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Flexibility quantification in the context of flexible heat and power for buildings

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Abstract

The European Horizon 2020 project Flexible Heat and Power (H2020 FHP) investigates how to exploit the thermal inertia of buildings and their Heating Ventilation and Air-Conditioning (HVAC) systems as a source of flexibility to offer Demand Response (DR) strategies. The goal of this project is to provide a framework that allows increasing the energy state of buildings during generation peaks and lowering their energy use when supply is scarce (and thus expensive), while respecting the indoor thermal comfort. In order to achieve that goal, a Dynamic Coalition Manager (DCM) architecture has been defined.
To estimate the cost of changing the demand behaviour a measure for flexibility is required as well, i.e., the capacity of the load to behave differently compared to the baseline scenario. This flexibility quantification is needed to estimate the flexibility offer that the DCM can make to other market players such as the Distribution System Operators (DSOs) and Balance Responsible Parties (BRPs). Hence, the chosen flexibility indicator must be scalable since it has to be aggregated for a cluster of buildings.
There already exist several ways of quantifying thermal flexibility of buildings. However, assessing and comparing the different definitions is a complicated task since the suitability of each indicator for its specific application is crucial. In this paper a flexibility quantification based on multiple Model Predictive Control (MPC) strategies is developed for an individual building, which is aggregated for a cluster of buildings. The flexibility indicator is demonstrated using grey-box models for the BAs.

Keywords: Model predictive control, Demand response, Energy flexibility, Building Agents

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1. Introduction

In the EU-28, the share of energy from renewable sources in gross final energy use increased from 8.5% in 2004 to 16.7% in 2015 [1], which is a clear evolution towards the European target of 20% for 2020. Integrating these intermittent energy sources in the supply mix is not straightforward because of their uncontrollable nature and the flat pattern of other energy sources that lower their assimilation in the grid. As a result, the power system operators are sometimes obliged to curtail the production from wind-farms and solar plants even when "free" natural resources are available.

Demand-Side Management (DSM) is a (part of the) solution that has been applied for already more than thirty years. This term was coined by Clark W. Gellings in the 1980's [2]. DSM refers to the generation of extra load at the demand side to allow the supply sector to run at its maximal efficiency. The capacity of the demand to vary its forecasted load behaviour is called flexibility. The first implementations of DSM arose in the industry using night tariffs and Time-of-Use (ToU) pricing. However, it is progressively being introduced also in the residential sector where it is necessary to aggregate several end-user energy devices in order to gather a sufficient amount of flexibility that allows to trade in the day-ahead, intra-day and the imbalance energy markets.

MacDougall et. al. [3] evaluated the economic potential of black-box machine learning models to forecast the aggregated flexibility of a cluster of heterogeneous devices. They showed that Heat Pumps (HP) have a much higher impact than other commonly found white goods in households. Also thermal mass of buildings represent an important source of flexibility [4, 5, 6, 7].

Furthermore, realistic trading strategies are needed to harness the available flexibility. The definition of a specific trading architecture is a huge challenge because of different reasons. First of all, the amount of available flexibility has to be predicted and valued. Secondly, the information that comes from the buildings has to be aggregated to respect end-user privacy. Finally, the buildings have to be able to respond to flexibility requests without threatening their thermal comfort. Managing the energy consumption of a set of buildings is a complex task. Therefore, the proposed solution has to be practical, scalable and feasible to enable its future large-scale implementation. A comparison of load shifting incentives for buildings with heat pumps was investigated by Patteeuw et al. [8].

The main goal of this paper is to explain and illustrate the functionality of the chosen flexibility indicator and architecture used to steer the flexibility of buildings and evaluate the potential of such approach. This paper consists of the following sections: Section 2 explains the proposed architecture and the buildings as a source of thermal flexibility; Section 3 proves the functionality of the approach with a simulation example; finally, Section 4 draws the main conclusions of this paper.

2. Methodology

In this study, flexibility is measured according to different Model Predictive Control (MPC) strategies. This approach is chosen because these types of optimal control strategies are able to predict the buildings' load according to an optimization criteria. Hence, the benefits are twofold: on the one hand, the controller itself is able to forecast the flexibility information from the buildings, which is required to perform DSM strategies. On the other hand, the buildings are optimally controlled towards a chosen objective.

