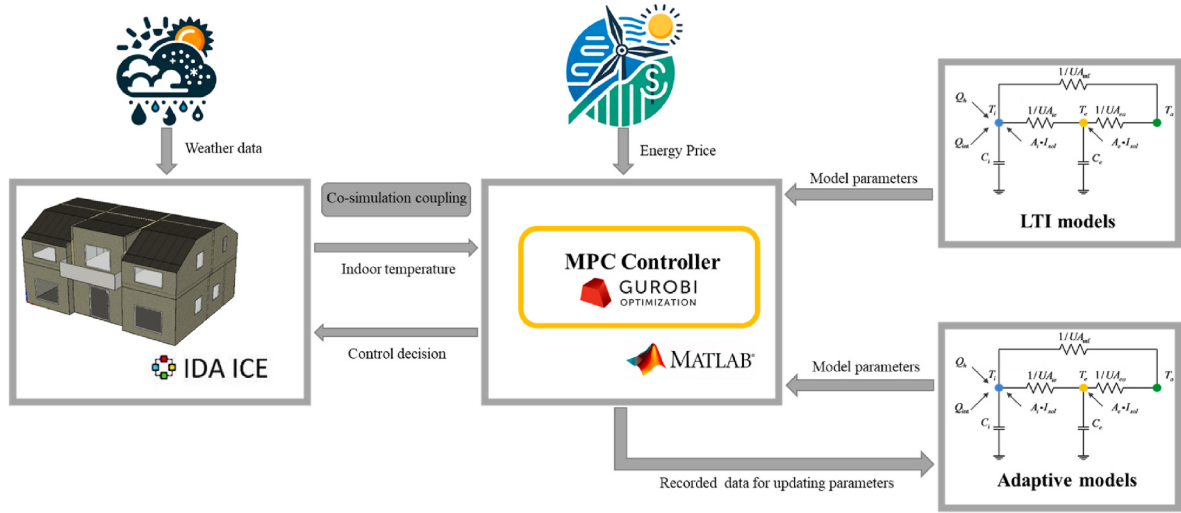


Fig. 3. Co-simulation setup between IDA ICE and MATLAB.

to 7 a.m. The indoor temperature bounds are defined as Equation (1). The indoor temperature limits are used as thermal comfort constraints for the MPC. For the sake of simplicity, the radiator in the IDA ICE model is assumed to be able to modulate its power by adjusting its part load ratio (PLR). The total heating power of all the radiators is 3220 W. Thus, the power constraint of the heating system is from 0 to 3220 W in the MPC.

$$\begin{aligned} 16 \leq T_i \leq 24 & \text{ if } t \in (23 : 00, 24 : 00) \\ 16 \leq T_i \leq 24 & \text{ if } t \in (0 : 00, 7 : 00) \\ 20 \leq T_i \leq 24 & \text{ if } t \in (7 : 00, 23 : 00) \end{aligned} \quad (1)$$

The electricity price profile is also needed for the MPC as an index for making decisions. It is generated from the historical electricity price from Nord Pool. The penalty cost for using electricity during peak hours is a predefined penalty profile that has two levels and is repeated daily. The electricity price profile and the peak hour penalty cost profile are given in Fig. 4 in Norwegian krone [NOK/kWh].

3. Methodology

3.1. Grey-box model

A considerable amount of research has already been done to investigate suitable mono-zone grey-box models for MPC implementation in

buildings [5,18,39–42]. However, a specific model structure in one piece of research is unlikely to be suitable for other buildings with different geometries and materials. Thus, selecting a suitable grey-box model structure for the MPC controller is the prerequisite of this study. A model structure that is too complex may lead to overfitting and increase the calculation cost drastically. A simple model structure can decrease the computational time for optimization but may lead to unacceptable prediction performance. In the previous study [31] using the same building, the second-order 3R2C grey-box model has proven to be a suitable trade-off between model complexity and accuracy. Therefore,

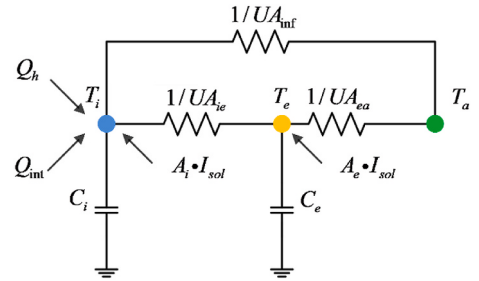


Fig. 5. 3R2C grey-box model.

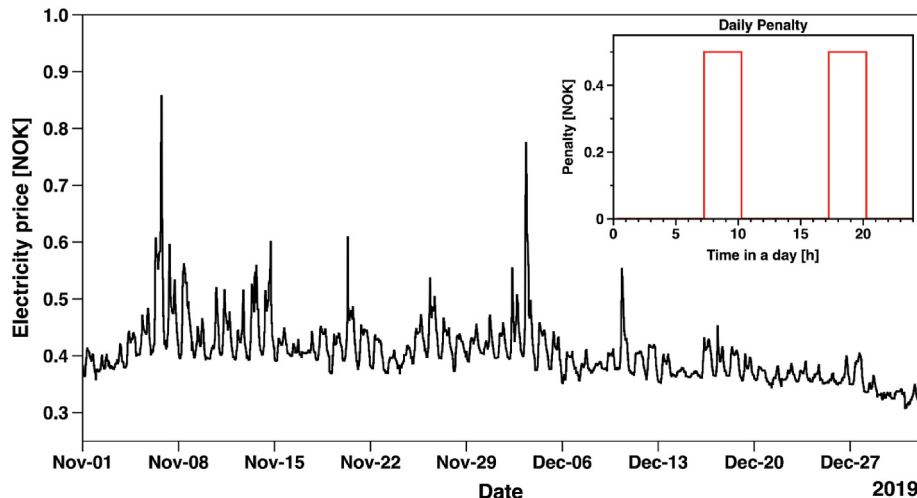


Fig. 4. Electricity and peak hour penalty cost profile (from November to December).

our study also takes the 3R2C as the prediction model structure, which is presented in Fig. 5. The definition of parameters for the model is given in Table 2.

