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# Model predictive control with self-learning capability for automated demand response in buildings

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**Abstract:**

This paper presents an optimal management strategy, called *Building Optimizer*, based on a Model Predictive Control (MPC) approach with self-learning capabilities for buildings. This research is framed in the development of an agent-based architecture to provide demand response services in an Energy Community to optimise the management of renewable energy sources and provide grid stability. The proposed MPC is a key enabler of cooperative demand response strategies at community level, ensuring the allocation of an optimal demand profile at each participating member of the community according to an optimal consumption reference defined by a complementary agent at community level. The MPC calculates the optimal setpoints of the HVAC system's terminal units, considering the expected usage of the buildings and the outdoor conditions, and exploiting the building's thermal inertia. The models embedded in the MPC are grey-box models representing a thermal zone of the building. To reduce measurement and model uncertainties, these models incorporate self-learning capabilities implemented as Moving Horizon Estimators that perform a continuous calibration based on real-time operational measurements. This solution allows full automation for model calibration and management of the terminal units. This paper presents a case study in which a baseline MPC with fixed model parameters obtained by an offline calibration is compared to the *Building Optimizer* with self-learning capabilities. The *Building Optimizer* is able to track a requested power consumption providing up to 20% of flexibility compared to the reference consumption without demand management and guaranteeing thermal comfort, at least 98% of the time. For this scenario, the *Building Optimizer* proves more reliable in guaranteeing the thermal comfort and a better match to the requested consumption compared to the baseline MPC. Demand-side management by the MPC can be translated into up to 15% energy shift from peak hours to valley hours.

**Keywords:**

Optimization; MPC; Building; Energy Community; Demand Response; Self-learning; Renewable Energy

## 1. Introduction

Building sector represents 40% of European energy consumption, of which 80% is covered by fossil fuels [1]. This sector also accounts for 35% of EU greenhouse gas (GHG) emissions [2]. In consequence, European decarbonization policies and strategies have this sector as one of the most relevant ones [3]. The renewable energy sources (RES) play a fundamental role in this decarbonisation path for switching to greener energy sources and lowering CO2 emissions. However, the increase in the renewable energy share in the energy generation entails some challenges due to the inherent unpredictability and intermittency of RES and the mismatch between the peak production periods and the peak demand periods, which can even lead to grid stability problems [4]. Demand Response (DR), which aims at modifying the consumption load curve, is a crucial tool for RES penetration in the electric system [5]. The residential sector has a great potential for DR that is still unlocked [6]. The residential sector's main end-use, accounting for between 60 and 80% of total energy consumption, is space heating [2]. Thus, there is a huge potential for the application of DR for heating

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[7], by exploiting buildings' thermal inertia. Moreover, considering the flexibility of a cluster of buildings, such as a Citizen Energy Community [8] or Renewable Energy Community [9], potentially increases the capacity to exploit flexibility [10]. Several studies focus on Demand response applied at building level. Most of these studies consider electric tariff prices to perform peak shaving actions. They often use *Model Predictive Control* (MPC) technique for the optimal management of the building, a widely used predictive technique for buildings [11]. The MPC uses a predictive model of the building that allows it to anticipate peak demand and take advantage of the building's inertia, thus improving thermal comfort compared to simpler controllers based on PIDs or on/off controllers. It also allows the inclusion of additional targets to be optimized, which opens a wide range of possibilities. The most widely used approach among MPC types is the so-called economic MPC that minimises the power consumption or energy cost consumption [12,13]. Some examples are [14] that manages the cooling demand of a house to reduce the peak periods, and [15] which proposes an economic MPC based on electricity variable prices. Some studies focus on demand response actions instead of a direct reduction on the power, such as [16] in which a hierarchical MPC is used for load shifting in a building, and [17] to perform DR actions at a building taking advantage of installed PV. However, less attention has been paid to DR oriented to a cluster of buildings, such as Energy Communities (EC), as [18] states. A few studies focusing on applying DR actions in an aggregated way can be found, such as [19] and [20]. The challenge for this approach is the scalability of the problem when the number of buildings increases. This paper proposes a solution for an MPC at building level, but which considers objectives at community level by allocating the requested power consumption at household level while guaranteeing the thermal comfort. This enables disaggregating the problem into the optimization of the Community and the building management, alleviating the scalability problem and facilitating the achievement of the community's energy-related objectives.