An MPC uses a mathematical model of the building together with weather and occupancy forecasts to predict the optimal heating inputs according to a chosen objective, taken constraints into account. Therefore, these controllers solve an optimization problem each time-step and for a given time horizon. The MPCs implemented in buildings usually include soft constraints for the comfort and hard constraints for the dynamics of the system and the HVAC technical limits. The decision variables are the power inputs; the optimization variables are the physical states; the disturbances are the ambient temperature, solar irradiation and occupancy profiles, but might be others. From each solution of the optimization, it is implemented only the first time-step. Then, the actual state is estimated from observations and a new optimization is performed with the horizon shifted one time-step.

A solution is proposed to steer such flexibility which is named the Dynamic Coalition Manager (DCM). The DCM consists of three agents: a Planner, a Tracker and a Forecaster. They interact by exchanging information and solving different optimization problems to transform the flexibility requests into actual deviations from the forecasted baseline consumption. The interaction between these agents is illustrated at Fig. 1 and their functionality is explained in more detail at Sub-sections 2.1.1, 2.1.2 and 2.1.3. This distributed control scheme is similar to the one proposed in [9]. One of the advantages of this layout is that sensitive information remains private, while the main disadvantage is that every player must cooperate to meet common constraints.

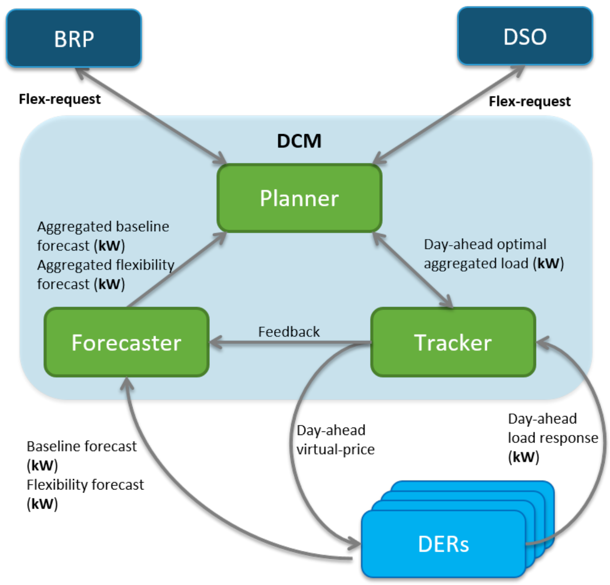


Figure 1: DCM architecture.

The day-ahead baseline consumption and flexibility are calculated by each building and sent to the Forecaster for their aggregation. This bottom-up aggregation allows to distribute the computational load between the buildings while respecting end-user privacy. Moreover, it can be proven that the global solution of the aggregated problem will remain optimal as far as the optimization sub-problems solved for each particular building are strictly convex.
The Planner will then elaborate a plan trying to accomplish the flexibility requested by the Distribution System Operators (DSOs) and Balance Responsible Parties (BRPs) using the available flexibility estimated by the buildings. This plan should minimize the overall cost and will probably differ from the aggregated baseline consumption. Then, the Tracker negotiates with the buildings to modify their behaviour. This negotiation takes place in an iterative way. At each iteration, the Tracker sends a day-ahead price profile to the buildings, which respond with their expected day-ahead load profile according to such price. The process ends when the Tracker considers the overall energy use of the cluster as close enough to the planned optimal power profile.
It is worth mentioning that the energy use is never imposed to the buildings. Conversely, the desired behaviour is promoted by virtual-price signals, but it is always up to the buildings to decide their own consumption. A direct load shaping is avoided in order to ensure thermal comfort in the buildings. Moreover, the buildings can choose an objective function of their preference (e.g. minimal cost, minimal energy use, minimal CO_2 emission, ...), meaning that they have the freedom to go for a more active trading or to follow a more conservative approach. Section 2.1 elaborates on the DCM. The Building Agents (BAs) are described in Section 2.2.

2.1. The Dynamic Coalition Manager

The DCM architecture is dynamic because of its capability to accept or to drop any building at any time. The participation is fully open and should be motivated by the buildings themselves. Once a building accepts to join, it will be part of a coalition, i.e. a cluster of buildings offering flexibility to the same DCM. This clustering is necessary in order to gather a reasonable amount of flexibility required to trade.

2.1.1. The Forecaster

The Forecaster estimates the future overall energy use and flexibility range of the cluster of buildings. To make such estimation, it should aggregate the baseline, lower and upper bounds for the flexibility forecasted by the BAs. In addition, the Forecaster predicts the aggregated background consumption of the buildings.