The corresponding state-space model in Fig. 5 is given by:

$$\begin{bmatrix} \dot{T}_e \\ \dot{T}_i \end{bmatrix} = \begin{bmatrix} -\frac{(UA_{ie} + UA_{ea})}{C_e} & \frac{UA_{ie}}{C_e} \\ \frac{UA_{ie}}{C_i} & -\frac{(UA_{ie} + UA_{inf})}{C_i} \end{bmatrix} \begin{bmatrix} T_e \\ T_i \end{bmatrix} + \begin{bmatrix} \frac{UA_{ea}}{C_e} & \frac{A_e}{C_e} & 0 & 0 & 0 \\ \frac{UA_{inf}}{C_i} & \frac{A_i}{C_i} & \frac{1}{C_i} & \frac{1}{C_i} & \frac{1}{C_i} \end{bmatrix} \begin{bmatrix} T_a \\ I_{sol} \\ Q_{int} \\ Q_{vent} \\ Q_h \end{bmatrix} \quad (2)$$

$$y(t) = [0 \ 1] \begin{bmatrix} T_e(t) \\ T_i(t) \end{bmatrix} \quad (3)$$

The MATLAB system identification toolbox [43] is used to fit the parameters of the grey-box models. The linear state-space grey-box model is formulated in the innovation form, i.e.,

$$\frac{dx}{dt} = Ax(t) + Bu(t) + Ke(t) \quad (4)$$

$$y(t) = Cx(t) + e(t) \quad (5)$$

where x is the state vector, A , B and C are the system matrices, u is the input vector (i.e., T_a , I_{sol} , Q_{int} , Q_{vent} , Q_h) and y is the output (i.e., indoor temperature, T_i). The stochastic model is an extension of deterministic model ($K = 0$) [13]. K is the disturbance matrix of the innovation form (Kalman gain) [44].

This study uses an optimization routine in two stages that combines a global optimization followed by a gradient-based optimization to avoid converging to a local optimum. Detailed information can be found in the previous study [31]. The first stage uses heuristic particle swarm optimization (PSO) to get a first estimation of parameter values. The second stage takes the gradient-based optimization function (*greyest*) of the MATLAB system identification toolbox to further polish the parameter values. The objective function $f(x)$ of the optimization is defined as Equation (6),

$$f(x) = \sqrt{\frac{\sum_{k=1}^N \|y_k - \hat{y}_k(\theta)\|^2}{N}} \quad (6)$$

where y_k is the measurement output, while $\hat{y}_k(\theta)$ is the prediction of the model (with parameter set θ).

The dataset in this study has two different time intervals (T_s). The dataset collected for the model training phase has a sampling time of 2.5 min, while the sampling time for the dataset collected during the MPC

co-simulation (operation phase) is 15 min, like the time interval of the MPC. The data collected during the operation phase is used to update the model parameters of the adaptive MPC controller. However, 15 min is a relatively long sampling time, which may be larger than the shortest time constant of the building thermal dynamics. Previous studies [31] have shown that this may prevent the identified parameter values from being physically plausible. In line with these two studies, a time shift, called anti-causal shift (ACS) [45], of the input is applied to the data collected during the operation phase (i.e., input delay = $-T_s$). It has proven to be beneficial for model identification with large T_s [31,45].

In the preliminary experimental MPC operation, the deterministic model shows similar prediction performance as the stochastic model. Therefore, the deterministic model is used when updating the parameters as it showed quicker convergence when updating the parameters.

3.2. Optimal control problem formulation

This study investigates the performance of the MPC controllers with two control objectives to make sure conclusions do not depend on the objective function.

- 1) Objective 1 (Energy Savings): Minimal total electricity use of the heating system while minimizing indoor thermal discomfort at the same time.
- 2) Objective 2 (Energy Cost Saving with Peak Reduction): Minimal total electricity cost and reduce electricity use during the peak hour of the grid while minimizing indoor thermal discomfort. The electricity spot price from Nord Pool and the historical weather data for 2019 are used in this study. An MPC minimizing energy costs is usually called economic model predictive control in other studies.

With these control objectives and the constraints defined in Section 2, the optimal control problem can be formulated. As previously mentioned, the time step of each control decision is 15 min. The prediction horizon of the MPC controller is set to be 24 h (96 slots, $N = 96$). This prediction length is a typical value in MPC building applications [16,46,47]. The prediction length is also acceptable considering the computational cost. The equations of the optimization problem are given below.

Case 1.

$$\argmin_{Q_h} \sum_{k=0}^{N-1} Q_h[k] + \varepsilon_1[k] L\mathcal{E}_1[k] + \varepsilon_2[k] L\mathcal{E}_2[k] \quad (7)$$

Case 2.

$$\argmin_{Q_h} \sum_{k=0}^{N-1} c_h[k] Q_h[k] + p_h[k] Q_h[k] + \varepsilon_1[k] L\mathcal{E}_1[k] + \varepsilon_2[k] L\mathcal{E}_2[k] \quad (8)$$

Subject to

Table 2
The physical interpretation of the parameters of all grey-box models.

Parameters	Physical interpretation and unit
T_i	Temperature of the internal node (i.e., indoor air, furniture) [$^{\circ}\text{C}$].
T_e	Temperature of the external walls [$^{\circ}\text{C}$].
T_a	The outdoor temperature [$^{\circ}\text{C}$].
C_i	Heat capacity including the thermal mass of the air, the furniture [kWh/K].
C_e	Heat capacity of the node external wall [kWh/K].
UA_{ie}	Heat conductance between the building envelope and the interior [kW/K].
UA_{ea}	Heat conductance between the outdoor and the building envelope [kW/K].
UA_{inf}	Heat conductance between the outdoor and the interior node (modeling components with negligible thermal mass, like windows and doors) [kW/K].
Q_{int}	Internal heat gain from artificial lighting, people, and electric appliances [kW].
Q_h	Heat gain delivered by the heat emitter [kW].
I_{sol}	Global solar irradiation on a horizontal plane [W/m^2].
A_i	The effective window area of the building corresponding to the node T_i [m^2].
A_e	The effective window area of the building corresponding to the node T_e [m^2].

$$x[k+1] = Fx[k] + Gu[k] + Ke[k], k \in N_0^{N-1} \quad (9)$$

$$T_i[k] = Cx[k], k \in N_0^{N-1} \quad (10)$$

$$T_{low}[k] - \varepsilon_1[k] \leq T_i[k], k \in N_0^{N-1} \quad (11)$$

$$T_i[k] \leq T_{up}[k] + \varepsilon_2[k], k \in N_0^{N-1} \quad (12)$$

$$0 \leq Q_h[k] \leq Q_{h,max}[k], k \in N_0^{N-1} \quad (13)$$

$$0 \leq \varepsilon_1[k]; 0 \leq \varepsilon_2[k], k \in N_0^{N-1} \quad (14)$$

where $x[k]$ is the state vector in discrete-time, F , G and C are the discrete system matrices trained from the system identification process, $u[k]$ is the input vector in discrete-time and $y[k]$ is the output. K is the tuned steady Kalman gain of the model. $Q_h[k]$ is the calculated optimal heat power at each step in the prediction horizon, while $Q_{h,max}[k]$ is the max power of the heating system. $\varepsilon_1[k]$ and $\varepsilon_2[k]$ are the slack variables of the soft constraints for the thermal comfort band. L is the weighting factor that is set to penalize thermal discomfort in the objective function. The soft constraints enable the solver to avoid infeasible optimization problems by allowing thermal comfort bands to be violated. $c_h[k]$ is the electricity price profile at each slot. $p_h[k]$ is the penalty cost for using electricity during peak hours. $T_i[k]$ is the predicted indoor temperature from the prediction model. $T_{low}[k]$ and $T_{up}[k]$ are the corresponding temperature boundaries inside the prediction horizon. The receding horizon is implemented in the MPC, so the above optimization problem is solved at each step (every 15 min) to get the optimal control decision. Then, the initial states of the control model and weather forecasts are updated with the receding prediction horizon. Thermal discomfort is not desirable. Thus, the penalty weight factor L of the slack variables is given with a large value. The baseline penalty weight factor L is set to 10^8 in this study, but L is also set to 10^6 in the sensitivity analysis. A solver that can solve quadratic programming optimization problems is needed due to the quadratic form of the slack variables ε_1 and ε_2 . The toolbox YALMIP [48] in MATLAB is used for the optimization problem formulation, and Gurobi [49] is used to solve the optimization problem.