Another important aspect tackled by this work is the handling of the uncertainties inherent to building modelling. The MPC performance is dependent on the reliability of the embedded model. In the case of the building modelling, this aspect is crucial as many uncertainties are present, especially those derived from the time-variant parameters, occupant behaviour characterisation and measurements [21]. A detailed physical modelling approach that captures all the parameter variations with time is not feasible as this would result in a computationally too expensive model that would not be suitable for optimization purposes. Thus, this paper proposes an approach based on integrating self-learning capabilities to the *Building Optimizer* to cope with these uncertainties in a computationally cheaper way. These capabilities consist of re-calibrating the model parameters during the operation with the latest measured data. This functionality is integrated through the Moving Horizon Estimation (MHE) technique [22], which has proven to give good results in studies such as [23–25].

The novel contributions of this paper include the following:

- An MPC-based solution that goes beyond the typical economic MPC for cost or energy savings. It acts as a key enabler of a cooperative DR solution at community level by managing the demand side and allocating the optimal power consumption at household level that contribute to achieving goals at community level.
- The proposed solution includes self-learning capabilities to reduce the uncertainties of the problem, such as those sources of uncertainty due to the time-variant and uncertain physical characteristics and occupant characteristics.

Finally, the paper is organised as follows: section 2 describes the methodology followed to define the *Building Optimizer*, section 3 describes a case study with the aim of illustrating the contributions of the *Building Optimizer* and section 4 gathers the main conclusions and future work.

# 2. Methodology

## 2.1. Agent-based architecture for residential demand response

The proposed MPC with self-learning capabilities for buildings, which is called *Building Optimizer* from this point onwards, is part of an agent-based architecture to provide DR services in an EC to effectively maximise the exploitation of RES and demand-side flexibility and provide grid stability. This multi agent-based architecture includes a Demand Response Optimizer (*DR optimizer*) which deals with both energy supply and demand side in a holistic manner and decides the optimal energy use profile of each household considering EC objectives. This agent-based architecture is proposed in EU HESTIA project, which develops holistic demand response services in European residential communities. The *Building Optimizer* acts as a key enabler, assuring that the optimal energy use calculated by the *DR Optimize*r is allocated at household level while respecting thermal comfort. Thus, the *Building Optimizer* manages the thermal demand in each household to assure they contribute to the EC goals.

To manage the building's thermal demand and assure the optimal consumption allocation, the *Building Optimizer* considers predictions on the weather conditions and estimates the internal heat gains, as both will influence the building's indoor conditions evolution. The *DR Optimizer* provides a day-ahead reference optimal power consumption that the *Building Optimizer* will have to allocate. The *Building Optimizer* solution must also be able to comply with the constraints defined by either the building operator or the users. To complete the inputs to the *Building Optimizer*, it will also receive real measurements from the system. The general scheme of the solution is presented in Figure 1.

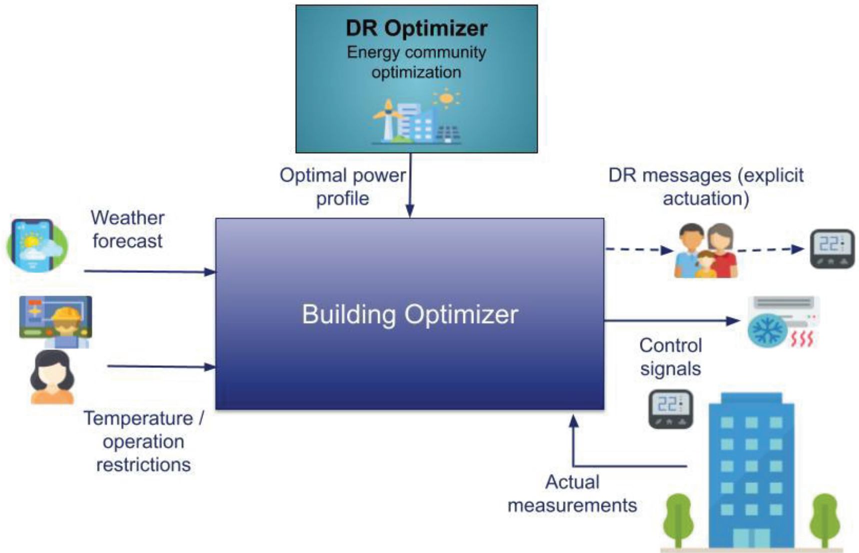


**Figure. 1.** Building Optimizer's input and output signals.

The *Building Optimizer* is prepared to work in two modes: (1) *explicit mode* with an automated DR actuation, and (2) *implicit mode* through manual DR actions suggested to the users. For the *explicit mode*, the automatic control signal is obtained (scalar value for on/off or modulated signal, depending on the HVAC actuation equipment capabilities). This actuation will cause the room temperature to be adjusted in a way that meets comfort but allows the demand to be reallocated in the requested way. For the *implicit mode*, the optimal temperature profile is translated into DR suggestions to the users. These suggestions would consist of requests to adjust their indoor temperature setpoint, and the users would oversee introducing this new setpoint manually. In this case, the HVAC is not commanded; the low-level controller of the thermostat would be working to operate the HVAC. This paper focuses on the first approach based on the automatic actuation.

