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Energy flexible buildings: An evaluation of definitions and quantification methodologies applied to thermal storage

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ABSTRACT

As demand response and energy flexibility are often suggested as key principles to facilitate high levels of renewable energy sources into energy markets, different studies evaluated the potential impact of energy flexibility in buildings. Nonetheless, due to differences in definition and quantification methodologies for energy flexibility, comparing results between such studies is difficult. With a review and applied evaluation of existing definitions and quantification methodologies this paper aims at assessing the applicability, benefits and drawbacks of each quantification methodology.

The conducted review shows that energy flexibility definitions found in the literature have their particularities despite sharing the same principle that energy flexibility is the ability to adapt the energy profile without jeopardizing technical and comfort constraints. The survey of quantification methodologies reveals two main approaches to quantify energy flexibility. A first approach quantifies energy flexibility indirectly using past data and assuming a specific energy system and/or energy market context. The second approach directly predicts the energy flexibility that a building can offer to the energy system in a bottom-up manner. While applications for both approaches were identified, this paper focuses on the latter. By applying methodologies that follow this second approach to a common case study, three common properties of energy flexibility were observed: i) the temporal flexibility; ii) the amplitude of power modulation; iii) and the associated cost.

1. Introduction

In many countries, the growing share of renewable energy sources (RES) goes hand in hand with the extensive electrification of demand (e.g. replacement of traditional cars with electrical vehicles or displacement of fossil fuel heating systems, such as gas or oil boilers, with heat pumps [1,2]). These changes impose new challenges to energy systems' management, such as the variability of energy supply, drastic loads variations over a day [3], grid operation closer to its limits, increasing energy use at peak periods, more complex control problems with shorter decision times and smaller error margins [4]. Flexible energy systems, which deviate from the traditional production response by integrating decentralized storage and demand response, are often proposed as an important part of the solution [3–7]. In this context, strategies to ensure the security and reliability of energy supply involve simultaneous coordination of distributed energy resources (DERs), energy storage and flexible schedulable loads connected to distribution networks [4,7]. As illustrated by the review of Denholm and Hand [3] and Lund et al. [6], a successful large-scale integration of solar or wind power must include these more advanced strategies. As buildings account for approximately 40% of the annual energy use worldwide [8], they are likely to play a significant role in providing the safe and efficient operation of the future energy system. Hence, they may deliver significant flexibility services to the system by smart control of their energy loads.

The term "flexible building" is understood differently depending on the research environment and target group. For instance, "spatial flexibility of a building" focuses on building modularity (i.e. the ability to easily adjust to the changing functions) [9]. The "structural flexibility of a building" is used by structural engineers and buildings located in earthquake zones (e.g. China, Japan, Cal-

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Nomenclature

Symbol	Definition (Unit)
Δ	Difference (-)
c_j^i	Price for variable j at time i (-)
η_{ADR}	Storage efficiency (-)
l_{ADR}	Duration of ADR event (h)
$\tau_{delayed/forced}$	Delayed/Forced temporal flexibility (h)
C	Thermal capacity (MJ)
E	Energy (kWh)
H	Heat transfer coefficient (W/K)
P	Power (W)
Q	Heating power (W)
R	Thermal resistance (K/W)
t	Time (s)
T	Temperature (°C)
Abbreviation	Definition
ADR	Active demand response
CHP	Combined heat and power
DER	Distributed energy resources
DSM	Demand side management
HP	Heat pump
HVAC	Heating ventilation and air conditioning
PSC	Power shifting capability
RES	Renewable energy sources
SOC	State of charge

ifornia (U.S.) [10–12]). This paper describes the "energy flexibility of a building," which is a relatively new concept that has gained interest in the "smart grid" framework. Although being part of the widely acknowledged concept of smart systems, it still lacks a common accepted definition and a uniform understanding. The lack of international uniformity for the requirements and properties of an energy flexible building leads to numerous definitions that are being developed in parallel. This inconsistency is even more pronounced for the quantification methodologies.

As building engineers are often not familiar with all technical aspects of energy networks engineering, and vice versa, the use of flexibility indicators that are easy to understand by both parties can support interaction. In order to create this common understanding of energy flexibility in buildings, the objectives of this work are the following: i) to review existing definitions of the "energy flexible building" concept (Section 2); ii) to survey existing methodologies for quantifying the aforementioned energy flexibility (Section 3); iii) to apply the reviewed quantification methodologies to a case study (Section 4). Using this applied review, this paper aims to assess the applicability, benefits and drawbacks of each quantification methodology in the context of thermal storage in dwellings. As such, the conclusions of the conducted analysis (Section 5) are a first step to bring out the key properties found among existing definitions and to support the development of a harmonized communication on energy flexible buildings between the interested parties, such as building and energy system designers and operators, aggregators and governments.

2. Terminology and definitions reported in the literature

With growing electrification of the energy demand and increasing share of renewable energy sources in the local distribution network, the ability to manipulate domestic demand in order to mitigate or solve operational bottlenecks of the energy system became a research question of many publications. In this context, modulation of building loads can be used to e.g. reduce the energy demand at peak periods (peak shaving), shift the energy consumption from high-cost periods to low-cost periods (load shifting), increase energy use during off-peak times (valley filling) or minimize curtailment time. Different components of a building structure and HVAC system can be activated to deliver this flexibility. The adjustability/flexibility of the heating and cooling system has been the subject of many studies. Hewitt [13] has illustrated on the example from UK and Ireland that heat pumps and hot water storage together with sufficient tariff system can significantly contribute to integration of wind power into the electricity network. Arteconi et al. [14] have presented different thermal energy storage (TES) systems within the building, which can be activated to shift electrical loads in time and thus become powerful instrument of the DSM strategies. In their later study [15], the authors have analyzed the flexibility potential of the TES systems coupled with a heat pump delivering heat to either radiators or underfloor heating in a residential house in UK. Hedegaard et al. [16] have illustrated with the example of the Danish energy system that individual heat pumps in combination of the passive heat storage, i.e. building thermal mass, are an important step in cost-effective integration of wind power. A number of studies have shown that the structural thermal mass can be easily activated and utilized for flexibility purpose, e.g. in both old and new residential buildings [17,18] and in non-residential buildings [19,20]. Much of the research on thermal mass utilization has been describing different control strategies that can be applied to maximize the building's and/or the smart grid's benefits [21–24]. For example, it is demonstrated in a variety of studies that smart operation of the heat pumps [25] (e.g. with frequency control [26] or with use of model predictive control (MPC) [27]) can contribute to limit the peak power demands of the building and to maximize the self-consumption of the locally produced electricity [28,29].

In addition to literature focusing on thermal loads, different studies demonstrate how much flexibility can be achieved by adapting the time of use of plug loads, such as washing machines, dishwashers and tumble dryers [30,31], by application of an optimal charging schedule of electric vehicles [32,33] or by controlling and varying temperature between the cooling units of a commercial multi-zone refrigeration system [34]. Few publications have studied the effect of simultaneous utilization of more than one DSM strategy, e.g. PV panels in combination with electric vehicles, heat pump, plug loads, storage (battery and thermal mass) [35,36] or PV panels with air-water heat pumps in a zero energy building [37].

In general, these studies investigate the impact of different DSM strategies either on the building level, (e.g. the occupants thermal comfort or energy and/or cost savings by increasing PV self-consumption) or on the energy infrastructure level (e.g. peak shaving, load shifting, valley filling or mitigation of production losses). A large share of the identified papers do not explicitly define or focus on the concept of energy flexibility, yet deal with the development of control strategies and algorithms for specific case studies.

Therefore, in order to synthetize the definitions about energy flexibility or energy flexible buildings found in the literature, Table 1 gives an overview of the typical focus points that were found in the respective definitions. Thereby, based on the analysis of the reviewed literature, the focus points in definitions were grouped into 5 categories. The first category groups definitions focusing on the energy infrastructure context. These studies generally specify an energy grid context, e.g. "*to improve the performance of the electricity grid*" [19] or "*to compensate power imbalances in the grid*" [22]. In the second category, studies that explicitly mention the electricity grid are considered, which is found to be the majority of studies. Although multiple opportunities exist as incentive for energy flexibility, the third category groups studies that explicitly use energy price as a means to activate energy flexibility. The fourth category includes studies that also take into account poten-

Table 1
Focus points addressed when defining energy flexible buildings in literature.