3.3. Conventional and adaptive MPC

This study uses two months of simulation to compare the performance between the conventional and adaptive MPCs. The conventional MPC is based on an LTI model, and the parameter values are kept unchanged during simulation. One primary objective of this study is to examine how the selection of the training data affects MPC performance. Thus, perfect weather forecast is assumed to exclude the variability of

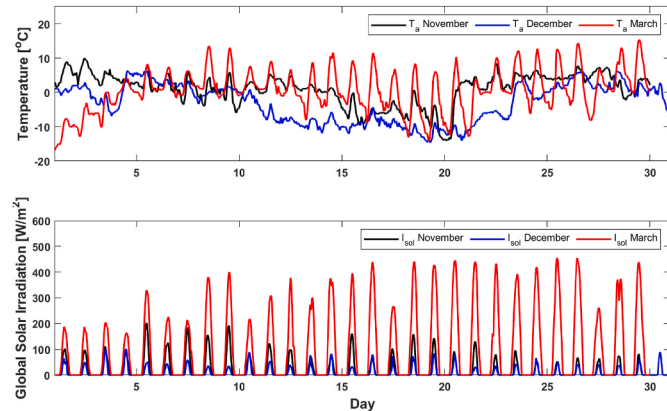


Fig. 6. Weather profile for November, December and March.

Table 3

Case summary of experiments.

Case	Excitation	Training Period
FullWinter	Intermittent on-off	11/01/2019 - 03/31/2020
PRBSNOV	PRBS	11/23/2019 - 11/30/2019
PRBSDEC	PRBS	12/24/2019 - 12/31/2019
ONOFFNOV	Intermittent on-off	11/01/2019 - 11/30/2019
ONOFFDEC	Intermittent on-off	12/01/2019 - 12/31/2019
ONOFFMAR	Intermittent on-off	03/01/2020 - 03/31/2020
Partially Adaptive	MPC operation	During operation
Fully Adaptive	MPC operation	During operation

weather prediction to simplify the analysis. The conventional MPC has six variants using different LTI models trained on different periods. The FullWinter model is trained with the entire winter season data where the building is heated using intermittent temperature setpoints. There are two LTI models trained using the data from PRBS experiments of November and December, respectively, called PRBSNOV and PRBSDEC. There are another three LTI models trained using the data from intermittent on-off experiments of November and December and the last month of the heating season, meaning March. These variants are called ONOFFNOV, ONOFFDEC and ONOFFMAR, respectively. The two adaptive MPCs take the FullWinter model as the initialization model. The weather profile for each month is depicted in Fig. 6.

It is unreasonable to use short training period data to update the model parameters as it leads the parameters to be completely unphysical or have large uncertainty. On the other hand, taking a long period of historical data for retraining is also not optimal since the adaptive MPC should be able to adapt the parameters for changing operating conditions. Pushed to the extreme, a very long retraining period will make the adaptive model converge towards an LTI model. Therefore, the length of the retraining period for updating the parameters is set to 7 days. Preliminary tests have shown that seven days of data using intermittent on-off heating leads to a model with physically plausible parameters and fair prediction performance. The cases of 14 days training period are added for comparison purposes. Given the duration of the retraining period, the adaptive MPC routines are not allowed to update parameters until the first m steps (i.e., $m = 672$ for 7 days training period) of simulation are completed.

The Partially Adaptive MPC only updates the effective window area (A_i) in the parameter set of the model during the simulation. The Fully Adaptive MPC updates all the grey-box model parameters during simulation. The pseudo-code to update the model parameter using the Partially Adaptive MPC and Fully Adaptive MPC is presented in Algorithm 1. In this operation, θ represents the parameter being updated. Specifically, θ refers to A_i in the context of Partially Adaptive MPC, and encompasses all parameters (C_e , C_i , UA_{ie} , UA_{ea} , UA_{inf} , A_e and A_i) in the case of Fully Adaptive MPC. A summary of the different cases is given in Table 3.

The sliding accumulated error φ is the sum of absolute prediction errors, serving as the index for determining the need for a parameter update. The absolute prediction error represents the absolute difference between the indoor temperature measurement in IDA ICE at a given time step ($T_{i[k]}^*$) and the indoor temperature predicted by the MPC for that time step ($T_{i[k]}^p$) over the preceding n steps (i.e., $n = 12$, which is 3 h).

The parameter updating routine is activated when φ exceeds a pre-determined threshold τ . The threshold is originally set $\tau = 5$ Kh in this study. A lower τ means a lower tolerance for error, which can be tuned based on the application scenario.

To investigate the influence of the training period and error threshold on the performance of adaptive MPC. The cases with $\tau = 2.5$ Kh and a training period of 14 days for updating the parameters with penalty weight factor $L = 10^8$ are also presented in the sensitivity analysis.

Algorithm 1. Pseudo-code for the Adaptive MPC**Algorithm 1: Adaptive MPC**

Initialize: Set φ_0 , τ initial value, Set FullWinter model as the prediction model of MPC.

