Evaluating the impact of insulation on activating energy flexibility in residential dwellings

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Abstract

Building sector could play an important role in tackling the issue of supply and demand mismatch. To this end, flexibility of the buildings should be harnessed. However, activating and quantifying flexibility of buildings requires advanced control strategies. Here, Model Predictive Control (MPC) is deployed to harness the flexibility. In addition, thermal properties of a building impact its provided flexibility. This paper aim at assessing the impact of the insulation level on the energy flexibility of a building using MPC. To do so, first a black-box predictive model of each building is developed. Thereafter, flexibility is activated by implementing MPC. Results reveal that by doubling the insulation level of the given use case, the flexibility index could be improved by 50%.

Highlights

- Effectiveness of insulation level in terms of increasing flexibility potential
- Building models should be developed based on relevant KPIs to properly harness flexibility
- Effectiveness of model predictive control in improving the flexibility index of buildings

Introduction

Increasing the penetration of Renewable Energy Sources (RES) into the overall energy system is essential for reducing the GreenHouse Gas (GHG) emissions on a global level. The building sector has a substantial share (>50%) of total electricity use amongst different major energy consumers. In spite of the increment in deploying RES in the past decade, GHG emissions of this sector has had an upward trend. The latter emphasizes on the urgency to accelerate integration of RES into the buildings' energy flow. However, the intermittent nature of many of the RESs pose challenges to the energy system, especially the electrical grid. The uncertainty of the availability of RESs makes the existing challenge of balancing the demand and supply of electricity even more complicated (IEA, 2022). Demand Side Management (DSM) includes a set of technologies and strategies that attempts to solve this issue looking at the stakes of the energy supplier as well as the end-user. DSM could be divided into different categories. Here we focus on Demand Response (DR), the most common category of DSM where penalty or price signals is introduced to the end user by the grid operator. This price signal is determined in a way that benefits the supplier e.g. a high energy price at the period of peak of electricity use and a lower energy price during the base load (Jensen, 2019). However, a question that remains to be answered is how much the building is responsive and compliant to such a signal and to what extent the load profile of the demand side matches with the desired profile of the supplier. The latter gives rise to the concept of energy flexibility. Energy flexibility of a building could be defined by its ability to alter its load profile based on the requirements of the energy provider, given the boundary conditions that it is subjected to (Jensen, 2019). In this study, a Time-of-Use (ToU) electricity price has been considered as the price signal from the grid operator.

Thermal properties of a building play an important role in its harnessed flexibility by affecting thermal mass and time constant of the building. One of the main contributors to the thermal resistance of a building and in turn its time constant is insulation level (Johra et al., 2019). In this study, the impact of the insulation level on the flexibility of a building is investigated. The building under study has been equipped with PhotoVoltaic (PV) panels and electrical battery as on-site generation and active storage units respectively. A few research studies have addressed the impact of building envelope on the resulting flexibility.

Johra et al. (2019) conducted a numerical study on Danish single-family households. They analyzed different building parameters and their effect on the energy flexibility potential. The flexibility index is used to show the ability of the building to shift its electricity from high electricity prices to low prices by accumulating thermal energy in the indoor environment during low price periods. It was found that the envelope insulation is the building parameter with the biggest influence on the flexibility index (Johra et al., 2019). A simulation-based study (Pedersen et al., 2017) was conducted to see how Economic Model Predictive Control (E-MPC) schemes can deploy thermal mass of an existing multi-story apartment block and eight retrofit scenarios to introduce DR objectives. E-MPC schemes led to a reduction of CO_2 emissions (up to 3%), an increase of cost savings (up to 6%) and reduced CO_2 emissions (up to 3%) as a function of increasing energy efficiency of the retrofit scenarios. The absolute amount of shifted energy from on-peak hours compared to a conventional controller was 2 kWh/m^2 heated net area across all retrofit scenarios compared to the existing buildings.

In another study (Reynders, 2015) showed that multiple building characteristics impact the achieved flexibility in a demand response scheme. In addition, the impact of building's thermal mass on the flexibility has been scrutinized using a rule-based controller. Findings show that even moderately insulated houses can provide flexibility to the grid. In addition, it was shown that floor heating provides more structural energy storage capacity and out-performs radiator heating systems in demand response context.