An important point to highlight is that the *Building Optimizer* can work as a part of the agent-based optimization architecture with the aim of achieving goals at community level, but it could also be used as a stand-alone solution for building operation. This paper will propose a procedure to generate a reference curve that aims for economic targets at building level.

## 2.2. Building Optimizer: technical solution definition

The *Building Optimizer* solution must comply with challenging technical requirements as the controlled system is a building, a highly nonlinear system with great inertia and with many uncertainty sources such as internal heat gains.

In this regard, the MPC is a type of controller adequate for this type of application. The MPC is an optimal control strategy that works with a prediction model of the system to be controlled and calculates the optimal setpoints of the controllable units in order to minimise an objective function [26]. In this case, it has a building model embedded and calculates either the optimal indoor temperature setpoint or the HVAC actuator setpoint, depending on the actuation mode. The MPC works with the expected usage and occupancy of the building, forecast and current measurements of the outdoor and indoor conditions and includes user- and system-defined constraints. Even if the MPC optimises the operation in the entire prediction horizon, just the setpoints of the first point are commanded. It works in a closed loop by receiving the real values of the controlled variables and applies the receding horizon control principle.

The MHE is an optimization-based state-estimation technique where the current states and the parameters of the system, henceforth referred to as variables of interest, are inferred based on a finite sequence of past measurements. It uses dynamic optimization and a backward time horizon of measurements to optimally adjust the variables of interest of the problem [27]. The MHE is integrated to work in coordination with the MPC: the MHE is used prior to the execution of the MPC to calibrate the parameters of the model embedded in the MPC. Moreover, in addition to the model parameter estimation, the MHE can also estimate other model variables that are difficult to initialise beforehand or are unmeasurable, which presents a great advantage for building applications.


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The following subsection will describe more in detail the main technical parts of the solution: the reduced order models for optimization, the MPC for optimal control, the MHE for self-learning capabilities and the software used for the problem implementation.

#### 2.2.1. Reduced order models for the building and the HVAC

One of the key points in the development of an MPC is the system model that is embedded, as the reliability of the system predictions and the achievement of the control and optimization objectives will directly be impacted by the model accuracy. One of the main challenges is reaching a trade-off between the accuracy of the model (that represents in a detailed and accurate way the dynamics and other complexities of the model) and the computational burden as the optimization problem should be solved in a time that allows real-time application (typically every 15 minutes for this paper's application).

The proposed model considers thermal building envelope, internal heat gains, and heat losses, caused by heat conduction, convection, and ventilation. Modelling is underpinned by calibrated reduced-order data-driven grey box models. The grey-box model used is based on an Resistance-Capacitance (RC) network for a thermal zone defined by [28], which considers both the physical parameters and disturbances that characterise unmeasured inputs, but that can be calibrated with other measured variables. The performance of this model has been demonstrated experimentally in [29].

Figure 2 illustrates the embedded RC network model structure for a single thermal zone. The thermal zone is defined as the area controlled by a thermostat and served by the HVAC, i.e., it can represent several rooms that are controlled by a unique thermostat. $T_z$ is the indoor zone air temperature and $T_w$ is a wall temperature representing averaged behaviours of the enclosures (walls, roof, and floor). $T_o$ is the outdoor air temperature. $C_z$ and $C_w$ represent the respective thermal capacitances of the zone and wall, and $R_{zw}$ and $R_{zo}$ are thermal resistances between the zone air and wall, and between the zone air and outdoor air, respectively. $Q_g$ represents unmeasured internal heat gains. $u$ is the modulation signal for the HVAC system, and $Q_{av}$ the available heat, so the resulting input heat from the HVAC system is $Q_u$.

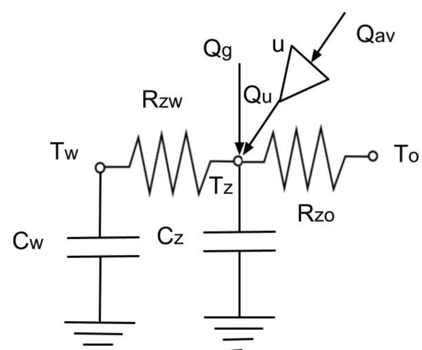


**Figure. 2.** Reduced order RC model for the building.

Equations (1) and (2) are the corresponding differential equations representing the thermal balance in the zone.

$$C_z \cdot \frac{dT_z}{dt} = \frac{T_w - T_z}{R_{zw}} + \frac{T_o - T_z}{R_{zo}} + Q_g + u \cdot Q_{av}, \tag{1}$$

$$C_w \cdot \frac{dT_w}{dt} = \frac{T_z - T_w}{R_{zw}}, \tag{2}$$

A simplified model for the HVAC is used, consisting of an equation to model the HVAC control, Eq. (3), and the power consumption of the HVAC, Eq. (4). This model will need to be further developed in future work to have a more accurate model of the air conditioning, but the present work focuses on the building part.

$$Q_u = u \cdot Q_{av}, \tag{3}$$

$$P_{HVAC} = \eta \cdot Q_u, \tag{4}$$

where $P_{HVAC}$ is the power consumption of the HVAC and $\eta$ its efficiency.