Data: $\{[T_{i[k-n+1]}^*, T_{i[k-n+2]}^*, \dots, T_{i[k]}^*], [T_{i[k-n+1]}^p, T_{i[k-n+2]}^p, \dots, T_{i[k]}^p], \theta(k), \varphi(k)\}$ updated at each time t_k

for $t = t_k$ **to** t_{final} **do**

 Solve MPC for u_k

 Calculate $\varphi_k = \sum_{i=k-n+1}^k |T_{i[k]}^* - T_{i[k]}^p|$

If $\varphi_k > \tau$

 Update parameters

$\arg \min_{\theta} \sum_{j=1}^m (T_{i[j]}^* - T_{i[j]}^p)^2$

$\theta_{k+1} = \theta_{[k]}$

else

$\theta_{k+1} = \theta_{[k]}$

end

end

3.4. Key parameters and KPI

The Fully Adaptive MPC updates all its parameters during simulation, and the time evolution of some key parameters of the model is monitored during the operation. These key parameters are the overall heat transfer coefficient (HTC), the thermal capacitances (C_i and C_e) and the dominant parameter for modeling the influence of the solar radiation, the effective window area (A_i). The overall heat transfer coefficient (HTC) is the total heat loss of the building in steady-state [31]. In a highly insulated and airtight building as considered in this study, heat conduction dominates the overall heat losses and this heat transfer process has good linear properties. Heat transfer by convection and long-wave radiation is nonlinear but is of secondary importance. The HTC is the combination of several resistances of the grey-box model. The definition of HTC for the 3R2C model is defined by Equation (15). A reference value for HTC is 85 W/K (identified by applying a step function of the space-heating to the IDA ICE model).

$$HTC = \frac{1}{1/UA_{ie} + 1/UA_{ea}} + UA_{inf} \quad (15)$$

The capacitances (C_i and C_e) are directly related to the building thermal dynamics. Based on ISO 13786:2017 [50], the reference value of the effective heat capacitance of the building (C_{eff}) is estimated to be 3.9 kWh/K using daily period temperature variations. The C_{eff} can be used as a reference for the sum of the parameters C_i and C_e . They should not be equal but have the same order of magnitude.

Regarding the KPIs for evaluating the MPC performance, the first test case (Energy Savings) takes the total energy use [kWh] and the thermal discomfort. The second case (Energy Cost Saving with Peak Reduction) considers the energy use during peak hours [kWh] and the total cost [NOK] combining the energy cost and the peak-hour penalty cost into the evaluation KPI. The thermal discomfort is quantified in Kelvin hours (Kh) outside the predefined thermal comfort band.

4. Results

This section compares the performance of the different MPC controllers for the two different control objectives. Therefore, the co-simulation results are evaluated successively based on the control

objectives. The trained parameter values of the three LTI models are shown in Table 4. As can be seen, the HTC and A_i are significantly different for the LTI model identified using the FullWinter data than the two LTI models using the PRBS excitation signal.

4.1. Energy savings (ES)

Energy savings is the most basic control objective of this study. Figs. 7 and 8 present a selected period of the indoor temperature profile under the operation of the different MPC controllers using this control objective for $L = 10^6$ and $L = 10^8$ penalty factors, respectively. The total energy use and the thermal discomfort (61 days) of those different MPC controllers with different penalty factors are calculated so that the MPC controller performance can be quantitatively compared in Table 5.

Results show that the FullWinter model makes inaccurate indoor temperature predictions, which causes the thermal comfort constraint to be frequently violated. The Partially Adaptive MPC shows a similar inaccurate prediction compared to the FullWinter MPC. The thermal comfort constraint is still frequently violated. With the lower penalty factor 10^6 , the thermal discomfort of Partially Adaptive MPC is even larger than FullWinter MPC. These two models consume less energy compared to the other models (i.e., the Fully Adaptive MPC and the PRBS MPC) because they are less accurate, which causes the indoor temperature to drop below the minimum indoor temperature threshold. The heating system is switched on far too late in the morning, resulting in significant thermal discomfort. It indicates that the LTI grey-box model trained using the data from the full space-heating season may not be as suitable as the prediction model in MPC.

PRBSNOV MPC and PRBSDEC MPC perform better than the FullWinter and Partially Adaptive MPC models in terms of avoiding thermal discomfort, which can be clearly seen in Figs. 7 and 8. PRBSDEC MPC performs better than PRBSNOV MPC in terms of thermal comfort leading to a slightly higher energy use. The influence of the penalty factor on PRBSNOV MPC is more evident than on the PRBSDEC MPC. The performance of ONOFFNOV MPC and ONOFFDEC MPC are almost identical. With the lower penalty factor 10^6 , the thermal discomfort is slightly higher than PRBSDEC. With the higher penalty factor 10^8 , the thermal discomfort is similar to PRBSDEC but the energy use is slightly lower. The ONOFFNOV and ONOFFDEC perform better than expected, they show even better performance compared to the model trained from PRBS excitation signal in November. This proves that intermittent on-off can also be a good choice for exciting the thermal dynamics of the building to obtain the data for training the parameters of the model.

Though the paper [29] suggests that the end of the heating season is the most robust period for training the model, ONOFFMAR MPC performance is much worse than the LTI MPC that trained from the corresponding operation period (ONOFFNOV and ONOFFDEC). However, ONOFFMAR MPC performs much better than the FullWinter MPC, which indicates that the model trained from the data at the end of the heating season is more suitable than the full winter LTI model. All the results above prove that it is important to use a model that is trained with data generated from weather conditions similar to the period when the MPC will be operated.

The Fully Adaptive MPC performs much better than the Partially Adaptive MPC in all KPIs due to more degrees of freedom to fit the model

Table 4
Trained parameter values of the LTI models.

Case	HTC [W/K]	C_e [kWh/K]	C_i [kWh/K]	A_i [m ²]
FullWinter	81.42	4.03	0.33	6.09
PRBSNOV	96.43	4.81	0.42	16.96
PRBSDEC	94.25	4.93	0.41	15.94
ONOFFNOV	85.19	4.09	0.46	9.43
ONOFFDEC	88.76	4.26	0.44	15.60
ONOFFMAR	84.77	4.59	0.47	4.36

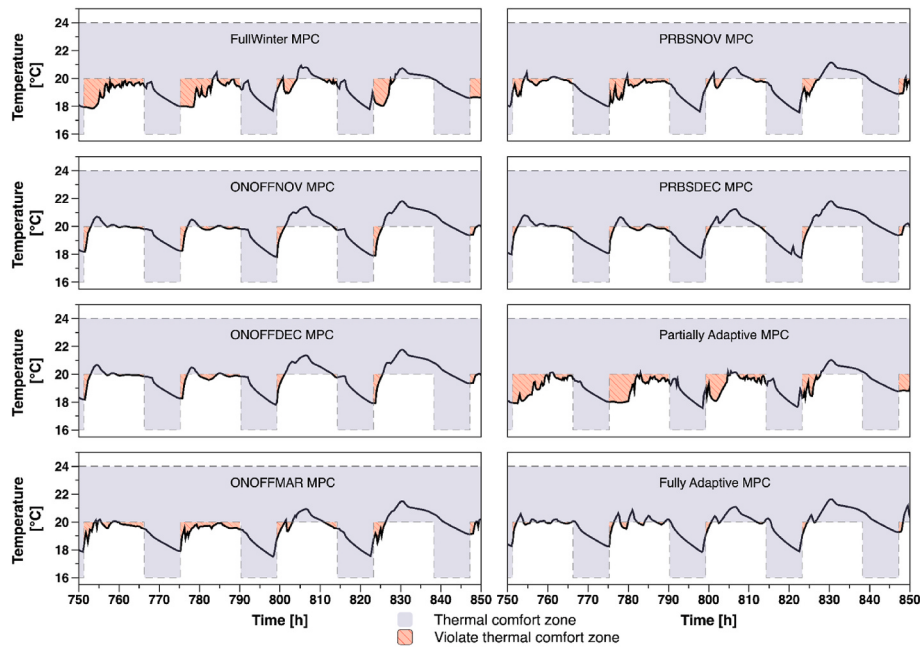


Fig. 7. Close-up of the indoor temperature profile under the operation of different MPC controllers with energy savings objective, $L = 10^6$.