2.1.2. The Planner

The Forecaster reports the baseline and the flexibility forecast to the Planner, after which the Planner negotiates with the DSOs and BRPs. More particularly, the Planner gathers the flexibility requests from these clients and identifies a day-ahead optimal plan minimizing the overall operational cost. The cheapest way of activating flexibility comes from the solution of an optimization problem during the time horizon T_h as is shown in [1].

$$\min_{\boldsymbol{\Delta P}} \sum_{k=1}^{N} (\lambda_{DA,k}(P_{bl,k} + \Delta P_k) + C_{f,k}|\Delta P_k|)\Delta t \tag{1}$$

$$s.t. \begin{cases} \underline{\boldsymbol{b}} \leq \boldsymbol{\Delta P} \leq \overline{\boldsymbol{b}}; \\ \underline{\boldsymbol{P}}_{\boldsymbol{DSO/BRP}} \leq \boldsymbol{P_{bl}} + \boldsymbol{\Delta P} \leq \overline{\boldsymbol{P}}_{\boldsymbol{DSO/BRP}} \end{cases}$$

Where N is the number of intervals in the time horizon T_h; $\lambda_{DA,k}$ is the day-ahead price of electricity at interval k in $€/kWh$; $P_{bl,k}$ is the forecasted, aggregated baseline load in kW; ΔP_k is the flexibility activation at interval k in kW; Δt is the time-step size of each interval in hours; $C_{f,k}$ is the cost of activating the flexibility at interval k in $€/kWh$; $\underline{\boldsymbol{b}}$ and $\overline{\boldsymbol{b}}$ are the lower and upper bounds, respectively, of the aggregated flexibility estimated by the Forecaster at interval k; finally, $\underline{\boldsymbol{P}}_{\boldsymbol{DSO/BRP}}$ and $\overline{\boldsymbol{P}}_{\boldsymbol{DSO/BRP}}$ are the lower and upper constraints, respectively, for the aggregated power profiles that are imposed by the DSO and the BRP and that are related with grid restrictions.
The solution to this optimization problem gives the amount of flexibility $\boldsymbol{\Delta P}$ that should be activated at each interval k in order to minimize the overall cost (notice that we use bold format to denote the vector variables). Adding this vector to $\boldsymbol{P_{bl}}$ we obtain an optimal aggregated plan, $\boldsymbol{P^*}$, that is then sent to the Tracker:

$$\boldsymbol{P^*} = \boldsymbol{P_{bl}} + \boldsymbol{\Delta P} \tag{2}$$

2.1.3. The Tracker

Once this plan is calculated, it is the responsibility of the Tracker to steer the buildings in a way that they follow the optimal behaviour as close as possible. The Tracker works on grid level to receive the control plan from the Planner and to dispatch this among all underlying buildings.
The mechanism used is a negotiation in price and power, which is realized by a distributed optimization with the Alternating Direction Method of Multipliers (ADMM). This method solves convex optimization problems by breaking them into smaller pieces. Each of these pieces in our application corresponds to one building with an objective f_i (i being the index for the building agents) that will be described more in detail in Sub-section 2.2. The optimization problem to be solved is defined in [3].

$$\min_{\boldsymbol{\lambda}} \sum_{i=1}^{N} f_i(\boldsymbol{P_i}, \boldsymbol{\lambda}) \tag{3}$$

$$s.t. \sum_{i=1}^{N_b} \boldsymbol{P_i} = \boldsymbol{P^*}$$

Being $\boldsymbol{\lambda}$ the daily virtual price profile sent to the buildings, N_b the number of buildings in the cluster, $\boldsymbol{P_i}$ the power response of agent i and $\boldsymbol{P^*}$ the optimal plan for the aggregated load that was calculated by the Planner. Notice that, in contrast to $\boldsymbol{\lambda_{DA}}$, the virtual-price is not fixed anymore but is the optimization variable instead and varies from one iteration l to the next one, $l+1$, according to Equation [4].

$$\boldsymbol{\lambda^{l+1}} = \boldsymbol{\lambda^{l}} + \rho(\overline{\boldsymbol{P}}^{\boldsymbol{l+1}} - \boldsymbol{P^*}) \tag{4}$$

Where $\boldsymbol{\lambda^l}$ is the daily virtual price profile in the l^{th} iteration, ρ is the regularization constant and $\overline{\boldsymbol{P}}^{\boldsymbol{l+1}}$ is the average of all agents' responses in iteration $l^{th}+1$.