#### 2.2.2. Model predictive control for building consumption and indoor conditions management

The dynamic optimization problem defined in the MPC can be formulated as follows:

$$w_{hi}^T e_{hi} + w_{lo}^T e_{lo} \tag{5}$$

subject to:

$$0 = f(\frac{dx}{dt}, x, y, u), \tag{6}$$

$$0 \leq g(\frac{dx}{dt}, x, y, u), \tag{7}$$

Equation (5) is the objective function of the MPC problem and represents the sum of the terms to be minimised through the prediction horizon, in this case, the higher $e_{hi}$ and lower $e_{lo}$errors of the controlled variables, that is, the indoor temperature in the room and the HVAC power consumption. It is defined based on the $l_1$-norm so that the absolute difference between the current measured value and the desired target value is computed. This operator does not have a continuous first and second derivative at x=0, but the software used, that is GEKKO, poses the problem in a way that this discontinuity is avoided, as explained in [30]. The lower error is computed as the difference between the variable and the lower bound, and the higher error is defined analogously. When the variable is between the defined limits, there is no penalty.

Equation (6) represents the equality constraints of the problem, derived from the model presented in section 2.2.1, and Eq. (7) the inequality constraints at which the problem is subjected, which consists of physical limits for the variables.

In the problem definition, $x$ represents the state variables, that is, the indoor zone temperature and the wall temperatures: $x^T = [T_z, T_w]^T$. The output is the HVAC power consumption $y = P_{HVAC}$. The manipulated variable is the modulation signal of the HVAC represented by $u$.

In the problem definition, an important tuning aspect is the weighting factors assignment in the objective function, represented in Eq. (5) by $w_{hi}$ and $w_{lo}$ for each of the variables. These weighting factors enable prioritising either the thermal comfort or the power consumption, and between the lower and higher errors.

The other important tuning factor is the prediction horizon, that is, the length of the forward time window for which the MPC computes the solution.

#### 2.2.3. Moving horizon estimator for incorporating self-learning capabilities

The basic idea of MHE is to minimise the discrepancy between the measured outputs of the system and the outputs predicted (target measurements) by a model of the system, subject to a set of constraints on the states of the system. This is formulated through a dynamic optimization problem, defined as follows:

$$w_{hi}^T e_{hi} + w_{lo}^T e_{lo}, \tag{8}$$

subject to:

$$0 = f(\frac{dx}{dt}, x, y, u), \tag{9}$$

$$0 \leq g(\frac{dx}{dt}, x, y, u), \tag{10}$$

Equation (8) is the objective function of the MHE problem and represents the sum of the terms to be minimised through the backward window of past measurements: the absolute difference between the real measurements of the controlled variables (indoor temperature and HVAC power consumption) and the predicted value with the calibrated model. Both the higher and lower errors are considered, and a dead-band or region around the measurement in which the error is not penalised is included in the problem formulation. This reduces the impact of the noise from the measurements in the model calibration. In this case, the objective function is also defined through the $l_1$-norm.

Equation (9) represents the equality constraints of the problem, derived from the model presented in section 2.2.1, and Eq. (10) the inequality constraints at which the problem is subjected, which are used to limit and penalise the rate of change of the variables that are adjusted by the MHE and to set absolute bounds.

The most relevant tuning consideration are the weighting of the terms in the objective function ($w_{hi}^T$ and $w_{lo}^T$) and the length of the time window of past measurements. Including more points in the time window allows the MHE to reconcile the model to more data but also increases computational time.

The outputs of the MHE are the model parameters, $R_{zo}, R_{zw}, C_z, C_w$, that are *fixed variables*, the available heat for the HVAC system and the estimated internal heat gains. These are the estimated values through the prediction horizon.

#### 2.2.4. Software for problem implementation

Python 3.11 is used to address this development. The algorithms for MHE and MPC have been implemented using the GEKKO library [31] for Python. This library is based on APMonitor [32]. IPOPT is the solver used in the *Building Optimizer*.

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# 3. Results and discussion

This section presents the simulation results of the *Building Optimizer* for a case study.