Another study (Masy et al., 2015) considered smart grid energy flexible buildings using heat pump and building thermal mass within the context of the Belgian residential building stock. The considered residential buildings are equipped with a heat pump that supplies hot water to either radiators or a floor heating system. Flexibility is quantified in terms of amount of load shifted and in terms of consumers costs avoided. Two smart grid-oriented predictive control strategies that respond to a time-varying electricity price profile are used. The results show that the smart grid-oriented strategies allow a reduction of consumer's cost by 13%. The flexibility is increased by 3% to 14% with the same range of indoor thermal comfort. The percentage of shifted loads increases with the insulation level of the building envelope. The percentage of load shifted is more than doubled with intermittent heating compared to continuous heating. As for the emission system it was shown that the flexibility is slightly higher with floor heating than radiators.

Another study (Clauß et al., 2019) investigates three types of Predictive Rule-Based Controllers (PRBC) in the context of demand response for heating a Norwegian residential building. The predictive nature of the RBC in their study stems from taking predictions of electricity price into account. The first PRBC strategy aims to reduce the energy costs of heating using the hourly spot prices as input, the second strategy aims to reduce annual CO2 emissions for heating and the third one's goal is to reduce the energy use during peak-load hours using a pre-defined schedule. The results show that the price-based PRBC leads to increased heating costs. This is due to the fact that potential cost savings for the tested PRBC are outweighed by the increase in electricity use for heating. As for the CO_2 based control, limited daily fluctuations of the CO_2 emission intensities limit the reduction of the annual equivalent emissions. However, the schedule-based control proved to be very efficient to reduce the energy use for heating during peak hours.

To properly exploit and quantify the flexibility of a building, the Building Energy Management (BEM) system needs to be equipped with a controller that is capable of appropriately responding to price signals from the grid operator. Suitability of demand-driven control strategies in optimization of building performance has been shown before (Jafarinejad et al., 2019). In this context, MPC has been employed for minimizing cost of energy in a building while maintaining the indoor comfort. MPC uses a simple model of the building to predict its energy profile over a given time span. Deploying this model enables MPC to optimize thermal behavior of a building over a horizon (Maciejowski, 2002). Therefore, MPC can harness the flexibility of a building in response to price or penalty signals from the operator while considering the constraints of the building climatization and even optimizing usage of different storage units in a building. Although the literature emphasizes on the significant impact of insulation on load shifting and harnessing flexibility of a building, there exists no study to the best of author's knowledge that assesses this impact (insulation on flexibility) using MPC for a prosumer building. This study aims at addressing this gap by assessing different levels of insulation for a given dwelling on its flexibility exploited by MPC. The findings of this simulation study is helpful both in design and renovation stages of a building in terms of the expected improvements of flexibility by improvements in insulation level. To this end, first a high-fidelity model of a building has been developed and validated. Thereafter, new simulation models were made with decreased insulation levels. The insulation level of the building envelope were reduced by 33% and 50% respectively. Next step is making simple yet accurate predictive models from each of the three cases. These models are then integrated within an MPC framework with the goal of harnessing the flexibility of the designated dwelling.

In the next section, first different parts of the study including building, PV panels, battery are briefly described. Second, framework and the Key Performance Indicators (KPI) using which flexibility is assessed, are explained and formulated. Then, results of harnessing flexibility of the three use cases are presented and discussed.

Methodology

In this section, first the building under study is introduced. Afterwards, different installed devices are presented along with their configuration in the flexibility scheme. Figure 1 shows an overview of the energy system defined here. P_{batt} denotes the delivered energy to the heating system from the battery, while pv_1 and pv_2 show the energy from PV panels to the heating system and the battery respectively. $Grid_{offtake}$ represents the energy bought from the electrical grid.

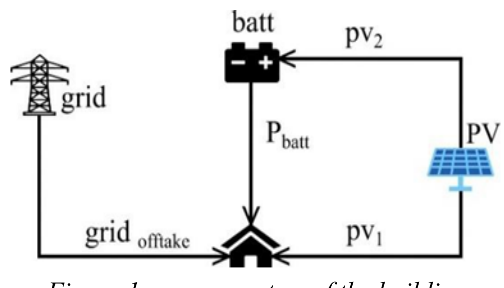


Figure 1: energy system of the building

Building

The subject of this study is a highly insulated, airtight detached dwelling located in Holzkirchen Germany (Figure 2), representing a single-family residence. The dwelling has served as a case in many research studies such as the IEA-EBC Annex 71 project (Fitton, 2021).