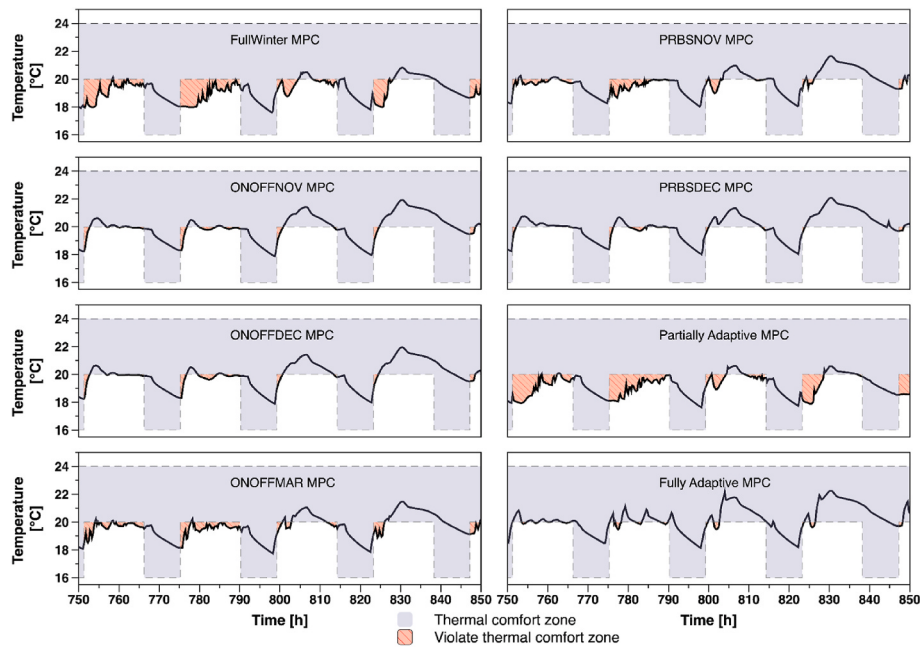


Fig. 8. Close-up of the indoor temperature profile under the operation of different MPC controllers with energy savings objective, $L = 10^8$.

parameters. The Fully Adaptive model performs the best among the MPCs in avoiding thermal discomfort, which can be clearly seen in Figs. 7 and 8. However, the lower thermal discomfort from Fully Adaptive MPC also results in higher energy consumption compared to good LTI MPCs like ONOFFNOV and ONOFFDEC MPCs.

Table 6 is the sensitivity analysis of the training period and error threshold on the performance of Fully Adaptive MPC. The cases involve two different training periods and error tolerances: the first case has a training period of one week with an error tolerance of $\tau = 2.5$, and the second case has a training period of two weeks with an error tolerance of $\tau = 5$.

From Tables 6 and it can be noticed that with the lower error tolerance $\tau = 2.5$ for the Fully Adaptive MPC, the results are almost

identical to the condition with error tolerance $\tau = 5$. However, with a longer training period of two weeks of data under MPC operation, the thermal discomfort significantly increases, which indicates that a too-long training period may not be suitable for the Fully Adaptive MPC.

4.2. Energy cost saving with peak reduction (EMPCPR)

The energy cost saving with the peak reduction case is generated by adding a penalty for energy use during the peak hour to the electricity price. Figs. 9 and 10 show the indoor temperature profile using the different MPC controllers with the energy cost saving and peak power reduction objective for both $L = 10^6$ and $L = 10^8$ penalty factors. The quantitatively calculated comparison results of MPC controllers

Table 5

Summary of the MPC performance for the energy saving (November and December).

Case	Energy Use [kWh] ($L=10^6$)	Thermal Discomfort [Kh] ($L=10^6$)	Energy Use [kWh] ($L=10^8$)	Thermal Discomfort [Kh] ($L=10^8$)
FullWinter	319.54	453.93	328.56	210.74
PRBSNOV	327.15	216.76	334.77	164.93
PRBSDEC	336.93	96.84	342.51	86.30
ONOFFNOV	337.79	112.60	341.11	85.40
ONOFFDEC	336.51	123.65	341.83	90.56
ONOFFMAR	326.56	198.10	332.79	185.57
Partially Adaptive	319.56	462.61	326.32	247.05
Fully Adaptive	341.75	79.74	353.89	50.68

Table 6

Summary sensitivity analysis of the Fully Adaptive MPC performance for the ES case (November and December).

	Fully Adaptive MPC	Fully Adaptive MPC (half error)	Fully Adaptive MPC (two weeks)	Penalty Factor (L)
Energy Use [kWh]	893.62	899.38	886.34	10^8
Thermal Discomfort [Kh]	72.04	73.51	132.44	10^6

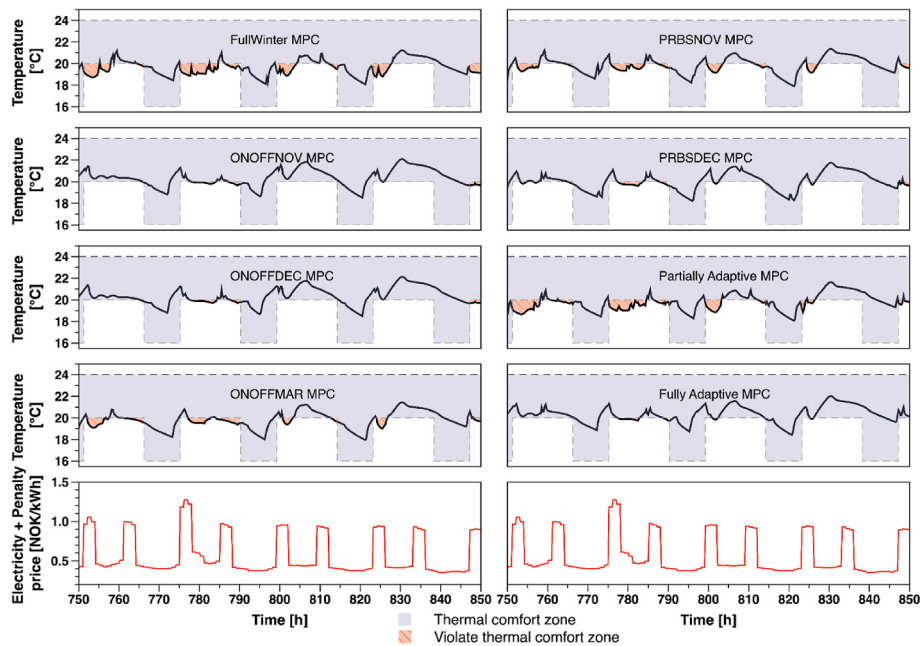
performance are shown in Table 7. The peak hour penalty is added to the hourly electricity price profile to reconstruct the new cost profile. The electricity energy cost is still the energy used at each time step multiplied by the corresponding electricity price. The total cost is the electric energy cost plus the peak hour penalty cost.