2.2. *The Building Agents*

Each energy user with the intelligence to vary its forecasted energy use is called a Distributed Energy Resource (DER). Therefore, these agents are the end providers of flexibility. The individual agent's primary task is to participate in grid actions while ensuring quality of service. In the particular case of buildings, we call them the Building Agents (BA) and the quality of service is normally related to the indoor climate comfort.

For MPC a mathematical model of the buildings' envelope and their HVAC systems is needed to predict the energy loads. Three modelling approaches can be used for these systems: white, grey and black box models. The inputs and outputs of these models might be the same, but they strongly differ in their structure and the way they are built up. While grey- and black-box models use monitoring-data to tune their parameters, which can be a cumbersome problem, the white-box approach uses only physical information of the system. The latter usually require engineering expertise or good model libraries and templates to be deployed. Moreover, all the details of the building need to be known. On the other hand, Black-box models are purely mathematical models. Finally, grey-box models include some physical insights to increase their applicability.

Any of these modelling approaches can be used. Grey-box models have been chosen in this paper due to their excellent trade-off between robustness and simplicity. These models use the analogy with electric circuits to represent the buildings' heat transfer dynamics resulting in linear properties when simulating the buildings' envelope, which leads to convex optimization problems.

The model equations are introduced as hard constraints in the optimization problem to take into account the dynamics of the buildings. In order to provide the necessary information for trading, each building should solve four optimal control problems subject to different optimization criteria: the baseline, the lower and the upper bounds for flexibility, and their price response. These four strategies are related to variable comfort set-points as is explained below:

The **baseline** is the power profile of a building in the reference case scenario, i.e., the response of a building without any DSM interaction. This baseline profile is chosen to be the estimated minimum power profile needed to keep the building temperature within a given thermal comfort range, which includes a safety margin $\boldsymbol{m}$, as formulated in the optimal control problem 5. This safety margin ensures comfort even when the controller model is not able to predict the thermal behaviour of the building accurately, i.e., when there exists model mismatch.

$$\min_{\boldsymbol{x},\boldsymbol{P}} \sum_{k=1}^{N} (P_k + w\Delta T_k)\Delta t \tag{5}$$

$$s.t. \begin{cases} g(\boldsymbol{x}, \boldsymbol{P}, \boldsymbol{d}) = 0 \\ \boldsymbol{x}(t=0) = \boldsymbol{x_0} \\ \underline{\boldsymbol{T}}_{\boldsymbol{set}} - \underline{\boldsymbol{\Delta T}} + \boldsymbol{m} \leq \boldsymbol{T} \leq \overline{\boldsymbol{T}}_{\boldsymbol{set}} + \overline{\boldsymbol{\Delta T}} \\ \underline{\boldsymbol{\Delta T}} \geq 0; \overline{\boldsymbol{\Delta T}} \geq 0 \end{cases}$$

Where $\boldsymbol{x}$ are all the states of the building system as modelled by the grey-box model; $\boldsymbol{T}$ stands for the building's

zone temperature that should be kept between the lower and upper comfort bounds: $\underline{\boldsymbol{T}}_{\boldsymbol{set}}$ and $\overline{\boldsymbol{T}}_{\boldsymbol{set}}$; $\boldsymbol{P}$ is the amount of power used to heat the building; $\underline{\boldsymbol{\Delta T}}$ and $\overline{\boldsymbol{\Delta T}}$ are the lower and upper discomfort vectors, which represent the lower and upper deviations, respectively, of the actual temperature with each comfort bound. This discomfort is weighted with a constant w that accounts for the different orders of magnitude between power and temperature. g is the model of the buildings that is able to predict the future states $\boldsymbol{x}$ for a given set of controllable power inputs $\boldsymbol{P}$ and disturbances $\boldsymbol{d}$.
The **lower bound** of flexibility is computed as the power profile of a building when minimizing its energy use. In this case, the indoor temperature is controlled to its lowest acceptable set-point. The objective function of this optimal control problem is shown in 6 and presents the same set of constraints as [5], but without any safety margin ($\boldsymbol{m} = 0$), which leads to a lower flexibility bound with respect to the baseline.

$$\min_{\boldsymbol{x},\boldsymbol{P}} \sum_{k=1}^{N} (P_k + w\Delta T_k)\Delta t \tag{6}$$

The **upper bound** of the flexibility is presented in [7]. It is computed as the power profile of a building when maximizing its energy use. In this case, the indoor temperature is controlled to its highest acceptable set-point. Again, it is applied the same set of constraints as [5] with $\boldsymbol{m} = 0$.