Heating is provided by means of electric heaters. Sensible heat gains have been additionally injected to the building to represent occupancy profiles of a residential dwelling (Flett & Kelly,2017). A realistic ventilation system operates to introduce sufficient fresh air to the building at a total of 200 m^3/h. Interested readers are referred to (Strachan et al., 2014) for further details on the description of the building under study.

Figure 2- floor plans of view of the experimental dwelling (Strachan et al., 2014)

Numerous measurement instruments were installed inside each room. This allowed us to make a highly granular simulation model of the building and validate it. The model was developed using OpenIDEAS library with Modelica language (Baetens et al., 2015). This white box model replaces the real building in our simulation environment. In order to evaluate the impact of insulation on the resulting flexibility, the original simulation model of the building (case of high insulation) was modified in the following way:

Table 1- insulation level of the cases

	Insulation type	high (cm)	medium (cm)	low (cm)
west	Mineral wool	12	8	6
east	PUR foam	7	4.67	3.5
south	Woodfiber	12	8	6
north	Woodfiber	12	8	6
ceiling (ground floor)	expanded polystyrene	5	3.3	2.5
roof	Mineral wool	18	12	9
floor	PUR Insulating Board	3	2	1.5
	Bonded Panel PUR	3.3	2.2	1.65

In addition to the insulation thickness of the external walls, roof and floor, the heating system of the houses has been re-sized for the cases on medium insulation and low insulation to be 8 and 10 kW respectively.

For thermal comfort consideration, for each building, all the zones are lumped and the building is seen as one thermal zone. The goal of the electric heaters are to maintain the volume-averaged temperature of the zones which is the target output of this study within the thermal comfort bands given in Table 2.

Table 2- thermal comfort requirements

	Lower comfort band (°C)	Upper comfortband (°C)
7 a.m – 11 p.m	21	24
11 p.m – 7 a.m	19	22

Photovoltaic

The simulated PV system represents a set of 32 "4x6 cells MW 1010x725 mm^2 (with edge j-box) ClearVision-Black (2x4 mm)" (Ciulla et al,. 2014) modules which each consists of 24 cells with maximum power point (P_{mpp}) of 120.8 W, short-circuit current (I_{sc}) of 8.551 A and open-circuit voltage V_{oc} of 17.552 V. The power temperature coefficient is equivalent to -0.28% /°C. The I-V characteristics in the one-diode model of a PV device are described by the following equation:

$$I=I_{ph}-I_{sat}\,[\exp(\frac{V+IR_s}{mN_sV_{th}})-1]-\frac{V+IR_s}{R_{th}} \quad (1)$$

In equation (1), I_{ph} represents the photo (or light) current, I_{sat} is the saturation current, R_s indicates the series resistance, V_{th} is the thermal voltage, m is the diode ideality factor, N_s is the number of cells connected in series and R_{sh} is the shunt resistance. Further details about the electrical model can be found in (Ciulla et al., 2014). The model has been validated with the measurements obtained from the real-life installation of the module in EnergyVille 2 building in Genk, Belgium. DC power generation profile of the PV panels has been simulated offline for the period of the simulations and is included in the MPC simulation later. It should be mentioned that the efficiency of the inverter is assumed to be 100%.

Battery

Batteries considered for this study are Lithium Iron Phosphate (LiFePo4) which have a very high charge and discharge efficiency. Charge and discharge efficiency have been considered to be 0.98. The round-trip efficiency of the batteries are not considered in this study. For the case of the highly insulated building, a battery of 5.12 kWh with a maximum charge and discharge rate of 2.56 kW has been used. As for the other two cases, the battery has been resized based on the RBC results and is explained later on under the flexibility results. State-of-Charge (SoC) of the batteries have been kept between 10% and 90% which is typically done to ensure a longer lifetime. The battery performance has been considered to be linear in the SoC range of 10-90%. This assumption would help in keeping the eventual optimization problem convex.