The MPC controllers switch off the heating during high price periods (e.g., at about 770 h) to decrease the total cost, which can be seen from the decrease in the indoor temperature.

Results show that the FullWinter and the Partially Adaptive MPCs are still performing poorly in the case of EMPCPR. Large thermal discomfort is still occurring due to the inaccurate prediction of the model. It can be clearly seen in Figs. 9 and 10 that the two MPC controllers choose to switch off the controller at the high price periods, even though the minimum indoor temperature constraint is violated. It consolidates the conclusion based on the previous two cases. An LTI model trained from full winter data is not appropriate to be used as the prediction model for MPC control. Only updating the effective window area of the FullWinter model leads to higher thermal discomfort. The reason is that the estimated effective area A_i of the Partially Adaptive MPC is higher than the FullWinter MPC in most of the operation time, which leads to a higher heat gain from solar radiation. In other words, the HTC value of the

FullWinter MPC is lower than the reference HTC value of the IDA ICE building, causing an underestimated heating demand. It neutralizes the effect of underestimated heating demand to a certain degree. Therefore, the correction of solar heat gain from the Partially Adaptive MPC has a negative impact on thermal comfort for this case study. The Partially Adaptive is not able to preheat the building enough because the control model overpredicts the solar gain which causes a higher thermal discomfort level.

Similar to the previous case, the PRBSDEC MPC performs slightly better than the PRBSNOV MPC in terms of thermal comfort. However, the PRBSDEC MPC causes an increased total cost and more peak hour electricity usage. In general, the two models generally have much better performance compared to the FullWinter and the Partially Adaptive MPCs. With the lower penalty factor 10^6 , the thermal discomfort of ONOFFDEC MPC is slightly higher than PRBSDEC, while ONOFFNOV MPC has a slightly lower thermal discomfort compared to PRBSDEC. The total energy costs of ONOFFNOV and ONOFFDEC MPC are lower. The ONOFFNOV and ONOFFDEC MPC also perform better than expected in the EMPCPR case. With the higher penalty factor 10^8 , the performance of ONOFFNOV MPC and ONOFFDEC MPC are also almost identical. They have lower thermal discomfort compared to the PRBSDEC and

**Fig. 9.** Close-up of the indoor temperature profile under the operation of different MPC controllers with energy cost saving and peak reduction, $L = 10^6$.

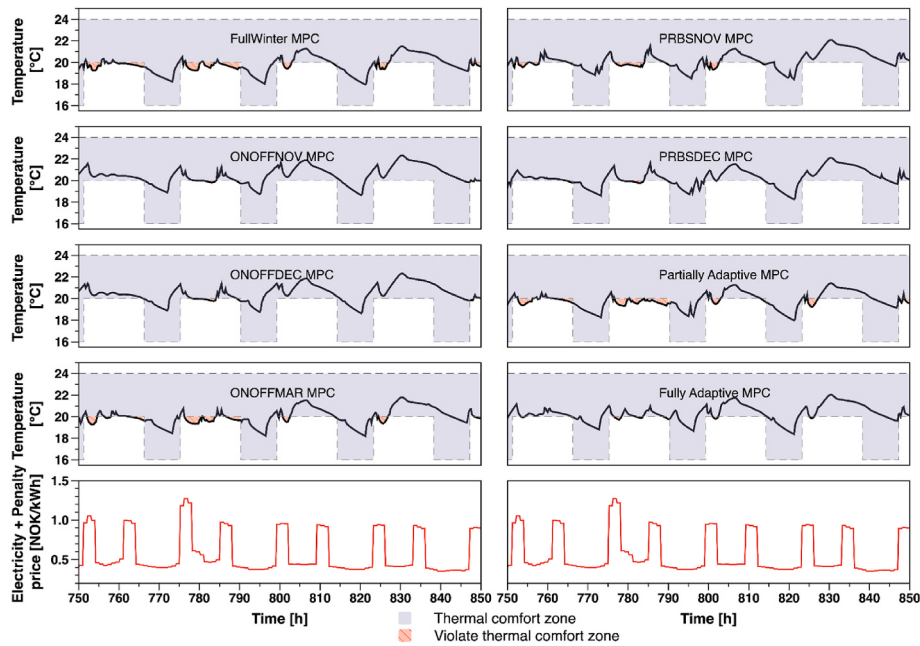


Fig. 10. Close-up of the indoor temperature profile under the operation of different MPC controllers with energy cost saving and peak reduction, $L = 10^8$.

Table 7

Results summary of MPC controllers' performance for energy cost saving (EMPCPR) case (November and December).

Case	Energy Cost [kWh] ($L=10^6$)	Total Cost [NOK] ($L=10^6$)	Thermal Discomfort [Kh] ($L=10^6$)	Peak Hour Energy [kWh] ($L=10^6$)	Energy Cost [kWh] ($L=10^8$)	Total Cost [NOK] ($L=10^8$)	Thermal Discomfort [Kh] ($L=10^8$)	Peak Hour Energy [kWh] ($L=10^8$)
FullWinter	328.67	405.38	312.18	38.36	327.53	396.37	200.11	34.42
PRBSNOV	330.36	384.13	169.55	26.89	345.13	420.98	96.51	37.92
PRBSDEC	338.94	403.31	81.12	32.19	348.70	430.05	44.98	40.67
ONOFFNOV	342.73	373.64	73.06	15.46	352.35	387.27	34.63	17.46
ONOFFDEC	343.09	375.22	84.28	16.06	353.59	389.76	37.96	18.09
ONOFFMAR	319.92	382.44	180.20	31.26	337.76	414.03	133.54	38.13
Partially Adaptive	328.17	408.80	311.81	40.31	325.81	397.32	220.24	35.76
Fully Adaptive	350.06	379.77	45.13	14.86	355.80	410.36	30.51	27.28

Table 8

Summary sensitivity analysis of the Fully Adaptive MPC performance for the EMPCPR case (November and December).