$$\min_{\boldsymbol{x},\boldsymbol{P}} \sum_{k=1}^{N} (-P_k + w\Delta T_k)\Delta t \tag{7}$$

The **price response** is the load profile estimated by the building when a certain virtual-price profile $\boldsymbol{\lambda}$, is given. This response is calculated according to the optimal control problem presented in [8]. In this case, the building will not minimize the energy use, but the cost of the energy needed. Therefore, in the cost function the energy is weighted with the price at each instant, λ_k. This will rise the power profiles in those periods where the electricity prices are low and reduce them when the electricity prices are high. The objective function associated with this strategy is the one used during the "negotiation" period between the BAs and the DCM. Consequently, the buildings should give a price response for each price profile delivered by the DCM at each iteration, l.

$$\min_{\boldsymbol{x},\boldsymbol{P^l}} \sum_{k=1}^{N} (\lambda_k^l P_k^l + w\Delta T_k^l + \frac{\rho}{2}(P_k^l - R_k^l)^2)\Delta k \tag{8}$$

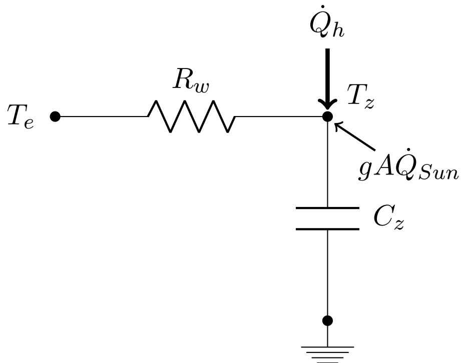
$$s.t. \begin{cases} g(\boldsymbol{x}, \boldsymbol{P}, \boldsymbol{d}) = 0 \\ \boldsymbol{x}(t=0) = \boldsymbol{x_0} \\ \underline{\boldsymbol{T}}_{\boldsymbol{set}} - \underline{\boldsymbol{\Delta T}} \leq \boldsymbol{T} \leq \overline{\boldsymbol{T}}_{\boldsymbol{set}} + \overline{\boldsymbol{\Delta T}} \\ \underline{\boldsymbol{\Delta T}} \geq 0; \overline{\boldsymbol{\Delta T}} \geq 0 \\ \boldsymbol{R^l} = \boldsymbol{P^{l-1}} - \frac{\boldsymbol{P^{l-1}_{total}} - \boldsymbol{P^*}}{N_b} \end{cases}$$

$\boldsymbol{R^l}$ is the regularization term to be used at iteration l. This term is passed from the Tracker to the agent at each iteration to keep the convergence stability of the global ADMM optimization. Therefore, the BA is free to change its objective, but should include a term to ensure global convergence. This is the last quadratic term weighted with the regularization constant ρ which penalizes the deviation from the previous estimated load $\boldsymbol{P^{l-1}}$. However, this penalization is relatively lower when the deviation from the previous overall estimated load of the N_b agents $\boldsymbol{P^{l-1}_{total}}$ with respect to the optimal plan $\boldsymbol{P^*}$ is large.
Therefore, this work quantifies flexibility as the load range between two bounds calculated using MPC strategies: the lower and the upper bounds. This flexibility range represent the estimated buildings' capacity to vary their baseline and is exploited through a distributed optimization methodology where a virtual price signal is

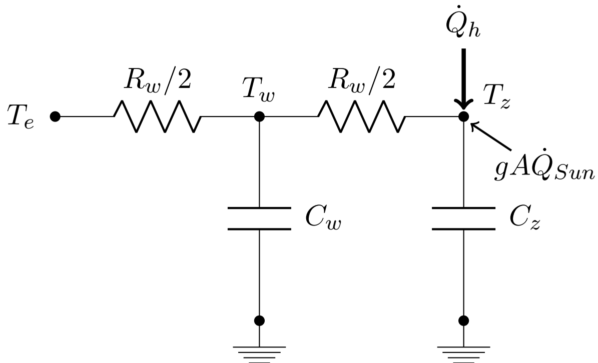
used to trigger a desired behaviour in the buildings.