## 3.1. Case study description

The presented case study has the following aims:

- Demonstrate that the *Building Optimizer* can guarantee thermal comfort.
- Evaluate to what extent the *Building Optimizer* can adjust to a requested power consumption.
- Evaluate if the *Building Optimizer* incorporating self-learning capabilities outperforms an MPC with fixed model parameters.

In order to assess these points, the case study will consider as a baseline an MPC with fixed parameters, and its performance will be compared to the *Building Optimizer* with self-learning capabilities.

The following subsections present the building that is considered for the case study, the boundary conditions, the uncertainty modelling to generate virtual forecast and the modelling of the flexibility request signal.

### 3.1.1. Study building description

In order to consider an actual building and to work with realistic values, the values of the case study presented in [28] and [33] are used, consisting of a single-story wood-built house having a floor area of 60m$^2$ with crawl and roof space. The main thermal characteristics of the building are: $C_z = 1.18\ \left(\frac{kWh}{°C}\right)$, $C_w = 3.99\ (kWh/°C)$, $R_{zo} = 0.48\ (°C/kW)$, $R_{zw} = 7.35\ (°C/kW)$. These values are considered as the real values of the building. The space is considered as a single thermal zone with one thermostat to monitor the indoor temperature and a controllable HVAC that can be modulated through a $u$ signal between 0-100%.

### 3.1.2. Boundary conditions description

For the weather conditions, the building is considered as located in Bilbao (Spain). The data of the outdoor temperature for February from the Typical Meteorological Year (TMY) of Bilbao (Spain) [34] is used for the simulations, which represents a typical winter heating demand situation.

The internal heat gains of the building are calculated using the ASHRAE standards [35] considering the profile for internal heat gains from people with a Hotel pattern (equivalent to a residential building), assuming the following values: *23.226 m$^2$/person*, and *73.268 W/person*. The profiles differentiate between weekdays, Saturdays, and Sundays. These profiles are represented in Figure 3.

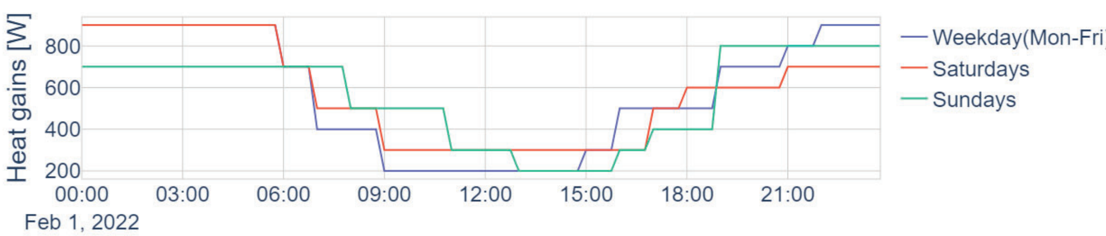


**Figure. 3.** Internal heat gains hourly profile for weekdays, Saturdays, and Sundays for a residential house.

### 3.3.3. Forecast uncertainty modelling

Modelling the errors in the weather and internal heat gain predictions is crucial, as they are a great source of uncertainty in the problem and its impact in the solution needs to be assessed.

The uncertainty in the indoor temperature is modelled through an autoregressive model shown in [36]. This generates a realistic error in the outdoor temperature prediction, trying to replicate a low-medium uncertainty scenario. For the error modelling, it is assumed that the outdoor temperature forecast is updated every 24h. Figure 4 shows the real outdoor temperature and the synthetic forecasts for the first week of February.

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**Figure. 4.** Real outdoor temperature for Bilbao for 1-7 February and simulated forecasts.

The internal heat gains profiles for the building are defined based on the ASHRAE profiles shown in section 3.1.2. The difference that can be found between the real occupancy patterns and the ones proposed by ASHRAE are modelled by modifying the ASHRAE curve. White noise is added to the internal heat gains through a gaussian distribution, and it is smoothened so that it resembles a real pattern. The synthetically generated data for the internal heat gains is used as the real profile of the internal heat gains and the ASHRAE profiles are considered as the forecasts for a whole week. Both profiles are illustrated in Figure 5.