Reference	Identified definitions and introductions to the concept of energy flexibility	Topics included in definition's body					
		Time/duration of the change	energy infrastructure context	focus on electricity	energy price	possibility of compromising other building performances	systems interaction
Hewitt [13]	"…the concept of using our building stock to effectively store energy for a number of hours prior to use is available…There are a number of methods available to balance the electricity network in times of high wind energy availability. It has been illustrated that the buildings themselves have some ability …. "	x	x	x			
Hedegaard et al. [16]	"flexible technologies such as large heat pumps, electric boilers, and heat storages in (combined heat and power) CHP systems, and electric vehicles can play a significant role in facilitating the integration of wind power… As such, ground heat pumps and air/water heat pumps can be operated flexibly by storing heat in the central heating system and in the construction.		x				x
Le Dréau et al. [17]	"This (flexibility) factor illustrates the ability to shift the energy use from high to low price periods."	x			x	x	
Reynders et al. [18]	"… short-term flexibility is shown to shift the electricity use for heating without jeopardizing thermal comfort."		x			x	
Xue et al. [19]	"Buildings can help improving energy performance of an electrical grid (…). However, characterization of power demand alteration potentials of buildings and their collective effect (…)."		x	x			
Arteconi et al. [20]	"From the utility point of view, TABS represent flexible energy demand systems because they allow a significant load control without requesting for particular design specifications on the original systems."		x				x
Oldewurtel et al. [22]	"… price information and economic incentive for end-consumers to react accordingly. This creates an important feedback in the system, acting against both peak grid loading and peak electricity demand, as grid-friendly consumer behaviour is rewarded."			x	x		
Tahersima et al. [23]	"… to deviate power consumption of the heat pump from its optimal value, in order to compensate power imbalances in the grid. The heating systems could be forced to consume energy, i.e. storing it in heat buffers when there is a power surplus in the grid; and be prevented from using power, in case of power shortage.	x	x			x	x
Hong et al. [24]	"to maximize the time window within which the heat pump operating time could be shifted without significantly affecting comfort or the hot water supply temperatures to the end-user"	x		x		x	
Kim et al. [26]	"Additionally, the significant energy storage capacity inherent in building structures allows buildings to be exploited as distributed energy resources, providing demand-side flexibility in electrical grids. In particular, the flexibility provided by the building's thermal inertia can be achieved via ancillary services of heating, ventilating, and air-conditioning (HVAC) systems."			x			x

(*continued on next page*)

Table 1 (*continued*)

Reference	Identified definitions and introductions to the concept of energy flexibility	Topics included in definition's body					
		Time/duration of the change	energy infrastructure context	focus on electricity	energy price	possibility of compromising other building performances	systems interaction
Halvgaard et al. [27]	In this paper, we use heat pumps for heating residential buildings with a floor heating system. We use the thermal capacity of the building to shift the energy consumption to periods with low electricity prices. In this way the heating system of the house becomes a flexible power consumer in the Smart Grid.	x		x			x
Fischer et al. [29]	"The most common parameters (…) characterizing the flexibility of a system are the amount of power change, duration of the change, rate of change, response time, shifted load and maximal hours of load advance. (…) it is suggested in this work that recovery time should also be included to the list of flexibility parameters, to know when a pool is ready to be used again by the operator after being used once."	x		x			
Dar et al. [37]	Two leading scenarios in this aspect are identified: (i) where the energy system is promoting the building's own energy supply security, and (ii) where the building's energy system is actively participating to reduce stress on the grid. The gap between these two scenarios could be seen as the flexibility that an all-electric Net-ZEB could offer to the grid.			x			
Six et al. [44]	"…flexibility, defined as the ability to shift the consumption of a certain amount of electrical power in time (number of hours or kWh). The flexibility of a heat pump in smart or intelligent grids can be seen in two different ways. Delay of (a part of) the electricity consumption of the heat pump over a limited period, although there is a demand for space heating and/or domestic hot water … Forced electricity consumption of the heat pump over a certain period although there is no or low demand for space heating and/or domestic hot water…"	x	x	x			x
Nuytten et al. [45]	"The flexibility of the installation allows for changes in the energy use over time and is a valuable property when the supply of energy has an increasingly intermittent character"	x	x				
D'hulst et al. [46]	"For such consumption changes to be acceptable, they may not impact the correct functioning of the appliances, nor reduce the comfort level of the users. This is what defines 'the flexibility' of the appliances: the power increases and decreases that are possible within these functional and comfort limits, combined with how long the changes can be sustained."	x				x	x
Linear [48]	"…the electricity consumption of several appliances is shifted to a more beneficial moment in time."	x		x			x
Šikšnys et al. [49]	"Flex-object is a multidimensional object capturing two aspects: (1) a time flexibility interval and (2) an amount profile with a sequence of consecutive slices, each defined by minimum and maximum bounds of the amount."	x					

tial (negative) secondary effects of activating energy flexibility (e.g. the impact on thermal comfort). Finally, the fifth category groups studies focusing on specific systems interacting with the building, such as studies that focus on heat pumps or electric boilers.

Although multiple definitions cover more than one of the identified focus points, Table 1 shows that none of the papers gives a comprehensive definition to encompass all properties. Nevertheless, all definitions are built upon the basic concept that energy flexibility represents the ability of a building to adapt its energy consumption to provide specific services (e.g. grid support). The ongoing IEA EBC Annex 67 project "Energy Flexible Buildings" [38] proposes a more comprehensive definition, which elaborates on the following: "*Energy Flexibility of a building is the ability to manage its demand and generation according to local climate conditions, user needs and grid requirements. Energy Flexibility of buildings will thus allow for demand side management/load control and thereby demand response based on the requirements of the surrounding grids.*" Other possible definitions are provided by locally organized workshops stating that flexibility is a service that can be provided by a customer (building). For example in the Energy Flexibility Workshop, CITIES project [39] energy flexibility was defined as: "*an energy system service provided by a customer. For each energy carrier: the amount of power and energy within a given period that can be changed on request – either permanently (fuel shifted) or temporary (time shifted).*" The definition brings up a new aspect of energy flexible buildings, namely fuel shifting. Nonetheless, most of the exiting literature was found to focus on the electricity grid (Category 2 in Table 1) and how the flexibility provided by buildings can contribute to e.g. mitigate the large voltage deviations, phase unbalances or overloading of the current infrastructure [40–43]. The interest from electricity grids stems from the high penetration of renewable energy sources in electricity production and the "smart grids" development. However, the fuel shift may become more important especially for the countries with heterogeneous energy infrastructure, i.e. district heating, power grid, gas network. Hence, the concept of energy flexibility could also be extended to multi-carrier energy systems. For the remainder of the article though, the definition of IEA EBC Annex 67 is followed since it is formal and comprehensive, placing the building in a central role.

3. Existing methodologies to quantify energy flexibility

Two approaches to analyze energy flexible buildings were identified in the literature. In the first approach, energy flexibility is quantified by evaluating the impact of applying a specific control strategy to a specific case study. These case studies assume a specific market and/or technical system and evaluate the possible contribution of energy flexibility in this context. The actual impact of energy flexibility is quantified indirectly by analyzing, for instance, the operational cost savings, reduction in CO_2-emission or peak power reductions. There are numerous studies of this type and they are mostly oriented towards design and evaluation of innovative control strategies [15–25]. Although most of these studies evaluate the controller performance (e.g. in CO_2-emission reductions or financial savings), some studies propose specific flexibility indicators. For instance, Le Dréau and Heiselberg [17] developed a flexibility factor that measures the ability of a building to shift its heating energy use from high to low price periods using energy prices information.

While studies following the first approach clearly demonstrate the potential for using energy flexibility, this paper focuses on a second approach, whereby a direct prediction of the energy flexibility is targeted. This second approach enables entities to have a direct quantification of the energy flexibility that a building can offer. By starting from the building's ability to adapt its demand, this type of energy flexibility indicators can be used to support both building and grid design, as well as resource planning in the energy network. Thereby, the rationale for quantifying this intrinsic flexibility is that it can be quantified on the level of individual technologies. Hence, it is a way to decouple the analysis of demand side technologies and the market operation. As building engineers are often not familiar with all technical aspects of energy networks and vice versa, the use of flexibility indicators that are easy to understand by both parties can support interaction. Therefore, the literature review in this paper focusses on identifying and contrasting methodologies that provide a bottom-up and direct predictive quantification of the available energy flexibility. Table 2 summarizes the differences between the identified studies.