Flexibility framework

MPC was chosen as the control strategy to activate flexibility of the building in this study. The general workflow of the MPC used in this study has been explained in a previous study (Erfani et al., 2021). MPC has been designed in Matlab while the building simulation model is developed in Dymola. Interested readers can refer to (Erfani et al., 2021) for further details on the designed MPC. The control horizon of the MPC used in this study has been set to 24 hours (N=24) as shown to be a long enough horizon to guarantee acceptable performance of the MPC in a previous study (Laguna et al., 2022). The time step of the controller and the thermal model of the building are both set to 1 hour as it was shown to be a suitable choice in a previous study (Erfani et al., 2023). Perfect weather forecast is considered here.

Flexibility formulation

In order to exploit the flexibility of each of the houses an MPC has been applied. It should be noted that dynamic ToU electricity price has been considered as the signal for activation of building's flexibility in this study which was taken from a supplier data in Belgium (Reynders et al., 2021). The formulation of the optimization of the buildings'energy flow is given in the following equations.

$$\int_{t_1}^{t_2} (p_t * grid_{offtake,t} + L * v_t - pv_{1,t} - pv_{2,t})\, dt \qquad (2)$$

•

$$T_{in,t} = f(\vec{x}_t, \vec{u}_t, \vec{d}_t) \qquad (3)$$

$$T_{in,t} + v_t \geq T_{low,t} \qquad (4)$$

$$T_{in,t} - v_t \leq T_{up,t} \qquad (5)$$

$$0 \leq pv_{2,t} + p_{batt,t} + grid_{offtake,t} \leq P_{hs,max} \qquad (6)$$

$$0 \leq pv_{2,t} + pv_{1,t} \leq pv_{gen,t} \qquad (7)$$

$$0 \leq pv_{1,t} \leq \frac{rate_{batt}}{\eta_{batt}} \qquad (8)$$

$$0 \leq p_{batt,t} \leq rate_{batt} * \eta_{batt} \qquad (9)$$

$$SOC_{k+1} = SOC_k + \eta_{batt} * pv_{1,t} - \frac{P_{batt}}{\eta_{batt}} \qquad (10)$$

$$0.1 * energy_{batt,max} \leq SOC_k \leq 0.9 * energy_{batt,max} \qquad (11)$$

$$0 \leq v_t \qquad (12)$$

In equation (2) the objective of the optimizer is to minimize thermal discomfort levels in terms of Kelvin hours (Kh) that the building's representative temperature is outside the comfort bands while simultaneously minimizing sum of the electricity price over the course of next day. In this equation $grid_{offtake}$ represents the energy bought from the electricity grid while p_t denotes the ToU pricing. The second term of the objective penalizes thermal discomfort. Inspired by Picard et al. (2016), a set of slack variables (v) are added in thermal comfort constraints. These variables allow the optimization to violate thermal comfort constraint which helps the solver to come up with a feasible solution. In turn, the value of these thermal discomforts is penalized in the objective function. (Picard et al., 2016). The value of these slack variables are penalized in the objective function in order to minimize thermal discomfort level. The scalar (L) is used to balance the penalty of energy cost and thermal discomfort to reach an acceptable range of thermal discomfort. Equation (3) represents the predictive model used in the MPC workflow to estimate the thermal behaviour of the building which is briefly explained in the next section. Equations (4) and (5) denote the soft constraints of the comfort requirements from Table 2. Equation (6) expresses the size and capacity of the heating system. Equation (7) limits the input from the panels to the maximum possible electricity generation from the PV panels (PV_{gen}) at each time step which is calculated prior to running the MPC. Equations (8)-(9) denote the maximum possible power of charging and discharging the battery ($rate_{batt}$). Equation (10) determines the SoC of the battery based on the amount of charged or discharged energy from it over an hour while Equation (11) limits the SoC of the battery to the range of [10-90]% in order to prolong its lifetime.

The objective function of the MPC (Equation (2)) is linear in the decision variables, the constraints imposed on the system are linear and the predictive model used in the study is linear as well. Hence, the optimization problem is linear and convex. For such a problem, many fast and efficient solvers exist which guarantee obtaining global extremum. Here, Linprog function of Matlab was used as the solver (*Global Optimization Toolbox*, 2021).