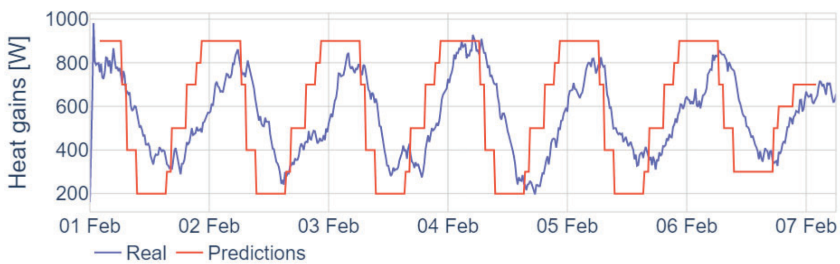


**Figure. 5.** Simulated internal heat gains for the building and the forecasts.

## 3.2. Building Optimizer with fixed parameter: model calibration

The Building Optimizer version that integrates an MPC with fixed parameter requires the values of the RC parameters $(R_{zo}, R_{zw}, C_z, C_w)$. An offline calibration is performed to calibrate these parameters based on simulation data of the study building, which is used as if it was operation data. The steps followed for the calibration are:

1. The plant model (building space with the HVAC) is simulated for a whole month with the real parameters from section 3.1.1 and the boundary conditions (weather, internal heat gains) presented in section 3.1.2. The model includes an on/off hysteresis controller, with a constant setpoint of 21.5 ºC, and a dead band of 0.5 ºC for the hysteresis that is used to control the indoor room temperature by calculating the HVAC operation.
2. An offline calibration is performed using the data of a whole week as reference. The fixed values of the model parameters $(R_{zo}, R_{zw}, C_z, C_w)$ are calculated minimising the deviation between the reference values from in Step 1 and the predicted values with the model for the whole week. The problem defined for the MHE is adapted so that it can be used for this calibration. The internal heat gains are set to a fixed value for the whole week. The results are verified by calculating metrics for the errors in the indoor temperature and the HVAC power consumption compared to the reference values.

Different reference errors are calculated for the indoor temperature deviation and the power consumption deviation, as the nature of these variables is different. The temperature is a potential variable, so the most suitable error to be applied to this variable is the *Normalised root-mean-square deviation* (NRMSD), which is defined in Eq. (11).

$$NRMSD(T_z) = \frac{RMSD(T_z)}{T_z^{max} - T_z^{min}} = \frac{\sqrt{\frac{\sum_{t=1}^{T}(\hat{T}_Z(t) - T_Z(t))^2}{T}}}{T_z^{max} - T_z^{min}}, \tag{11}$$

where $RMSD(T_z)$ is root-mean square deviation of the indoor temperature, $T_z^{max}$ and $T_z^{min}$ are the maximum and minimum value of the indoor temperature, respectively, $T_z(t)$is the real indoor temperature value, $\hat{T}_z(t)$ is the indoor temperature obtained with the calibrated model, and $T$ is total simulation time.


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In the case of the power consumed by the HVAC, it is a non-negative scale variable which cannot have negative values, so the mean value is used to normalise the error. Thus, the *Coefficient of Variation of the root-mean-square deviation* (CV(RMSD)) is used as reference, which is described in Eq. (12).

$$CV(RMSD(P_{HVAC})) = \frac{RMSD(P_{HVAC})}{\bar{P}_{HVAC}} = \frac{\sqrt{\frac{\sum_{t=1}^{T}(\hat{P}_{HVAC}(t)-P_{HVAC}(t))^2}{T}}}{\bar{P}_{HVAC}}, \quad (12)$$

where $RMSD(P_{HVAC})$ is root-mean square deviation of the power consumption, $\underline{P_{HVAC}}$ is the mean value of the power consumption, $P_{HVAC}(t)$ is the real power consumption value, and $\hat{P}_{HVAC}(t)$ is the power consumption obtained with the calibrated model.

**Table 1.** Calibration errors for the building fixed parameter model.

| | $NRMSD(T_z)$, % | $CV(RMSD(P_{HVAC}))$, % |
|---|---|---|
| Verification, weekdays | 20.96% | 0.73% |
| Verification, Saturdays | 25.76% | 0.72% |
| Verification, Sundays | 14.73% | 1.85% |
| Verification, general | 16.50% | 1.89% |

The errors in the temperature are greater than in the power consumption. This introduces a great uncertainty in the modelling part, especially in the indoor temperature modelling. Nevertheless, the errors in the power consumption are low, which may be due to the simplified HVAC model that makes it easier to be adjusted.

### 3.3. Flexibility provision evaluation

Both the baseline MPC with the fixed model parameters calculated in section 3.2 and the *Building Optimizer* incorporating the self-learning capabilities are simulated for the same boundary. A simulation of a whole week of February is conducted, with the real and virtually generated forecasts of outdoor temperature, and the synthetic internal gains described in section 3.1.3.

The flexibility request is sent to the *Building Optimizer* through a power consumption reference profile that the optimizer needs to track to allocate the power consumption. This signal, in the solution structure presented in section 2.1 and shown in Figure 1, comes from the DR optimizer. In this case, the signal will be synthetically generated. The procedure explained here also reflects how the *Building Optimizer* can work as a standalone solution by including the generation of the signal as a part of the solution.