Sections 3.1–3.6 elaborate on the reviewed methodologies explaining their theoretical background. For the technical implementation and detailed examples using these methodologies, the reader is referred to the corresponding articles. The main theoretical differences and similarities between the methodologies are discussed in Section 3.7. Furthermore, Section 4 gives an extensive, applied evaluation of the identified methodologies using a common case study.

3.1. Methodology A

Six et al. [44] first proposed a methodology to quantify energy flexibility that was extended to the application of thermal systems in buildings by Nuytten et al. [45]. It was applied to quantify the energy flexibility of residential heat pumps coupled to a water storage tank [44] and the energy flexibility of Combined Heat and Power (CHP) systems coupled to thermal storage [45].

The methodology interprets energy flexibility as the availability of multiple possibilities to get a system from energy state A at time $t = 0$ to a state B at time $t = t_{end}$. In that context, the authors predict the "flexibility profile", which represents the union of different energy paths that can be followed to reach a specific state at the end of the prediction horizon while subjecting the systems to normal operation boundaries (i.e. technical and comfort constraints). Thereby, future demand and boundary conditions (e.g. climate) are considered. While intermediate energy paths may be possible, Methodology A derives the flexibility profile by two extreme energy profiles that represent the envelope of the flexibility profile as shown in Fig. 1. As defined in [45], the flexibility profile of the CHP system combined with thermal energy storage is characterized by the minimum (MIN_t) and maximum (MAX_t) boundaries of the flexibility profile, which correspond to the accumulated energy profiles assuming that the storage tank is kept respectively at minimum and maximum state of charge (SOC), respectively.

When Q_t (or its prediction) is known for the prediction horizon, the MIN_t and MAX_t profiles are calculated as:

$$MIN_{t+1} = MIN_t + \Gamma_{MIN}(t)P\Delta t + E_{AUX,t} \tag{1.a}$$

$$MAX_{t+1} = MAX_t + \Gamma_{MAX}(t)P\Delta t + E_{AUX,t} \tag{1.b}$$

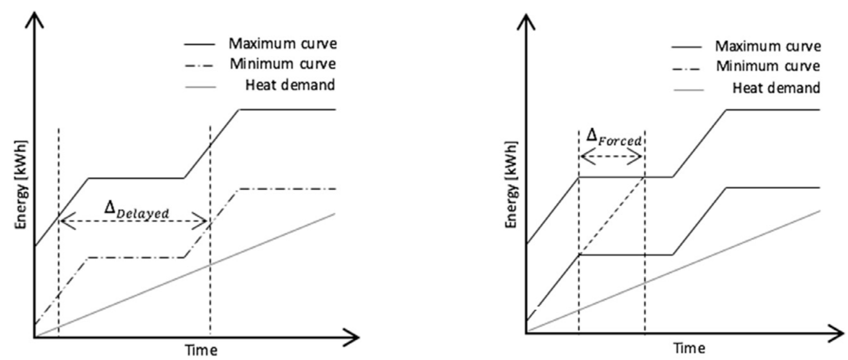
$$\Gamma_{MIN(t)} = \begin{cases} 1 \ if \ Q_{t+1} - Q_t > E_{buffer,t} \\ 0 \ if \ Q_{t+1} - Q_t \le E_{buffer,t} \end{cases} \tag{1.c}$$

$$\Gamma_{MAX}(t) = \begin{cases} 1 \ if \ Q_{t+1} - Q_t \ge P\Delta t + E_{free,t} \\ 0 \ if \ Q_{t+1} - Q_t < P\Delta t + E_{free,t} \end{cases} \tag{1.d}$$

Whereby, according to Nuytten et al. [45], P is the thermal power of the CHP and Δt is the model time step. $E_{AUX,\ t}$ is the heat production from auxiliary heating, $E_{buffer,\ t}$ is the remaining energy inside the storage tank, $E_{free,\ t}$ is the remaining storage capacity in the storage tank. $\Gamma_{MIN(t)}$ and $\Gamma_{MAX(t)}$ are indicator functions describing the operation of the CHP system in respectively the minimal and maximal SOC scenarios. Fig. 1 presents a conceptual example

Table 2
Bottom-up energy flexibility quantification methodologies.

Methodology	Authors	Quantification	Case study
A	Six et al. [44] Nuytten et al. [45]	Flexibility quantified by the number of hours the respective energy consumption can be delayed or anticipated.	i) the energy flexibility of a residential heat pumps combined with thermal energy storage [44]; and ii) the energy flexibility of a CHP system with thermal energy storage [45]
B	D'Hulst et al. [46]	Flexibility quantified by the power increases or decreases, combined with how long these changes can be sustained.	Based on measured data, D'Hulst et al. quantified the flexibility offered by five different types of domestic electrical devices.
C	Stinner et al. [46]	Flexibility quantified by temporal flexibility, power flexibility and energy flexibility.	Heating system with thermal storage tank that is used for space heating and domestic hot water.
D	De Coninck and Helsen [50,51]	Flexibility quantified by cost functions, which comprise the amount of energy that can be shifted at a specific time and the associated cost compared to a reference plan	Heating systems that use buildings' thermal mass.
E	Oldewurtel et al. [52]	Flexibility quantified by efficiency curves, depicting the maximum power increase or decrease against the power shifting efficiency.	Heating systems that use buildings' thermal mass.
F	Reynders et al. [56]	Flexibility quantified by the available storage capacity, the storage efficiency and the power shifting potential	Heating systems that use buildings' thermal mass.



(a) Delayed flexibility (b) Forced flexibility

Fig. 1. Energy flexibility profiles of a Combined Heat and Power (CHP) system combined with thermal energy storage [45].

where the referred boundaries are represented together with the accumulated energy demand (Q_t).

Starting from the flexibility profiles (MIN_t and MAX_t), the researchers quantify energy flexibility by the number of hours the energy system can be delayed or forced to operate: i) Forced Operation Flexibility (Δ_{Forced}); and ii) Delayed Operation Flexibility (Δ_{Delayed}). The former expresses the amount of time (Δ_{Forced}) the CHP can be forced to operate while the excess heat produced is stored for later use. The latter expresses the amount of time (Δ_{Delayed}) the operation of the CHP can be delayed while the energy demand is met by the storage tank. Hence, Δ_{Delayed} is represented graphically as the horizontal difference between MAX_t and MIN_t (Fig. 1).

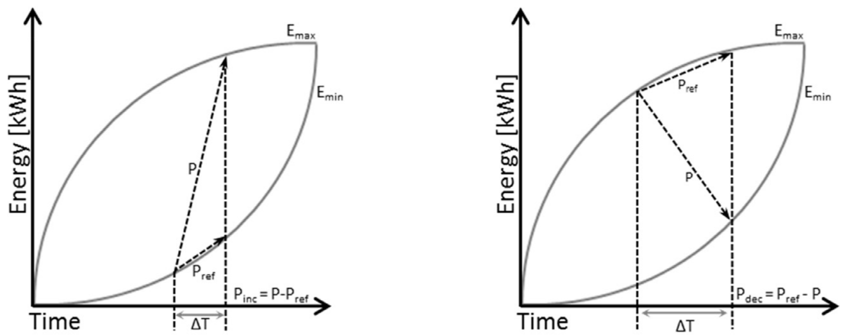
3.2. Methodology B

In contrast to Methodology A, which characterizes the temporal aspect of energy flexibility, D' Hulst et al. [46] developed a generic methodology that quantifies energy flexibility as the possible power increase (P_{inc}) or decrease (P_{dec}) within functional and comfort limits, combined with how long these changes can be sustained. The methodology can be applied to measure the energy flexibility offered by different types of devices and to aggregate the respective results, given that the initial and the final states of the system are specified. Under the scope of the LINEAR project, they quantified the flexibility offered by five different types of electrical devices (washing machines, dishwashers, tumble dryers, electric hot water buffers and electric vehicles) based on measured data.