3. A Simulation Example

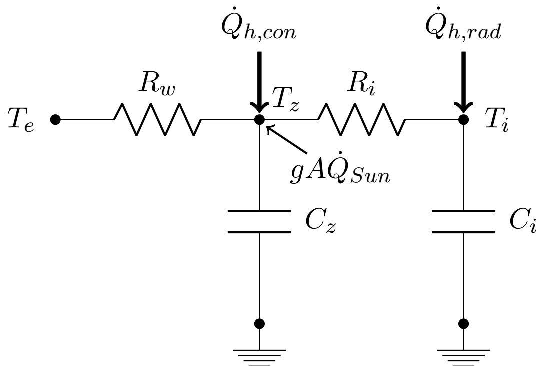
This section shows the performance of a cluster of 100 buildings offering flexibility to a DCM as determined by a simulation. For simulation purposes, each building from the cluster is emulated using a grey-box model where different architectures are considered, as shown in Fig. 2. The purpose of using different model structures is to mimic the different dynamics that exist in buildings. In these models, the disturbances are the environmental temperature, T_e and the solar irradiation per square meter, $\dot{Q}_{Sun}$; the controlled variable is the zone temperature T_z; other states included in the models are the wall and internal temperatures, T_w and T_i, respectively; the controllable input is the overall heating injected into the building, $\dot{Q}_h$; for those models with an internal temperature state, this heat is split in, convective and radiative terms, which leads to $\dot{Q}_h = \dot{Q}_{h,con} + \dot{Q}_{h,rad}$. For this example, we assume that the electric power consumed is the same as the thermal power injected $\dot{Q}_h$, i.e., we consider an ideal thermal resistor as the heating source. The parameters of these models are randomly populated around physically meaningful values which are shown in Table 1.



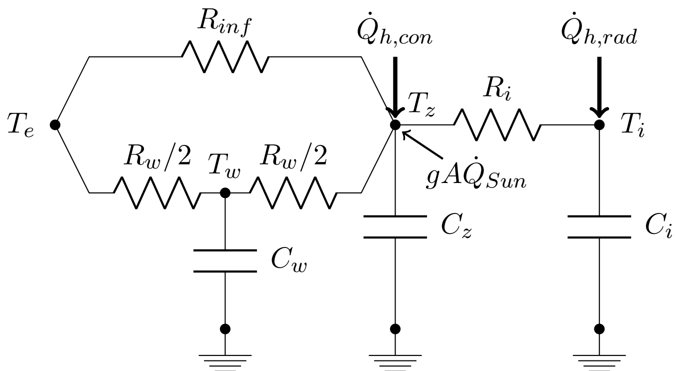
(a) RC circuit of first order: Zone temperature.



(b) RC circuit of second order: Zone and Wall temperatures.



(c) RC circuit of second order: Zone and Internal temperatures.



(d) RC circuit of third order: Zone, Wall and Internal temperatures.

Figure 2: Grey-box models used to emulate the cluster of buildings.

Table 1: Reference values used to populate the parameters of the grey-box models.

Symbol	Parameter	Units	Reference value
C_z	Zone capacitance	J/K	10^8
C_w	Wall capacitance	J/K	10^7
C_i	Internal capacitance	J/K	10^7
$T_{z,0}$	Initial zone temperature	$°C$	20
$T_{w,0}$	Initial wall temperature	$°C$	18
$T_{i,0}$	Initial internal temperature	$°C$	22
R_i	Internal thermal resistor	K/W	10^{-3}
R_w	Wall thermal resistor	K/W	10^{-2}
R_{inf}	Infinite thermal resistor	K/W	10^{-1}
gA	Total solar transmittance	m^2	10

The time horizon T_h is taken to be one day. Belgian day-ahead prices from the 31st of December, 2017 are used for the simulation. This day is considered as a suitable candidate to exemplify the potential of the solution presented because of its negative prices during several hours of the day. Real data of the ambient temperature and solar irradiation for that day in the region of Leuven are used. This data is obtained from [10], and [11, 12] have been used to correct the direct normal and diffuse horizontal irradiation from the cloud fraction. The constant for the regularization term is set to $\rho = 1$. After a fine-tuning exercise, this value is found to drive the Tracker to convergence after a few iterations with the buildings. Between 10 and 15 iterations are enough to converge towards an accepted error threshold of $10kWh$ for the whole day.
Several cost values C_f are set for the activation of each kWh of flexibility to investigate how this value affects the results. The higher the cost, the less flexibility will be activated during curtailment (at those moments when the prices are negative) because that would increase the overall cost. The energy use during curtailment for different prices of the flexibility activation is shown in Fig. 3. These values are to be compared with the baseline consumption during curtailment which is of $5147.15kWh$.