Flexibility indicators

The KPIs used to assess the quality of the optimizer are divided into two categories. The first category denotes the KPIs regarding thermal comfort, energy and cost savings. The second category quantifies the flexibility of the building. These KPIs include Load Cover Factor (LCF) of the energy system and the Self-Consumption (SC) of the PV system where the equations for defining these KPIs are given below (Gergely et al., 2022):

$$LCF = \frac{\int_{t_1}^{t_2} \min[P_{hs}(t), PV_{gen}(t) + P_{batt}(t) - PV_2(t)]dt}{\int_{t_1}^{t_2} P_{hs}(t)dt} \qquad (13)$$

$$SC = \frac{\int_{t_1}^{t_2} \min[P_{hs}(t), PV_{gen}(t) + P_{batt}(t) - PV_2(t)]dt}{\int_{t_1}^{t_2} PV_{gen}(t)dt} \qquad (14)$$

The LCF or self-sufficiency (equation (13)) represents the ratio of direct use of RES-generated energy by the HVAC system while SC (equation (14))quantifies share of total production from renewable sources, which is directly used by the building and its applications. Here, P_{hs} denotes the power demand of the heating system, PV_{gen} shows the generated power by PV, P_{batt} shows battery's discharge and PV_2 represents the charge of battery by the PV panels. Additionally, the flexibility of the building is described in terms of the Flexibility Index (FI) (Jensen et al., 2019). which shows how flexible the building is to the requirements of the grid operator. In this study, the grid operator signal is described by a ToU pricing structure. The FI is given based on the equation ((15)) in which $Cost_{RBC}$ denotes the cost of electricity resulting from implementing a Rule-Based Controller (RBC) which is unaware of the price signal from the grid and $Cost_{MPC}$ denotes the operational cost of the building achieved by an MPC which takes the price signal from the grid operator into account.

$$FI = 1 - \frac{Cost_{MPC}}{Cost_{RBC}} \qquad (15)$$

This index indicates how responsive a given building is to the price or penalty signal from the grid.

Results

In this section, the findings of applying the MPC for flexibility activation are presented. The simulation in which the MPC is applied is done for the months of January, February and March. The simulation for all three case studies has the same initial conditions. However, the first day of the simulation has not been considered for calculation of the KPIs to make sure the initialization does not have an impact on the KPIs. Before the MPC can run for the aforementioned time period the predictive model needs to be constructed. This is done in 2 steps: First, a proxy dataset from the building simulation model is generated. Consecutively, this dataset is used for training the parameters of the predictive model (Equation (3)). These two steps are briefly explained here.

Dataset

The dataset is required for training and validation of data-driven models. The information in such datasets should be rich enough so that the resulting model would capture the dynamics of the system. To this end, a Pseudo-Random Binary Sequence (PRBS) has been generated to excite the heating system of each of the use cases. This PRBS signal determines the on/off status of the heating system while a uniform noise is deployed to determine the amount of injected heat to the building. As an example, the resulting temperature profile of the medium insulated building is illustrated in Figure 3. It should be noted that obtaining such a large range of indoor temperature in practice has many implications and is mostly deemed infeasible. Therefore, obtaining such a dataset is only possible in a simulation study. In future work it will be investigated how more realistic temperature profiles affect the accuracy of the predictive model.