The concept of the methodology is shown in Fig. 2 and starts with the calculation of two cumulated energy profiles similar to those of Methodology A. E_{max} and E_{min} represent the energy consumption profile when the energy consumption is started respectively as early as possible and as late as possible. The E_{min} and E_{max} profiles are thus considered as two extreme paths to get the system from state A at time $t = 0$ to state B at time $t = t_{end}$. Based on these profiles, the energy flexibility is expressed by the possible increase (P_{inc}) or decrease (P_{dec}) during an interval ΔT. These values are obtained by comparing the power P when flexibility is asked to the reference power P_{ref}, which represents the appliance's power consumption when the energy flexibility usage is started. When the flexibility of the appliance is used to increase or decrease the power consumption during a time interval ΔT, P is respectively the maximal or minimal resulting power consumption of the appliance that does not violate comfort or technical constraints and is obtained by finding the intersections. A mathematical description of the methodology, when applied to the case of thermal storage, is given in Section 4.2.

3.3. Methodology C

In line with Methodologies A and B, Stinner et al. [47] present a methodology based on temporal flexibility (forced and delayed operation times), power flexibility and energy flexibility. While these indicators have a similar interpretation to those obtained



(a) Power increase (b) Power decrease

Fig. 2. Conceptual representation of the quantification methodology. (a) Flexibility used to increase the power consumption. (b) Flexibility used to decrease the power consumption [46].

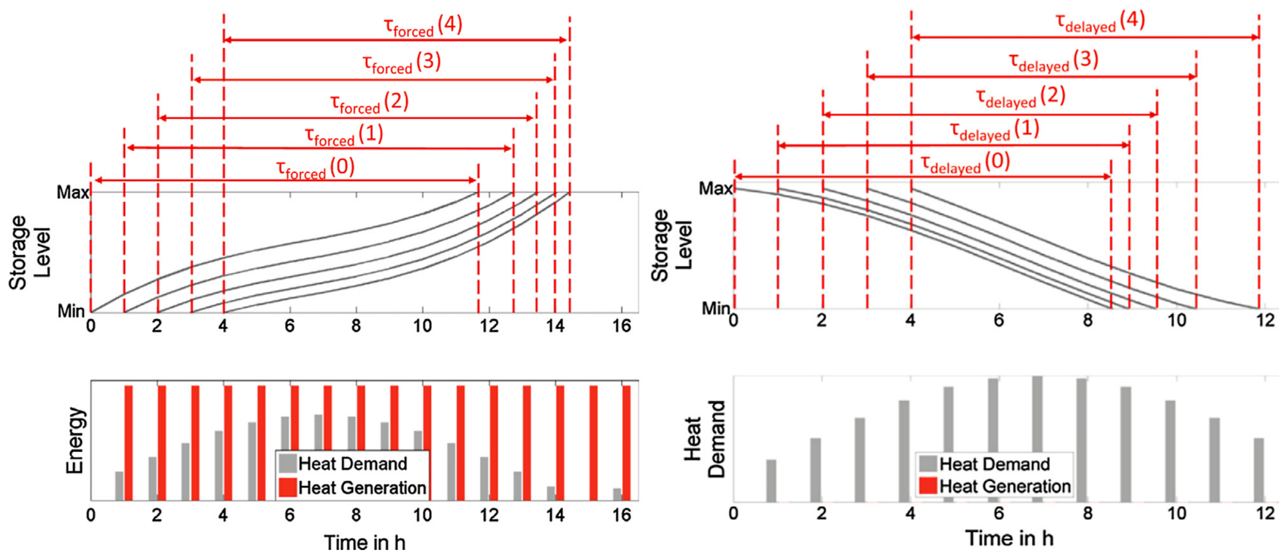


Fig. 3. Schematic representation of forced operation time (left) and delayed operation time (right) according to methodology C [41].

from Methodologies A and B, the quantification process differs. Most importantly, it does not start from cumulated energy profiles, but from the simulation of specific events. More precisely, Stinner et al. start the quantification of the energy flexibility by simulating 2 events whereby a completely charged storage tank (SOC = 1) is depleted (SOC = 0) and vice versa. Based on these 2 simulations, they first calculate the forced (τ_{forced}) and delayed operation times ($\tau_{delayed}$) by respectively analyzing the time it takes to charge a water storage tank from the minimum (SOC = 0) to the maximum (SOC = 1) tank temperature and to deplete the capacity from its maximum to its minimum SOC.

As $\tau_{delayed}$ and τ_{forced} depend upon the demand for hot water and the boundary conditions of the storage tank (i.e. surrounding temperature), these 2 simulations are repeated at each time step. This process is schematized in the upper plots of Fig. 3 where the SOC of the tank is shown for the heating up (left) and cooling down (right) events. The red arrows above the graph represent the resulting forced (left) and delayed (right) operation times for different start times.

In addition to the temporal aspect of energy flexibility, Stinner et al. quantify the power flexibility (ΔP) and energy flexibility (ΔE) by comparing the power demand during normal (non-flexible) operation to the increase or decrease in power during the forced or delayed operation period:

$$\Delta P_{forced}(t,\ \xi - t) = P_{max}(\xi) - P_{ref}(\xi)\ \xi | t \le \xi \le t + \tau_{forced}(t) \tag{2.a}$$

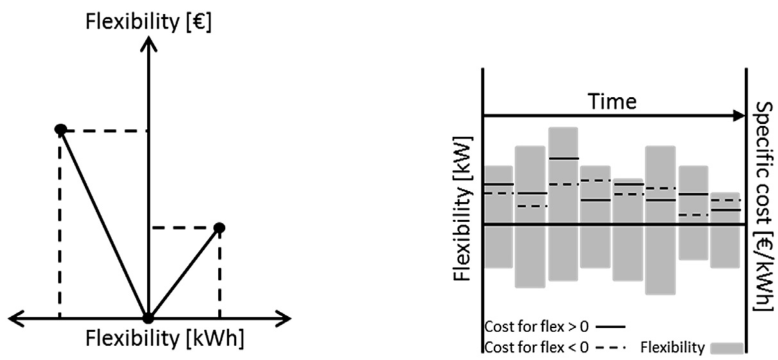
$$\Delta P_{delayed}(t,\ \xi - t) = P_{ref}(\xi) - P_{min}(\xi)\ \xi | t \le \xi \le t + \tau_{delayed}(t) \tag{2.b}$$

$$\Delta E_{forced}(t) = \int_0^{\tau_{forced}(t)} \Delta P_{forced}(t,\ \xi) d\xi \tag{2.c}$$

$$\Delta E_{delayed}(t) = \int_0^{\tau_{delayed}(t)} \Delta P_{delayed}(t,\ \xi) d\xi \tag{2.d}$$

with P_{ref} the reference demand and ξ an integration variable. Note that using the formulations in Eq. (2) the power and energy flexibility at each point in time t are obtained as profiles over an integration horizon equal to the $\tau_{forced}(t)$ or $\tau_{delayed}(t)$. In their work, Stinner et al. [47] propose alternative representations using for instance the average power to communicate the results.

The authors demonstrate the methodology by studying the energy flexibility of a hot water storage tank used for space heating and domestic hot water. Both combined heat and power (CHP) and heat pumps (HP) are compared. In addition to the impact of the system design on the obtained energy flexibility, the authors emphasize that flexibility should be evaluated by taking into account the combined temporal and power (or energy) flexibility. Moreover, they emphasize that the available flexibility varies over time. By quantifying the forced or delayed operation from an empty or



(a) Single cost curve (b) Energy flexibility profile

Fig. 4. Energy flexibility quantification by cost curves. a) single cost curve. b) time dependent energy flexibility profile [51].

completely filled storage, respectively, they argue that the methodology quantifies an upper bound for the available flexibility.

3.4. Methodology D

De Coninck and Helsen developed a methodology based on the evaluation of three optimal control problems that quantifies energy flexibility as the amount of energy that can be activated over a specific duration in relation to the associated energy cost [50,51]. As such, they represent energy flexibility by flexibility "cost curves" as shown in Fig. 4(a). They consist of information regarding (i) the amount of energy (ΔE) that can be shifted to or from a specific time slot and (ii) the associated local cost (ΔC) when compared to a reference plan. Note that the implementation of this optimal control formulation is detailed further in Section 4.2.