The flexibility request is generated considering the Spanish electricity tariff schemes that apply an hourly discrimination and divides the day into the following consumption periods: the peak period (with higher tolls and charges), the flat period (with intermediate values for the costs) and valley periods (with the lowest costs) [36]. The procedure is the following one:

1. The case study model is simulated with the *Building Optimizer* applying just thermal comfort objective, so no actions are taken regarding the power consumption. In this way, a baseline of the typical power consumption in the building is achieved, without demand-side management. This profile is used as a reference for the power consumption.
2. The following assumption is made regarding the flexibility requests that are expected: the power consumption is requested to be reduced in the peak periods, this power consumption should be reallocated in the valley period, and the flat periods should not be modified. This would match with the general requests from the grid point of view but would also be in line with the electric tariff periods, so the benefits would not be just flexibility share increase, but also economic benefits.
3. The baseline power consumption from step 1 is decreased in a percentage in the peak periods, it is maintained in the flat periods, and it increases in the valley. A set of simulations are defined varying the percentage of flexibility request from 10% to 30% by increasing a 5% in each step.

The scenarios requesting different percentages of flexibility are simulated for both the baseline MPC and the *Building Optimizer* incorporating self-learning capabilities.

For the assessment of the thermal comfort guarantee, the thermal discomfort duration is evaluated. This is measured as the percentage of the time that the indoor temperature is outside the defined thermal comfort limits (21-22ºC). The accuracy in the power consumption tracking is evaluated by the deviation compared to the reference curve, using the CV(RMSD) defined in Eq. (12). Table 2 presents these metrics for the different flexibility scenarios. The first simulation day is not considered as it is highly dependant on initialization conditions and does not reflect the normal operation.

**Table 2.** Temperature and power consumption error comparison for different flexibility scenarios.

| Flexibility request | Thermal discomfort duration [%] | | Power deviation [%] | |
|---|---|---|---|---|
| | Baseline MPC | Building Optimizer | Baseline MPC | Building Optimizer |
| 10% | 7.07% | 0% | 2.22% | 0% |
| 15% | 14.14% | 0% | 3.31% | 3.29% |
| 20% | 18.71% | 1.25% | 7.44% | 6.63% |
| 25% | 25.37% | 8.12% | 9.24% | 9.35% |
| 30% | 31.11% | 17.9% | 12.1% | 12.16% |

The results from Table 2 show that the *Building Optimizer* can track the requested power demand with a lower impact in the thermal comfort. It can even reach a 20% flexibility provision with a minimum impact on the thermal comfort (guaranteeing it 98% of the time) and a 25% flexibility provision with a thermal discomfort duration below 10% of the total time. For higher percentage of flexibility requests, there is an accuracy loss in temperature tracking to achieve the other objective of the cost function, that is, the power tracking.

The difference in performance to guarantee thermal comfort between the two analysed scenarios is due to the capacity of the *Building Optimizer* to reduce the uncertainty. The main sources of uncertainty in the problem come from both the inherent uncertainties to the modelling and the input predictions. In the case of the baseline MPC with fixed parameters, the calibrated model parameters present an error when predicting the real building behaviour, as explained in section 3.2. Even if the MPC can reduce this uncertainty using the real measurements of the system, this uncertainty cannot be completely avoided. The *Building Optimizer* tackles this problem by updating the model parameters based on the last real measurements of the system. Regarding the predictions, both scenarios are simulated with outdoor temperature predictions with an uncertainty integrated, which deviates the response from the predicted one. In the case of the internal gains, the baseline MPC uses the predictions of the internal gains from ASHRAE (Figure 5), which introduces a great uncertainty source. On the contrary, the *Building Optimizer* uses the estimated last value of the internal gains by the MHE as prediction. Even if this is an approximation that introduces also considerable uncertainty, this approximation gives better results than using the ASHRAE predictions according to the results.

The scenario for a flexibility request of 20% is analysed to illustrate the performance of both controllers. In Figure 6, the comparison of the indoor temperature of the thermal zone for both the baseline MPC and the *Building Optimizer* is shown, together with the upper and lower thermal comfort limits.


**Figure. 6.** Indoor temperature with the baseline MPC and the Building Optimizer.

Figure 6 shows how the indoor temperature deviates for longer periods from the thermal comfort conditions in the baseline scenario, for the reasons explained above.

Figure 7 presents the same comparison between the baseline MPC and the *Building Optimizer*, but for the power consumption.