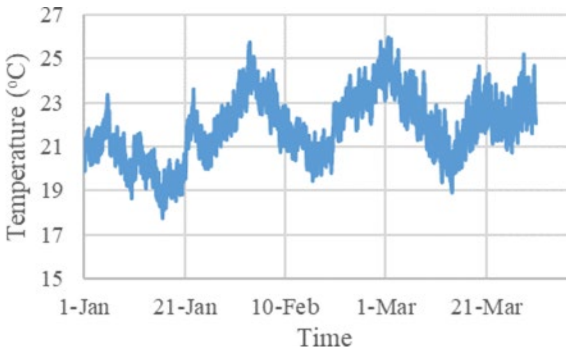


Figure 3- Temperature profile resulting from PRBS implementation

Model development

In this study, State Space (SS) modelling has been chosen to capture the thermal dynamics of the buildings. SS is a powerful modelling technique. Many of the linear modelling methods such as grey-box, ARX and transfer function could be expressed in terms of state space models. Even white-box simulation models of the buildings could be expressed as SS models (Picard et al., 2015). SS models have been successfully integrated in model-based optimization schemes for buildings (Bourdeau et al., 2019). The same set on inputs have been chose to carry out the prediction task. These inputs are heat injected to the building via heating system (H_{in}), ambient temperature (T_{amb}), Global Horizontal Irradiance (GHI) and Internal Heat Gains (IHG) representing artificial occupants. The first two months of data were used to identify the parameters of the state space model while data from the third month serves as the test dataset for validation. Error of the developed models for each of the cases is given in Table 3. The parameters of these models are identified using the Matlab system identification toolbox. The identification algorithm focuses on simulation error rather than on the prediction error. The latter is due to the findings of previous studies where it was shown that prediction error of the model (one-step ahead error) is not sufficient for reporting the quality of predictive models used in MPC and modelers should take into account model's performance throughout the whole control horizon rather than only one-step ahead (Erfani et al., 2021). Therefore, modelling error both for one-step and multi-steps ahead in time are reported in terms of Coefficient of Variation of Root Mean Square Error (CVRMSE) (ASHRAE 14, 2014). It could be seen that the accuracy of the state space models are very similar for the three pre-defined test cases.

Table 3-Summary of predictive models

Use case	One-step ahead error (%)	Multi-step ahead error (Maximum over horizon)(%)
High insulation	0.47	2.5
Medium insulation	0.67	2.45
low insulation	0.43	2.47

Cost-ignorant controller

As mentioned earlier, the FI quantifies the flexibility of a building based on a controller which does not consider the cost or penalty signal from the grid operator. To this end, first a traditional RBC has been developed and well-tuned. This well-tuned RBC primarily aims at minimizing indoor thermal discomfort. It is composed of a hysteresis controller which determines the on/off mode of the heating system. In case the heating system is on, a proportional controller determines the amount of heat injected to the building. Here, the hysteresis band and its set-point have been tuned in order to minimize thermal discomfort of the indoor air temperature. This process has been repeated for the three case studies separately. Energy use, energy cost and thermal comfort levels of the tuned RBCs are reported in Table 4.

Table 4- RBC results

Insulation level	Discomfort (Kh)	Cost (€)	Grid offtake (kWh)
High	28	197.5	3436
Medium	36	243.8	4265
Low	33	265.1	4643

Flexibility results

Here, the results of applying the MPC -as a candidate of cost-aware smart controllers- for flexibility activation of the buildings are presented. These results are obtained by applying MPC to each of the use cases over a time span of three months. In addition, controller time step and horizon are 1 and 24 hours respectively. Weather data used from this study is from Uccle Belgium. An hourly ToU electricity price is included in this study which is repeated every day. The ToU pricing has an average of 54 €/MWh with a standard deviation of 9.5 €. The average time required to run the co-simulation between the MPC and Dymola model for a duration of 3 months is 260 seconds. KPIs of the MPC simulations are reported in Table 6. For each of the cases, scalar *L* has been tuned in a way to make a reasonable balance between penalty of discomfort and energy cost. Consequently, thermal discomfort is within an acceptable range of 0-50 Kh for a period longer than half of the heating season (Freund & Schmitz, 2021).

Table 5- normalized battery and PV system

Insulation level	Number of panels	Battery size (kWh)	Battery charge/discharg erate (kW)
High	32	5.12	2.56
Medium	40	6.35	3.17
Low	44	6.9	3.45

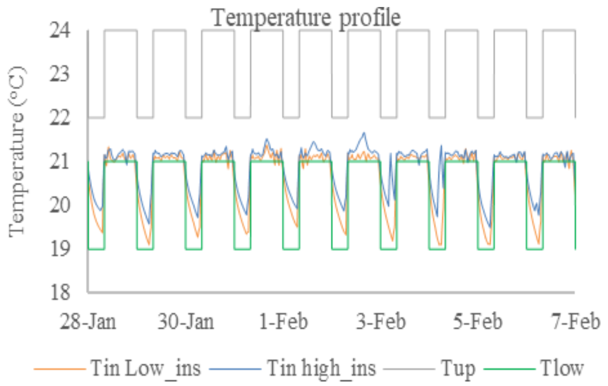
In addition, in order to be able to better assess the impact of insulation on building's flexibility, number of PV panels and the size of the battery have been normalized based on the offtake from the grid in the case of RBC (Table 5).