The underlying assumption in this methodology is that energy flexibility is a deviation from a reference profile due to an external incentive. As a reference, the authors assume that without an external incentive to activate the energy flexibility of a building, an optimal control strategy will try to minimize the energy cost of the building for a reference price profile. Next, to calculate each pair of energy change and associated cost, 2 additional optimal control problems need to be solved. These include an additional cost term that respectively maximizes or minimizes the energy consumption during the period $[t : t + l_{ADR}]$ to quantify the upward and downward flexibility at time t. The resulting change in energy consumption during the period $[t : t + l_{ADR}]$ is then equal to ΔE.

Since the reference plan is the result of an optimal control problem that minimizes the energy costs over a prediction horizon while preserving the building's indoor temperature within the comfort boundaries and without considering an 'external' demand for energy flexibility. Using this optimal reference plan, all control actions that use the system's flexibility to deviate the energy consumption from the reference plan result in an additional cost. Hence, the cost for activating the flexible load (ΔC) is given by an increased value of the resulting cost function evaluated for the original (base load) price profile. The system can thus offer a certain flexible amount of energy at any point in time at a corresponding cost. Different curves can be aggregated to quantify the flexibility provided by a system consisting of several subsystems. Additionally, if a cost curve is calculated at each time step, then the resulting information can be aggregated to obtain a time dependent energy flexibility profile as shown in the illustrative example of Fig. 4(b). It is important to note that if flexibility is used at a specific point in time, the cost curves should be revaluated, since this will affect the availability of flexibility at future time points.

3.5. Methodology E

Without specifically using the term energy flexibility, Oldewurtel et al. [52] developed a methodology to quantify the energy flexibility potential. They defined the energy shifting potential ΔP as the amount of power that can be increased or decreased during a specific amount of time compared to the baseline power consumption. As for Methodology D, the authors rely on a series of model predictive control problems whereby the energy cost is minimized over a time horizon using a price profile s. As a reference scenario, a constant price profile s_0 is used as shown in Fig. 5 (left), minimizing the energy use over the time horizon. The available upward and downward flexibility during a specific amount of time is quantified by respectively decreasing or increasing the price s during these events as shown in Fig. 5 (left), without allowing any anticipation for such events by pre-heating or pre-cooling the building. As acknowledged by De Coninck [51], this optimal control formulation is equivalent to that presented in Methodology D. In contrast to Methodology D, the obtained results are visualized using efficiency curves where the maximum possible power increase or decrease during a time interval is depicted against the power shifting efficiency (denoted as ΔE). This power shifting efficiency refers to the ratio between the amplitude of the induced change in power consumption during the flexibility event and the additional energy consumption of the system over a test period T. Δ is thus also a measure of the cost (increase in energy use) of activating energy flexibility. An illustrative example of an efficiency curve is presented in Fig. 5(right), where the maximum possible power increase or decrease during a time interval is depicted against the power shifting efficiency.

3.6. Methodology F

In line with Heussen et al. [53], Reynders et al. [54,55] presented a quantification methodology for energy flexibility by representing a demand response technology as a virtual storage capacity. The researchers characterized the properties of this virtual storage capacity and hence the characteristics of energy flexibility by quantifying the available storage capacity (C_{ADR}), the storage efficiency (η_{ADR}) and the power shifting capability (PSC). C_{ADR} is defined as the maximum amount of energy that can be added to the virtual storage capacity during the duration of a specific flexibility event (ADR event). The storage efficiency then quantifies the energy losses associated to the activation of the storage capacity. Thereby, as for Methodology D, the authors assume that a reference control would try to minimize the energy consumption of a building and hence activation of the energy flexibility would lead to an increase of the total energy use over the whole quantification

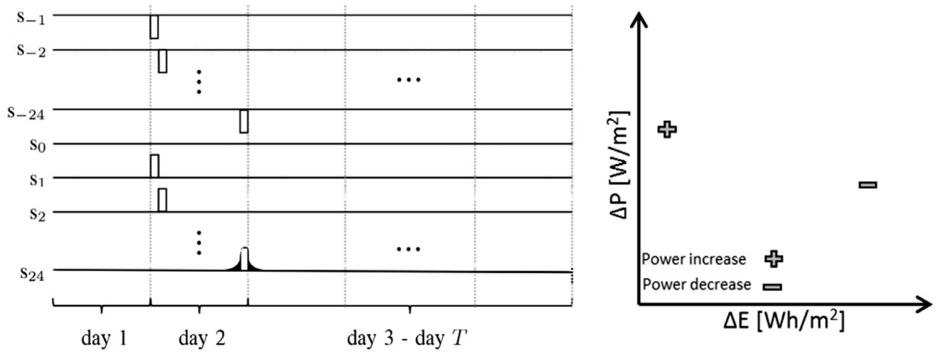


Fig. 5. Qualitative overview of the price signals *s* with upward and downward price step functions to induce demand shift (left) and example of an resulting efficiency curve (right) according to Methodology E [52].

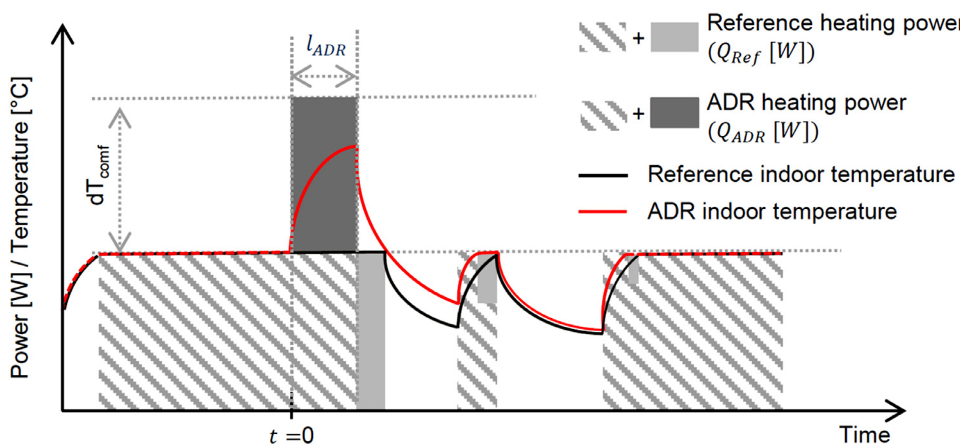


Fig. 6. Schematic representation of the quantification methodology for C_{ADR} and η_{ADR} as defined in [54].

period. Both characteristics are quantified for a specific flexibility event, or ADR event, which is defined as a limited period in time (duration l_{ADR}) during which the temperature set point is increased by dT_{comf}. A schematic representation of the event is given in Fig. 6. C_{ADR} and η_{ADR} are calculated by comparing the power profile for the simulated ADR event (Q_{ADR}) to the reference profile Q_{Ref}

In addition to C_{ADR} and η_{ADR}, the PSC is defined to capture the relationship between the (i) level to which a system can deviate its power demand (or output) from the reference scenario and (ii) how long this shift can be maintained without affecting normal behavior. The PSC is obtained by simulating the temperature profile of a building whereby from $t = 0$ the heating power is changed with ΔP compared to the reference profile. The methodology then quantifies the duration Δt until the comfort boundaries are violated. The PSC is then represented by the combination of ΔP and Δt.

Reynders [56] applied this methodology to analyze the relationship between the demand response potential of structural thermal energy storage and building design parameters. This researcher emphasizes that all indicators are strongly affected by the dynamic boundary conditions and that the energy flexibility of thermal mass itself is thus a dynamic property. Moreover, the authors acknowledge the link with the methodologies of De Coninck and Helsen [50,51] and Oldewurtel et al. [52] as they quantify the amount of energy and power that can be shifted during a specific time period and its associated cost.

3.7. Discussion

This section discusses the differences and similarities identified based on the description of the methodologies presented in Sections 3.1–3.6. As highlighted in this discussion, differences are often subtle and significant overlap is identified between the characteristics that are defined to quantify energy flexibility. Therefore, the high-level and theoretical evaluation presented in this section serves to identify research questions that will be tackled in the case study of Section 4.