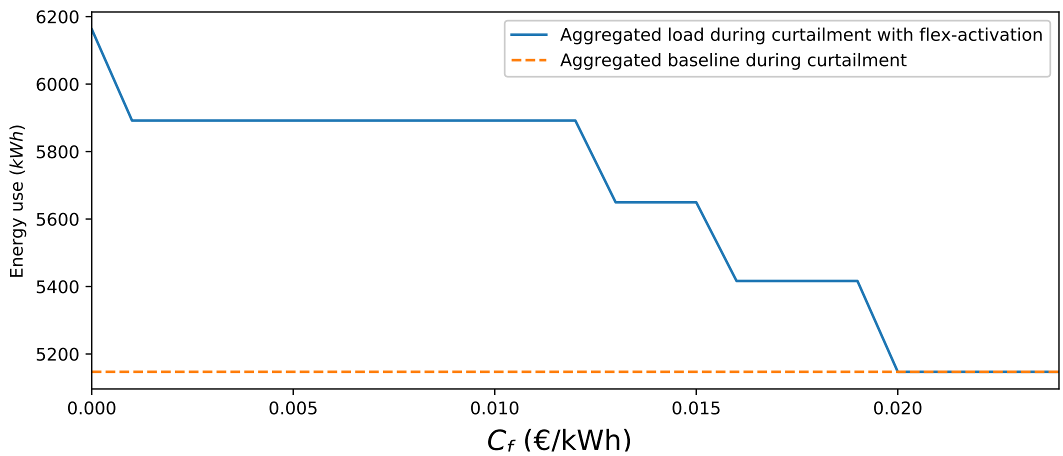


Figure 3: Aggregated energy use during curtailment for different values flexibility activation cost

In Fig. 4 the aggregated load profiles when $C_f = 0.01€/kWh$ are plotted. Fig. 4 shows the forecasted baseline, the optimal plan calculated by the Planner and the convergence achieved by the Tracker during its negotiation with the buildings. The aggregated flexibility offered by the buildings is represented by the yellow coloured region. The day-ahead price is also depicted in Fig. 4 to highlight that the Planner increases the energy use of the cluster when there are negative prices and minimizes it as much as possible at those moments when the prices are higher.

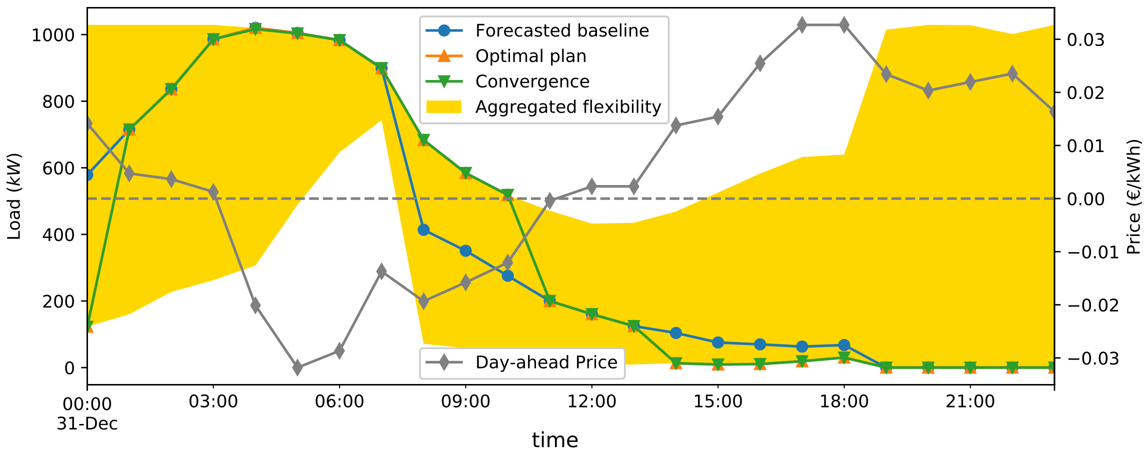


Figure 4: Aggregated load profiles

The aggregated load after negotiation overlaps the optimal plan, meaning that the Tracker success in its goal of steering the flexibility of the buildings. Fig. 5 shows the expected state evolution in one example building of the cluster. The building has the model structure of Fig. 2d, i.e., it has three states: the zone, wall and internal temperatures. The zone temperature and load evolution are shown for both cases: with and without flexibility activation. The yellow area represents the flexibility region for the temperature and the load calculated according to [6] and [7] that seek to minimize and maximize, respectively, the energy use of the building. However, as can be seen in Fig. 5, the limits of this region can be exceeded since they do not represent the instantaneous minimum and maximum achievable values, but a strategy to minimize and maximize energy use. This emphasizes the potential of a less restrictive flexibility indicator able to relax the constraints of the Planner which would lead to more flexibility activation.
The price with which the Tracker achieves convergence is also plotted in Fig. 5 together with the load history. It is important to recall that this price is physically meaningless since it is just a signal used as a tool to steer the flexibility in the cluster. Nevertheless, a similar shape as the day-ahead price is observed.