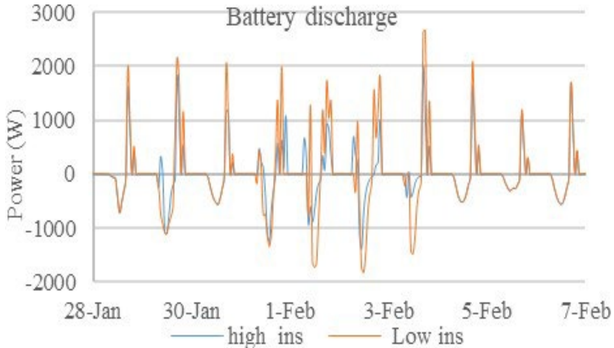
Table 6- Flexibility results

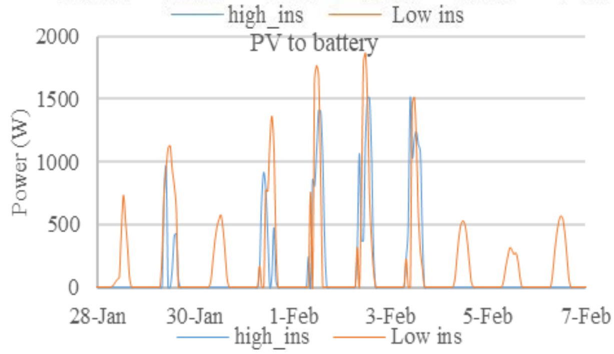
Insulation level	discomfort (Kh)	cost (€)	grid offtake (kWh)	SC (%)	LCF (%)	FI (%)
High	24 (12.3%)	159	2906 (+15.4)	99.4	12.3	19.4
Medium	41 (-14.9%)	200	3671 (+13.9)	99.3	12.4	17.6
Low	28 (18.9%)	232	4111 (+11.4)	99.0	12.1	12.4

Table 6 shows that the increase in the insulation level of the building has a positive impact on the flexibility of the building in regard to price signal from the grid operator.

Percentage of improvements in thermal comfort and grid-offtake compared to RBC are included as well. In this case, by doubling the insulation thickness of the walls, the flexibility index of the buildings increases from 12.4% to 19.4%. In other words flexibility of the building increases by 56% by doubling the insulation thickness in the external walls, roof and floor. The difference could be explained by the fact that higher insulation results in a higher time constant (defined as the effective thermal mass multiplied by the thermal resistance of the envelope) by increasing the thermal resistance of the envelope (Johra et al., 2019). Therefore, building envelope is able to store thermal energy and release it in a longer time span compared to a case with lower insulation level. Hence, MPC has more autonomy in shifting the heating demand of the building. Consequently, insulation level has a notable impact on the achieved flexibility. In addition to the flexibility index, the load cover factor of the three cases are very similar which is due to the re-sizing the PV panels and the battery. Self-consumption of all three cases is above 99%. It shows that almost all of the energy generated from the PV panels is directly used and the PV surplus is negligible (less than 1%). For all three cases, the discomfort level is quite small ranging from 0.27-0.46 Kh/day. However, the level of discomfort could be changed by altering the weighting scalar (L) in Equation (2) to obtain optimal profiles with different levels of discomfort and cost. By doing so, it has been observed that the impact of thermal discomfort within the range of the MPC and RBC results (20-50 Kh) on the achieved cost savings and flexibility index is miniscule. Table 6 reports the optimal profile which yielded thermal discomfort closest to the case of RBC.