Note that Methodologies A and B have not explicitly been developed to quantify the energy flexibility using structural thermal storage. This is reflected by how these two methodologies quantify energy flexibility by analyzing the different paths that can be followed to get a system from state 1 to state 2. In these two methodologies, the quantification is bounded by a specific time when state 2 must be reached (e.g. the storage tank must be fully charged at 8 AM). Nonetheless, it can be argued that for a continuous process, such as space-heating, the final state is not well defined, as specific charging periods are typically not defined. In contrast, the system tries to keep the building within comfort ranges at all times. Hence, it is not clear how to define the state in which the thermal mass needs to be at the end of the optimization horizon (T_{end}). Therefore, two scenarios are compared in this paper.

Firstly, the quantification methodologies can be divided into 2 main groups. On the one hand, Methodologies A and B calculate their flexibility characteristics from cumulated energy profiles for two extreme scenarios. In the case of thermal storage, these scenarios correspond to a minimum SOC and maximum SOC scenario. Both methodologies thereby assume that the difference between the cumulated profiles at time t corresponds to the energy stored within the buffer at time t and that this energy can be completely recovered. In other words, they assume storage losses can be ignored. Hence, it can be expected that the obtained flexibility characteristics may lose interpretability for systems with high thermal losses, such as the thermal mass of a building. Moreover, the energy paths are defined as scenarios to get a system from state 1 to state 2. This implies that the final state (state 2) must be reached at a specific time (e.g. the storage tank must be fully charged at 8 AM). Nonetheless, it can be argued that for a continuous process, such as space-heating, the final state is not well defined, as specific charging periods are typically not defined. In contrast, the system tries to keep the building within comfort ranges at all times. Hence, it is not clear how to define the state in which the thermal mass needs to be at the end of the optimization horizon (T_{end}).

In contrast, Methodologies C–F quantify the flexibility characteristics based on simulations of specific flexibility events. The case study in Section 4 will be used to analyze whether these event-based quantification allows preserving interpretability for systems with multiple time constants and relatively high thermal losses. Note that, for the event-based quantification a deviation can be made between methodologies that rely on optimal control (D and E) and on rule-based control (C and F). The benefit of the optimal control formulation is also analyzed in Section 4.

Secondly, analysis of the six identified methodologies shows that three aspects return when characterizing energy flexibility, i.e. time, amplitude and associated cost. Methodologies A and C focus on the temporal flexibility by quantifying the forced or delayed operation as the time needed to fill or deplete a storage capacity. Methodology A quantifies the temporal flexibility from the cumulated energy profiles, while Methodology C simulates heating up and cooling down events at each time step. Thereby, the system is forced to operate in maximum or minimum power, respectively. Methodologies B and F (PSC) additionally try to capture the relation between the deviation in power and the time this deviation can be maintained before comfort constraints are violated. Thereby, it should be noted that Methodology B captures this relation in an inverse formulation using the duration as independent variable. The corresponding power is then obtained directly as dependent variable from the cumulated energy profiles. In Methodologies D, E and F (C_{ADR} and η_{ADR}), the temporal aspect is implicitly included as these methodologies quantify the flexibility during specific flexibility intervals.

The amplitude of change is either quantified in terms of power (Methodologies B, C, E and F) or energy (Methodologies C, D and F). Nonetheless, as all methodologies explicitly or implicitly quantify the amplitude in relation to the duration of the change, power and energy are interchangeable. Additionally, significant differences can be expected in the power profiles obtained for the optimal control and rule-based control formulations. These differences are further analyzed in the case study of Section 4.

As a third characteristic, Methodologies D, E and F formulate a quantification of the cost of activating energy flexibility. This cost is based on the assumption that the building, without an external demand for flexibility, would optimize its own consumption in order to reduce costs. Hence, when providing flexibility the building deviates from this optimal profile generating a cost for energy flexibility. Methodology D deduces this cost from analyzing the cost function of the optimal control problem. For a flat tariff as reference price, the cost of flexibility would correspond to the increase in energy use. Hence, for the flat tariff reference price, the outcome of Methodology D and F should be highly comparable. This is further analyzed in Section 4.

Finally, all methodologies clarify that they only provide a prediction of the available energy flexibility as function of time. They acknowledge that this availability will depend upon dynamic boundary conditions and will thus vary in time. Moreover, in the case of Methodologies D, E and F, the quantification starts from a system in a certain state at time $t=0$ and assume a certain reference energy demand over the prediction horizon. Consequently, when energy flexibility is used at a specific moment in time, the state of the system will change, and the quantification of the available flexibility of the following periods should be re-evaluated. In contrast, Methodology A, B and C quantifies flexibility starting from a storage capacity which is either empty or fully charged. Consequently, the predicted flexibility does not depend on the actual state of the system and hence only depends on the boundary conditions. As such, the obtained values only give the absolute upper bound of the flexibility that a system may provide. For Methodologies D – F, an upper bound of the available flexibility is also obtained but it is corrected for the current state of the system.

4. Evaluation of quantification methodologies

While the analysis of the methodologies summarized in Section 3.7 discusses the differences and similarities between the methodologies based on their definitions, some important overlap in the description of the methodologies and the goals of the indicators was identified. In order to get a clear view on the - sometimes subtle - differences between the quantification methodologies, this section describes the application of the methodologies to a theoretical case study. This case study was part of a common exercise that is carried out in the framework of IEA EBC Annex 67 and consists of a detached single-zone building equipped with a simplified low-temperature radiator heating system coupled to a heat pump which only provides space heating. The energy flexibility is generated by thermal energy storage using the structural thermal mass of the building and a 250-liter domestic hot water tank.

The models and assumptions for the analysis of the thermal mass and the domestic hot water tank are summarized in Section 4.1. In Section 4.2, the specific implementation of the different quantification methodologies applied to the case study is presented. Therefore, the specific modeling steps and required assumptions needed to apply the quantification methodologies of Table 2 on this case study are highlighted. Finally, the results and comparison of the quantification methodologies are elaborated in Section 4.3. Note, thereby, that the goal of this analysis is not to give a detailed quantitative assessment of the energy flexibility of this case study building, but rather to use the case study in order to investigate to what extend physical phenomena associated to energy flexible buildings can be captured by the analyzed methods. In other words, a qualitative assessment of the quantification methods is envisioned.

4.1. Case study description

The building analyzed in this case study is based on the building description obtained from the TABULA project for a Belgian detached single family house built between 1990 and 2005. The building geometry and the steps taken to transfer the TABULA description to the dynamic reduced-order model are presented in detail in [56]. A graphical representation of the building is shown in Fig. 7a.

As explained further in Section 4.2, the application of all methodologies, except Methodology F, on the case of thermal mass in buildings requires the formulation of an optimal control problem. Therefore, the building and storage tank are modeled using a simplified, lumped-capacity model. The dynamic behavior of the building is modeled using a linear state-space model obtained from a RC-representation of the thermal dynamics using 4 thermal capacities as shown in Fig. 7b. The resulting model equations are

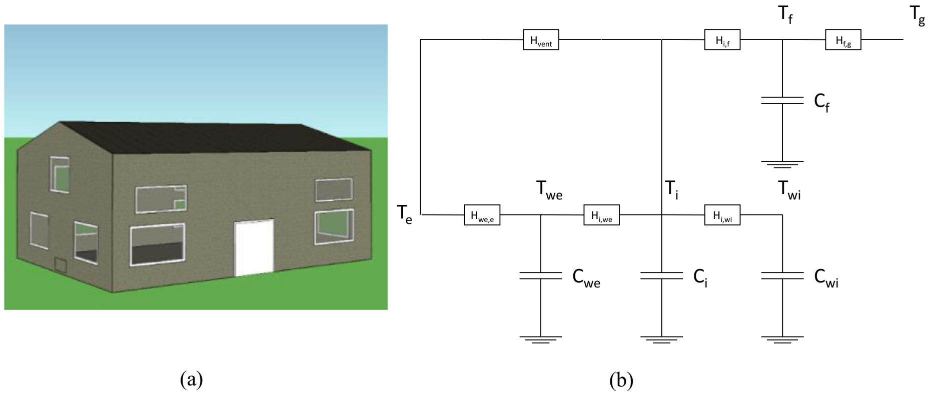


Fig. 7. Graphical representation of (a) the considered building and (b) the applied 4th order RC model given by Eq. (3).