4. Conclusions

This paper presents the Dynamic Coalition Manager architecture developed to steer flexibility of buildings in a DSM context, and proves the potential of flexibility offered by a cluster of buildings in a simulation example. Multiple MPC strategies are used by each building to estimate its baseline and flexibility range. These profiles are then aggregated by the DCM and an optimal plan is followed using the Alternating Direction Method of Multipliers for distributed optimization. It has been shown how this solution steers the flexibility of one hundred simulated buildings without violating their indoor comfort.
The impact of the flexibility activation cost has been studied too. The maximum cost for flexibility activation is found to be $0.02€/kWh$ the 31st of December for this particular case. Above this price, the Planner does not see an added value in flexibility activation and the optimal aggregated load profile is equal to the baseline. Moreover, the results suggest that a less restrictive flexibility indicator has the potential to lead to more flexibility activation.

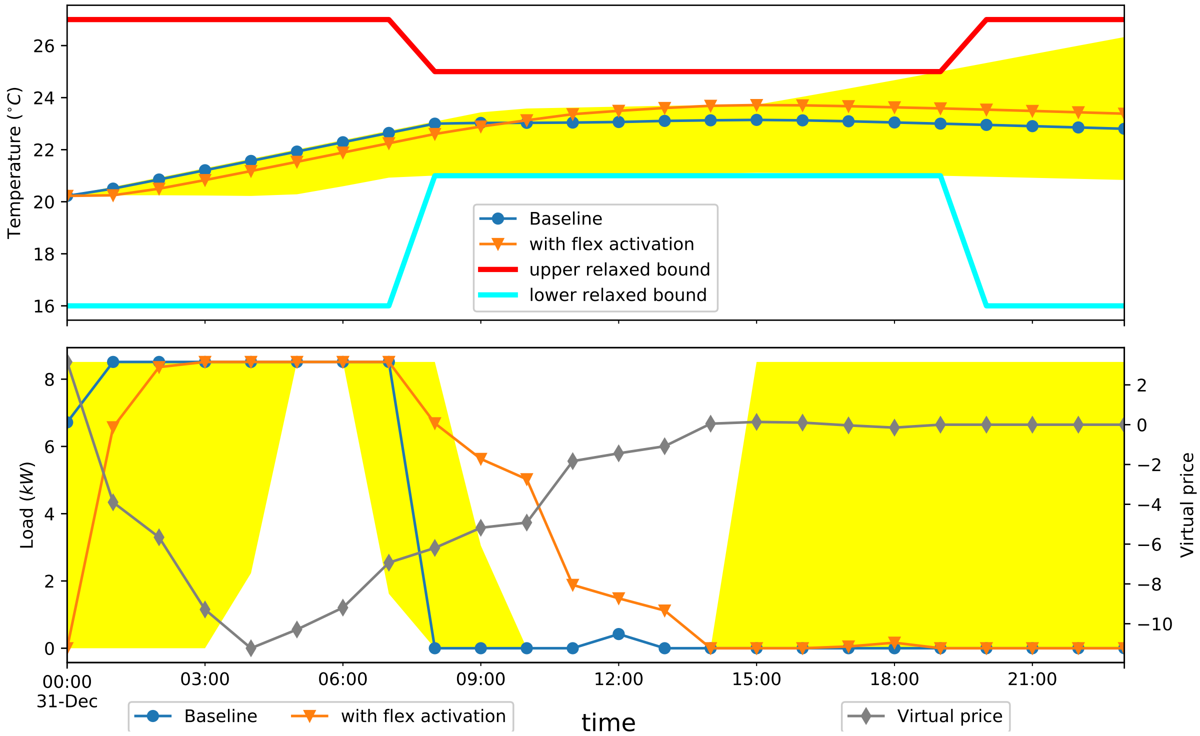


Figure 5: Zone temperature and load evolution of a building agent modelled with three states: Zone, Wall and Internal

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