	Fully Adaptive MPC	Fully Adaptive MPC (half error)	Fully Adaptive MPC (two weeks)	Penalty Factor (L)
Energy Cost [NOK]	355.80	365.06	358.81	10^8
Total Cost [NOK]	410.36	418.20	440.62	10^8
Thermal Discomfort [Kh]	30.51	17.99	48.15	10^8
Peak Hour Energy [kWh]	27.28	26.56	40.90	10^8

PRBSNOV with even lower energy costs. This proves that intermittent on-off can also be a good choice for exciting the thermal dynamics of the building to obtain the data for training the parameters of the model. Like the previous ES case, ONOFFMAR MPC performs much worse than the LTI MPC that was trained from the corresponding operation period and better than the FullWinter MPC and Partially Adaptive MPC. This confirms that the model trained from the data at the end of the heating season is more suitable for the full winter LTI. However, all the results above affirm again the importance of using a model that is trained with data generated from weather conditions similar to the period when the MPC will be operated.

The EMPCPR case clearly shows that the Fully Adaptive MPC outperforms the other MPCs in avoiding thermal discomfort. The best MPC based on LTI that could compete with the Fully Adaptive MPC was the ONOFFDEC MPC. In the EMPCPR case with the lower penalty factor $L = 10^6$, the Fully Adaptive MPC gives better performance for most KPIs compared to ONOFFDEC except for slightly higher energy costs. In the EMPCPR case with the higher penalty factor $L = 10^8$, the thermal

discomfort of Fully Adaptive MPC is lower than ONOFFDEC MPC. However, the total energy cost and energy use during peak hours are higher. The main reason is that the Fully Adaptive MPC operates with the FullWinter model during the first seven days before it is allowed to perform a first adaptation of the model parameters.

Table 8 is the sensitivity analysis of the training period and the error threshold for the EMPCPR case. The thermal discomfort is reduced with the lower error tolerance $\tau = 2.5$, the total cost is also slightly increased compared to the baseline Fully Adaptive MPC (error tolerance $\tau = 5$). The Fully Adaptive MPC updates parameters based on two weeks of data and performs worse than the baseline Fully Adaptive MPC in all KPIs, which confirms again that a long training period may not be suitable for Fully Adaptive MPC.

4.3. Time evolution of the model parameters

The physical plausible properties of the parameters are also monitored in this study. This section presents the time evolution of the

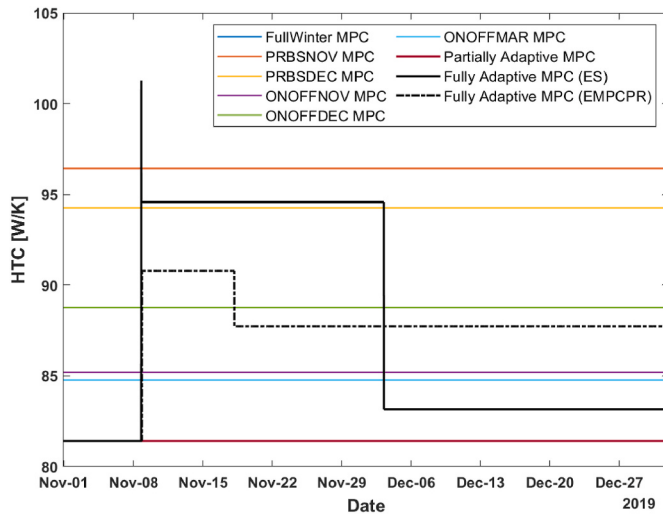


Fig. 11. History of the HTC value during the two months of MPC operation.

updated parameters with the high penalty value $L = 10^8$. Fig. 11 presents the history of the HTC value. The values of the FullWinter MPC and the Partially Adaptive MPC are overlapped due to the identical value. The results of the Fully Adaptive MPC have been distinguished with different line styles for the two different test cases. It can be seen that the Fully Adaptive MPC has two significant parameter updates during the simulation period, but the time when these updates occur is not identical depending on the objective function. The obtained HTC values for the Fully Adaptive MPC are within the range to be physically plausible, the HTC difference being within 10%. The results indicate that the Fully Adaptive MPC training the parameter using seven days of data can give satisfactory prediction performance with reasonable parameter values for a relatively long simulation period and does not need to update the parameters frequently.

Fig. 12 shows the history of parameter A_i . The results of the three cases are also distinguished with different line styles. The results show that the A_i updating history of Fully Adaptive MPC follows a similar trend to the Partially Adaptive MPC by first increasing in November and then decreasing in December. However, the updating history of A_i for the Fully Adaptive MPC is larger in amplitude compared to the Partially Adaptive MPC. Furthermore, parameter A_i is updated very frequently by the Partially Adaptive MPC, which indicates that the prediction error from the model is constantly large during the simulation. This confirms

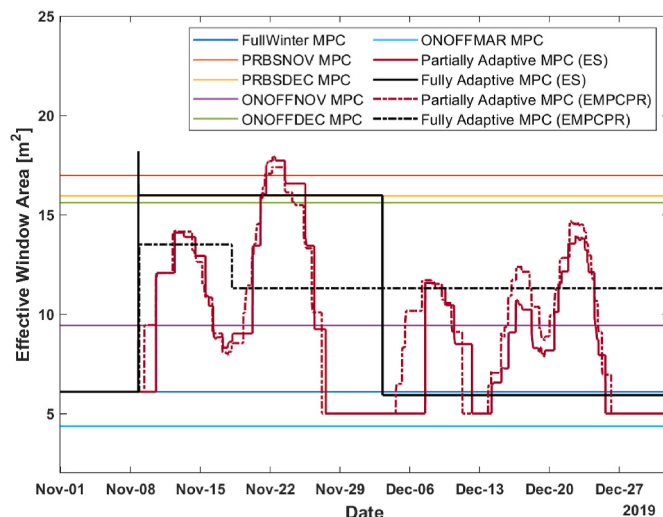


Fig. 12. History of the A_i value during the two months of MPC operation.

the previous conclusion regarding the FullWinter MPC and Partially Adaptive MPC: the FullWinter model cannot provide satisfactory prediction performance and the model cannot be corrected by only updating parameter A_i . The Fully Adaptive only updates A_i two times during simulation and the value is also changing significantly. It indicates that parameter A_i may not play a dominant role in the prediction performance over a long timescale, though it has a significant influence on short-term temperature based on existing research [18,26].

Fig. 13 presents the updating history of the sum of capacitances C_e and C_i , named C_{eff} . Results show that the values of the Fully Adaptive MPC are within the physically plausible range compared to the reference value C_{eff} of 3.9 kWh/K, although the values are different for the three cases. However, it is worth mentioning that the value of C_{eff} is also correlated with the value of the HTC and A_i . Considering the fact that the model only takes seven days of data under MPC operation to update the parameters, it is reasonable that the obtained value of HTC and C_{eff} has some uncertainties in the value as long as it can deliver decent prediction performance.

5. Discussion

The complementary discussion in this section is based on the analysis of the results.