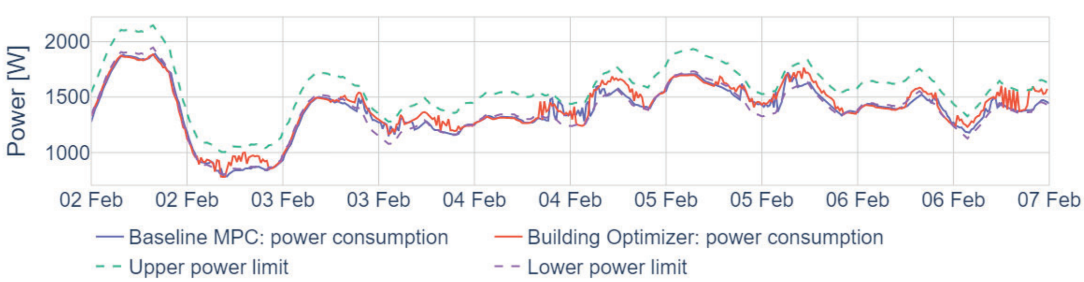


**Figure. 7.** HVAC power consumption with the baseline MPC and the Building Optimizer.


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The power tracking shown in Figure 7 reflets that the power is deviated very similarly in both scenarios. This is the expected conclusion as the calibration errors for the baseline MPC were lower for the power consumption.

Another important aspect to consider is the percentage of energy that is displaced from peak periods to valley periods. This indicator is also a reflection of the ability to perform power shifting actions. This percentage is presented in Table 3.

**Table 3.** Percentage of energy consumed during peak periods shifted.

| Flexibility request scenario | Peak period shifted energy, % |
|---|---|
| 10% | 8.06% |
| 15% | 11.03% |
| 20% | 14.22% |
| 25% | 15.21% |
| 30% | 16.77% |

This reduction in the peak periods could be directly translated into economic benefits and a flexibility provision capacity in accordance with the typical request that may appear from the grid side.

## 4. Conclusions and future work

In the present work, a control strategy called *Building Optimizer* is developed, consisting of an MPC with self-learning capabilities to manage the thermal demand of a building. The Building optimiser can allocate a requested power consumption in a building while guaranteeing thermal comfort so that an objective at community level is achieved. The capacity for the power consumption management is crucial to integrate demand response in the residential sector, with a great unlocked potential. This boosts the integration of RES in the current energy system as a better match between the intermittent production of renewable sources and the demand at building levels can be achieved. The moving horizon estimation technique is used for incorporating self-learning capabilities, which uses real-time measurements from the plant to recalibrate the model at real time and calculate unmeasurable inputs, such as the internal heat gains. This functionality is relevant for buildings, a system with a wide range of uncertainties due to its characteristics and the occupancy patterns.

A case study is presented for a building represented by a single thermal zone with a controllable HVAC. The performance of an MPC with fixed parameters model is compared to the *Building Optimizer* including the self-learning capabilities. To calibrate the MPC with fixed parameters, a calibration technique is proposed, using the data for a whole week of the study building. A flexibility request scenario is simulated, generating this request through a curve that decreases the power consumption at peak electric prices periods and increases them in valley periods with respect to a reference curve in which demand side management is not performed. The scenario is simulated for different percentages of flexibility request with both the *Building Optimizer* and the fixed-parameter baseline MPC. The simulations are conducted including uncertainty sources in the used predictions for the boundary conditions. It is concluded that 20% is the maximum flexibility at which the deviation in the indoor temperature with respect to the thermal comfort boundaries has a duration lower than 2% of the time. In this scenario, the *Building Optimizer* improves the temperature tracking and the power consumption allocation compared to the baseline MPC, and it can shift up to 14% of the energy that is consumed during peak hours to valley periods. This demonstrates that incorporating self-learning capabilities can improve the performance of this type of controllers.

The studied building is of residential type, but the proposed reduced order model can be extended to other type of buildings, such as commercial buildings or offices. The solution is scalable in terms of the number of buildings, as each building would have its own MPC to ensure that it consumes what is required by the community. The scalability of the solution in terms of the building size and the number of thermal zones to be modelled within the building will be one of the crucial challenges to analyse in further work, as including more thermal zones increases the computational cost of the problem. Future work should expand the inclusion of a more detailed model of the HVAC too.


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## Nomenclature

$C$ thermal capacitance, kWh/(ºC)

$P$ power, W

$Q$ heat, W

$R$ thermal resistance, ºC/kW

$T$ temperature, °C

$u$ actuation signal, %

$w$ weighting factor, -

$x$ state variables, -

$y$ output variables, -

**Greek symbols**

$\eta$ efficiency

**Subscripts and superscripts**

$av$ available

$g$ internal gains

$hi$ higher

$lo$ lower

$o$ outdoor

$u$ actuation signal

$w$ wall

$x$ states

$z$ thermal zone

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