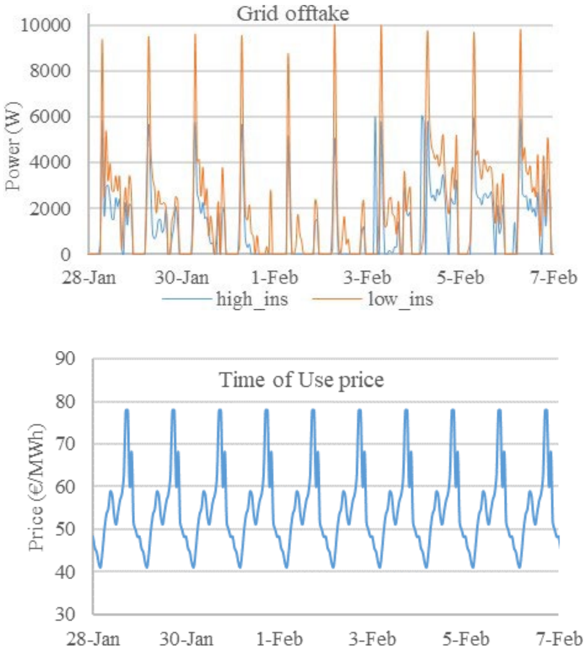


Figure 4- Temperature and power profiles resulting fromMPC

Figure 4 shows the results of applying MPC for flexibility activation of the high and low insulation case. This figure represents the results of a period of 10 days from 28th of January to 7th of February where the electricity generation of PV panels is at its highest. First of all, the temperature profile shows that the MPC is able to successfully keep the indoor air temperature of the building (lumped zones) within the thermal comfort bands. Secondly, combining three sub-figures of the battery discharge, the PV to battery and electricity price, one can see that before the price peak takes place, PV charges the battery so that during the peak hours the battery is discharged (positive values represent discharge of battery and negative values indicate charging). This behaviour is visible in the offtake from the grid as well where during the hour of peak price, offtake from the grid is at a local minimum (if not zero). The price-aware controller takes advantage of the valley of the price and takes the maximum allowed power from the grid where part of it is used to charge the battery and the rest goes to the heating system. Comparing the results of the low insulation case and high insulation case in the case of grid offtake, one can deduce that the grid offtake peaks happen almost at the same time for the two cases. However, in some days (e.g. 3rd and 4th of February) there is a shift in time in terms of grid offtake for the high insulation case. Comparing this shift to the electricity price, it is seen that this shift is in sync with the minimum electricity price. In other words, grid offtake increases in the high insulation case sooner than the low insulation case. This could be an indication of the higher thermal inertia of the high insulation case which allows the heat to be dissipated in a longer time span into the space. Comparing battery discharge, same behaviour is visible where the battery is in some days discharged sooner in case of high insulation compared to the low insulation. Therefore, one can conclude that by increasing the insulation level in a building, MPC has more autonomy in shifting grid offtake. Hence, it can harness more flexibility for a building with high insulation. Considering the grid offtake as an indicator of CO_2 emissions, using MPC for flexibility activation decreases CO_2 emissions by 15.4%, 13.9% and 11.4% for high insulation, medium insulation and low insulation case respectively. In this study, maximum allowed power taken from the grid is set to the maximum power of the heating system as well. Normalizing the size of battery and number of panels, narrows down the contributing factors to insulation. However, the impact of battery and PV system size should be investigated together with the insulation from a techno-economical point of view. Consequently, MPC is capable of successfully responding to the price signal of the grid operator while maintaining main service of a dwelling i.e. providing indoor thermal comfort.

Conclusion

This study conducts a simulation study to evaluates the impact of building's insulation on the achieved flexibility. To properly use the flexibility options that a building offers, first a high-fidelity simulation model of the use case has been developed and validated. To harness building's flexibility, MPC has been used as a prominent delegate of cost-aware controllers. In this work Time-of-use pricing has been used as a representative of the signal from the grid operator. The structure of the three use cases only differs in terms of insulation levels, where the insulation thickness of the best insulated use case has been reduced by 33% and 50% to form the two other use cases. In order to filter out impact of other variables on the flexibility, heating system, number of PV panels and the capacity of the battery have been resized to match the energy demand of the use cases. Considering the grid offtake as an indicator of fossil-fuel based electricity generation, using MPC for flexibility activation decreases CO_2 emissions by 15.4%, 13.9% and 11.4% for high insulation, medium insulation and low insulation case respectively. The results further show that MPC is capable of activating the flexibility potential of the buildings. In addition, findings of this paper reveal that by doubling the insulation level of the given use case, the flexibility index could be improved by 50%. This shows the considerable impact of insulation on the flexibility of a building and could guide practitioners and policymakers to put more emphasis on insulation improvement for renovation plans and CO_2 emission reduction scenarios respectively.

Future studies could analyze impact of deploying heat pumps in the building's energy system along with electrical vehicles. Impact of battery and PV system sizing should be assessed together with insulation level from a techno-economical outlook. In addition,integration of comfort elasticity on the harnessed flexibility of a household is an interesting extension of thecurrent work.

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