given by:

$$\begin{bmatrix} \dot{T}_i \\ \dot{T}_{we} \\ \dot{T}_{wi} \\ \dot{T}_f \end{bmatrix} = A \begin{bmatrix} T_i \\ T_{we} \\ T_{wi} \\ T_f \end{bmatrix} + B \begin{bmatrix} T_e \\ T_g \\ Q_{sun} \\ Q_{int} \\ Q_h \end{bmatrix} \tag{3.a}$$

$$A = \begin{bmatrix} -\frac{H_{i,we}+H_{vent}+H_{i,wi}+H_{i,f}}{C_i} & \frac{H_{i,we}}{C_i} & \frac{H_{i,wi}}{C_i} & \frac{H_{i,f}}{C_i} \\ \frac{H_{i,we}}{C_{we}} & -\frac{(H_{i,we}+H_{we,e})}{C_{we}} & 0 & 0 \\ \frac{H_{i,wi}}{C_{wi}} & 0 & -\frac{H_{i,wi}}{C_{wi}} & 0 \\ \frac{H_{i,f}}{C_f} & 0 & 0 & -\frac{(H_{i,f}+H_{f,g})}{C_f} \end{bmatrix} \tag{3.b}$$

$$B = \begin{bmatrix} \frac{H_{vent}}{C_i} & 0 & \frac{abs_1}{C_i} & \frac{f_1}{C_i} & \frac{f_1}{C_i} \\ \frac{H_{we,e}}{C_{we}} & 0 & \frac{abs_2}{C_{we}} & \frac{f_2}{C_{we}} & \frac{f_2}{C_{we}} \\ 0 & 0 & \frac{abs_3}{C_{wi}} & \frac{f_3}{C_{wi}} & \frac{f_3}{C_{wi}} \\ 0 & \frac{H_{f,g}}{C_f} & \frac{abs_4}{C_f} & \frac{f_4}{C_f} & \frac{f_4}{C_f} \end{bmatrix} \tag{3.c}$$

$$Y = [1\ 0\ 0\ 0] \begin{bmatrix} T_i \\ T_{we} \\ T_{wi} \\ T_f \end{bmatrix} + [0\ 0\ 0\ 0\ 0] \begin{bmatrix} T_e \\ T_g \\ Q_{sun} \\ Q_{int} \\ Q_h \end{bmatrix} \tag{3.d}$$

C_i, C_{we}, C_{wi}, C_f are the thermal capacities of, respectively, the indoor air, the outer wall, the inner walls and the slab-on-ground floor at corresponding temperatures T_i, T_{we}, T_{wi} and T_f. The indoor temperature (T_i) is the only output, while the outdoor temperature (T_e), the ground temperature (T_g), the solar gains (Q_{sun}), the internal gains (Q_{int}) and the heating power (Q_h) are inputs. $H_{x,\,y}$ are the heat transfer coefficients between components x and y. Solar gains and other gains are distributed over the different states using, respectively, the absorption factors abs_i and distribution factors f_i. This model structure and parameter values are based on a grey-box modelling study described in [56] and summarized in Table 3. The models have been restructured to a discrete time formulation using a sample time of 15 min. The outdoor temperature and solar gains are taken from TMY climate data for Uccle (Belgium) while an occupant profile for the internal gains was generated using the stochastic occupant behavior toolbox StROBe [57].

The storage tank is assumed to be perfectly mixed and is therefore represented by a single state RC-model:

$$C_w \dot{T}_w = \frac{T_{amb} - T_w}{R} + Q_{dhw} - Q_{use} \tag{4}$$

Q_{use} is the enthalpy flow due to hot water consumption given as a model input and obtained from StROBe, R is the thermal resistance of the storage tank, C_w is the thermal capacity of the water volume, T_{amb} is the ambient temperature, which is assumed to be constant at 20 °C. T_w and Q_{dhw} are respectively the water temperature and the heating power. For the latter, as for space heating, only the net delivered heat is considered. Hence, a power limited, ideal heat source is assumed. The maximum thermal power of the system is 12.5 kW for space heating following the EN 12,831:2003 using an outdoor design temperature of −10 °C and 5 kW for domestic hot water. Both are assumed to work independently. The values for the model parameters in both the building and tank model are given in Table 3.

Note that the same model descriptions (Eq. 3 and 4) is used in all optimization and simulation cases to avoid discrepancies in the results for different quantification methodologies due to the use of different models.

4.2. Implementation of quantification methodologies

As described in Section 3, not all methodologies have been formulated explicitly for the case of structural thermal mass and/or thermal storage tanks. In the corresponding papers, Methodologies A, B and C were applied to heating systems coupled to thermal storage tanks whereby the thermal mass of the building is not used as a source of flexibility. Methodology B was however formulated in a generic way and has also been applied to quantify the flexibility of e.g. appliances. In this section, the implementations of the methodologies for application to the case study is presented. Thereby, some additional assumptions were needed to guarantee the applicability of the methodologies to both thermal storage in the thermal mass of buildings and in the hot water storage tanks.

As described in Section 3, Methodologies A and B quantify flexibility by considering two extreme energy profiles, called flexibility profiles. The first one minimizes the “state of charge” of the storage by charging the storage as late as possible. The second optimization maximizes the “state of charge” by charging the storage capacity as soon as possible. While the original papers of Methodologies A and B obtain these energy profiles by a rule based control formulation, as shown in Eq. (1), an optimal control formulation has been used for this case study. This optimal control formulation allows to translate the single-state tank model formulation of

Table 3
Model parameters for the building and domestic hot water tank as represented by Eqs. (3) and (4).

Parameter	C_i [MJ/K]	C_{we} [MJ/K]	C_{wi} [MJ/K]	C_f [MJ/K]	H_{vent} [W/K]	$H_{i,\,we}$ [W/K]	$H_{we,\,e}$ [W/K]	$H_{i,\,wi}$ [W/K]	$H_{i,\,f}$ [W/K]	$H_{f,\,g}$ [W/K]
Value	3.9	32.2	102	12.7	218	1286	157	1112	590	48
Parameter	f_1	f_2	f_3	f_4	abs_1	abs_2	abs_3	abs_4	C_w [MJ/K]	R [K/W]
Value	0.81	0.056	0.12	0.019	0.049	0.27	0.58	0.097	1.05	0.68

Eq. (1) to the application on the higher-order building model used for the thermal mass and implicitly accounts for thermal losses. In both cases, the simplified expression of the optimization problem can be formulated as:

$$\min_{T_j^i,\,\Delta T_j^{comf}} \sum_j^{hor} c_j^i T_j^i + c_j^{comf} \Delta T_j^{comf} \tag{5.a}$$

$$\text{Subject to :} \quad \forall j : f\left(T_j, Q_j^h\right) = 0 \tag{5.b}$$

$$\forall j : \Delta T_j^{comf} \geq T_j^{min} - T_j^i \tag{5.c}$$

$$\forall j : \Delta T_j^{comf} \geq T_j^i - T_j^{max} \tag{5.d}$$

$$\forall j : \Delta T_j^{comf} \geq 0 \tag{5.e}$$

$$\forall j : 0 \leq Q_h \leq Q_{Nom} \tag{5.f}$$

$$j = 0 : T_j = T_0 \tag{5.g}$$

$$j = hor : T_j = T_{end} \tag{5.h}$$

In this formulation, T_j^i and Q_j^h are respectively the indoor air temperature and heating power at time j. The minimization and maximization of the "state of charge" (SOC_{min} and SOC_{max}) over the prediction horizon (*hor*) – here 24 h - are obtained by respectively setting c_j^i equal to 1 and −1. Note that the scenarios SOC_{min} and SOC_{max} correspond to respectively the latest and earliest start scenarios as defined by Nuytten et al. [45] and D' Hulst et al. [46]. The relation between the indoor temperature and the heating power is given by Eq. (5.b), which corresponds to the state space model defined in Eq. (3). Eq. (5.c)–(e) quantify ΔT_j^{comf}, which represents the level of discomfort. This level of discomfort is included in the cost function using a high value for associate cost c_j^{comf} (here 10,000) to assure that the temperature stays within the comfort limits given by T_j^{min} and T_j^{max}. Note that soft constraints were needed here as potential overheating cannot be avoided in summer due to the absence of a cooling system. Eq. (5.f) imposes the technical constraints, limiting the heating power to stay below the nominal power of the system (12.5 kW). Finally, Eq. (5.g) and (5.h) fix the initial and final states of the system. As argued in Section 3.7, it is unclear how this final state should be defined in the context of thermal mass. Therefore, 2 scenarios are implemented in this paper. In scenario 1, constraint (5.h) is omitted and T_{end} is a free optimization variable. In scenario 2, it is assumed that T_{end}- the vector of temperatures of the states - should be equal to the temperature of the corresponding states in the reference scenario.[1] As such, the use of energy flexibility during the optimization horizon (*hor*) will not affect the following periods as the final state of the system is the same as for the reference scenario that does not use energy flexibility. As will be shown further on (Fig. 12), the latter is a conservative assumption in the case of thermal mass.