- The Fully Adaptive MPC gives the best controller performance among the MPC controllers in this study. After the Fully Adaptive MPC updates parameters for the first time, the violation of the thermal constraint is significantly reduced. Furthermore, the results also show that the obtained parameters during simulation are different for the two test cases but are within a reasonable range. The explanation for that is the different timing and different data used to update the parameters. The performance of Fully Adaptive MPC also confirms that it is possible to use a data period of medium length (7 days) under regular operational conditions to train the model parameters as long as the parameters can be updated continually during operation. The sensitivity analysis also shows that using a longer period of 14 days could also lead to worse MPC control results compared to the one trained with 7 days data. A lower error tolerance value can decrease the thermal discomfort but with a higher cost. Finding a good balance between energy cost and thermal discomfort level is important in real operations.
- The analysis is based on virtual experiments and the limited simulation length of two months for the virtual experiments is due to the long co-simulation time. The co-simulation was operated on a

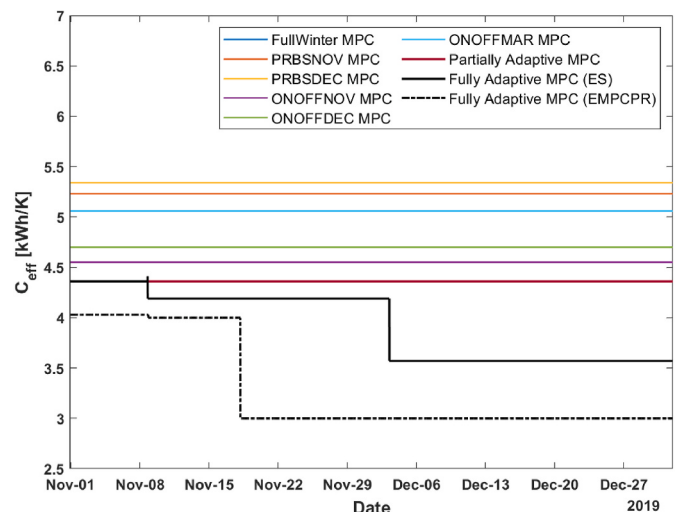


Fig. 13. History of the C_{eff} value during the two months of MPC operation.

workstation with an Intel Xeon E5-2697 18-core CPU clocked at 2.30 GHz, 64 GB RAM running a 64-bit version of Windows 10 Enterprise. The co-simulation of two months takes approximately 20 h on average to be completed. The EMPC case of the Fully Adaptive MPC is taken as an example to illustrate the time consumption. The total duration of the virtual experiment is 18.8 h; the total time for updating the parameters is 95 s, and the time for MPC optimization is 18.38 h. The remaining time is spent for co-simulation and data exchange with IDA ICE. The co-simulation for the Partially Adaptive MPC can take much longer time due to frequent updates of the parameters.

- Due to the inherent modeling simplifications in BPS, the conclusion might be different for real field experiments. For generalization purposes, results should be reproduced in other simulation platforms or on a real experiment performed over a long period of time. Many MPC studies using field measurements are based on a short period of experiments, see e.g. Ref. [7]. The analysis can also be repeated for other building types or other thermal performances of the building envelope. The test building in our study is highly insulated so that solar gains contribute significantly to the space-heating and the air infiltrations are limited. With an older building, the situation would be the opposite (i.e., the insulation level would be lower and air infiltrations higher), which would give a different dependence on the variations in the weather conditions during the space-heating season.
- The internal gains are assumed known in our study. However, they are prone to uncertainty and are variable by nature. Therefore, the need for model adaptation may also be driven by internal gains [20].
- The MPC in this study uses a mono-zone model. It has been explained that this choice is relevant for the building test case in this study. However, a mono-zone model may not be sufficient for all types of buildings and building operations (e.g., in residential buildings, bedrooms may have a different temperature than the living areas). If a multi-zone MPC needs to be designed, new criteria to update the parameters also need to be developed.
- The grey-box models investigated in our study are all linear. It means that the entire building thermal dynamics has been linearized. This may explain the limited extrapolation capabilities of LTI models and the superiority of the Fully Adaptive MPC for different weather conditions. In future work, more complex grey-box models, such as non-linear models, could be considered as an alternative to improve the extrapolation capabilities.

6. Conclusion

In this study, the MPC uses the thermal mass of the building as short-term thermal storage to perform DR. The paper investigates the robustness of MPC based on LTI grey-box models operated over a long period of time and the need for adaptive models. The performance of MPC based on LTI models and two adaptive MPC controllers based on a linear grey-box model is compared for two different control objectives. The model performance is assessed from the degree of completion to fulfill the defined objectives and the avoidance of thermal discomfort. This study uses a highly insulated detached house simulated using the BPS software IDA ICE as the emulator. The IDA ICE model is coupled with MATLAB in a co-simulation setup. The control signal is calculated by the MPC controller implemented in MATLAB and sent to the heating system so that the indoor temperature of the building in IDA ICE can be controlled.

Regarding MPC based on LTI grey-box models, results show that an LTI model trained using the data from the entire space-heating season (FullWinter model) is not suitable to be used as the prediction model for a long period of operation in MPC. It shows that a longer training period is not always a synonym for better model performance. The MPC based on two LTI models training using two short periods of data using a PRBS excitation (PPRBSNOV MPC and PRBSDEC MPC) generally performs better than the FullWinter if the training period is close enough to the

period where the MPC is in use. It is suggested in Ref. [29] that the end of heating season to train the model for MPC for the winter. The performance of ONOFFMAR performs much better compared to FullWinter, but still worse than the models trained with November and December data. This confirms that if an LTI grey-box model is used in MPC, it should be trained with data generated during similar weather conditions to the period when the MPC will be operated, but the resulting LTI model cannot be accurate enough for the entire space-heating season. The performance of ONOFFNOV and ONOFFDEC is better than expected, which proves that intermittent on-off signals can also be a good selection for exciting the thermal dynamics of the model to collect the training data. This needs to be validated in more in building MPC scenarios.

Regarding adaptive MPC, only updating the window area of the model (Partially Adaptive MPC) is not enough to correct the baseline LTI model and it sometimes even has negative effects on the results. The Fully Adaptive MPC outperforms the two PRBS MPCs. Even if the thermal dynamics of the building envelope is less non-linear than solar gains according to the weather conditions, it demonstrates the need to update all the model parameters if this model is to be used during the entire space-heating season. The Fully Adaptive model gives more accurate prediction, which causes the thermal discomfort to be significantly reduced.

For further work, it would be interesting to test the adaptive MPC controller performance for other building types under other simulation platforms or conduct the experiment in a real building to generalize the conclusions of this work. The influence of the stochastic behaviour of occupants on the results should also be investigated. Finally, the study could also be repeated using linear black-box models.

CRediT authorship contribution statement

Xingji Yu: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Zhengru Ren:** Writing – review & editing, Validation, Methodology, Investigation, Conceptualization. **Peng Liu:** Writing – review & editing, Visualization, Validation. **Lars Imsland:** Writing – review & editing. **Laurent Georges:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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