In Methodology C, the temporal and power flexibility defined are quantified as functions of the start time by simulating a heating up and cooling down curve starting from the SOC_{min} and SOC_{max} results, respectively. In the paper describing methodology C, the initial and final states are defined by the minimum and maximum temperature in the storage tank. Nonetheless, the SOC of thermal mass is not defined by a unique temperature (e.g. air temperature) but by a combination of states. Hence also for this method, 2 optimal control problems are solved to find the SOC_{min} and SOC_{max} of the thermal mass. These are obtained by the same optimization problem as Methodologies A and B (Eq. 5). In contrast to Methodologies A and B, the time horizon for the optimization problem (Eq. 5) is set to 7 days as there is no specified limit on the end time or the end state for Methodology C. Given the initial state obtained from the optimal control problem, t_{forced} and $t_{delayed}$ are computed by finding the intersection of the heating up and cooling down curve with the indoor temperatures of the SOC_{min} and SOC_{max} results for each starting time t. Using the indoor temperature from the SOC_{min} and SOC_{max}, instead of directly using the comfort limits, implies that thermal comfort can be guaranteed in the following time step. As such, the additional checks that were included in [46] are implicitly included. The corresponding power flexibility is computed from the average difference between heating up (12.5 kW) and cooling down power (0 kW) and the power during the reference case (SOC_{min} or SOC_{max}, respectively).

As for Methodologies A and B, a close relation is found between Methodologies D and E. In both cases, an optimal control problem is defined, whereby during a short period of time (the flexibility horizon, l_{ADR}) at the beginning of the prediction horizon (*hor*), the power of the heating system is maximized (upward flexibility) or minimized (downward flexibility). For Methodologies D and E, the optimal control problem can be reformulated as:

$$\min_{Qh,\,\Delta T_j^{comf}} \sum_j^{hor} c_j^i Q_h^i + c_j^{comf} \Delta T_j^{comf} \tag{6.a}$$

$$\text{Subject to :} \quad \forall j : f\left(T_j, Q_j^h\right) = 0 \tag{6.b}$$

$$\forall j : \Delta T_j^{comf} \geq T_j^{min} - T_j^i \tag{6.c}$$

$$\forall j : \Delta T_j^{comf} \geq T_j^i - T_j^{max} \tag{6.d}$$

$$\forall j : \Delta T_j^{comf} \geq 0 \tag{6.e}$$

$$\forall j : 0 \leq Q_h \leq Q_{Nom} \tag{6.f}$$

$$j = 0 : T_j = T_0 \tag{6.g}$$

where constraints (6.b)–(6.g) correspond to those in (5.b)–(5.g). In contrast to Methodologies A and B, c_j^i is taken not constant over the prediction horizon but is a function of time j, where $c_j^i = 1$ for $j > l_{ADR}$. To calculate the upward flexibility, c_j^i is set equal to zero for $0 \leq j \leq l_{ADR}$ while to calculate the downward flexibility c_j^i is set

[1] *Note* that in all evaluated methodologies, the reference scenario corresponds to the solution of the optimal control problem which minimizes the energy consumption.

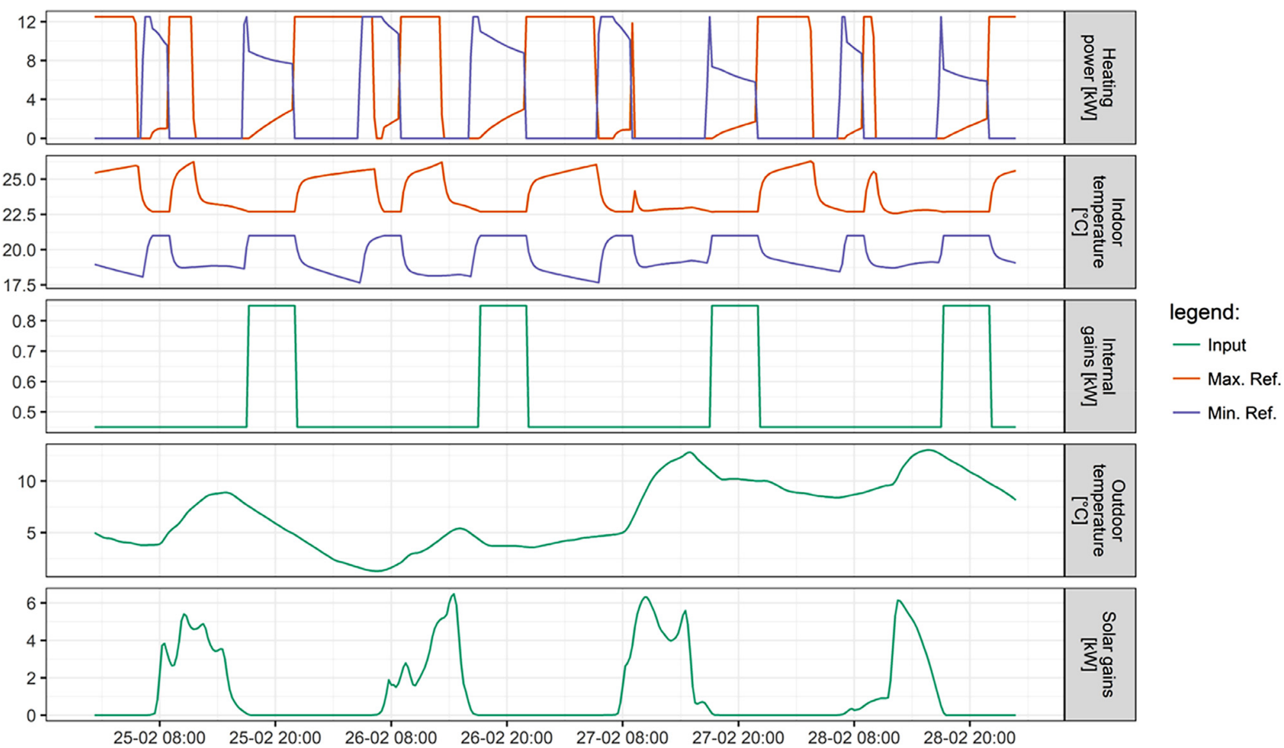


Fig. 8. Time series of input indoor air temperature and heating power obtained for the minimum and maximum SOC reference scenarios according to the control problem of Eq. (5) for the case of thermal mass only assuming T_{end} is free. The bottom graphs show the input data for outdoor temperature, solar gains and internal gains.

to a high value (here 10,000). As described in [52], to quantify the energy flexibility as a function of time, this optimal control problem should be solved for each time step, as a receding horizon problem. This prevents the control from anticipating to the flexibility event by pre-heating or pre-cooling the building. Each point in the curves of Figs. 14 and 15 is thus the result of an optimal control problem.

Finally, for Methodology F, a rule-based control is implemented, whereby during an energy flexibility event (l_{ADR}), the set point temperature for heating is temporarily increased to T^{max} (here 23 °C). The available storage capacity and storage efficiencies are then quantified using the difference between the heating power for this energy flexibility event (Q_{ADR}) to a reference scenario (Q_{Ref}). For the reference scenario, the set-point for the indoor temperature is equal to the indoor temperature obtained from the optimal control problem that minimizes the energy use over the prediction horizon. This differs from the formulation in [54] where a deterministic schedule is used, but it is implemented here to increase the comparability of the numeric results with those obtained by Methodology D and E by starting from the same reference profile.

4.3. Results

To compare the results of the different methodologies, they have been grouped based on the identified overlap in quantification methodologies as described in Section 4.2. Firstly, the results of Methodologies A, B and C are discussed for the building thermal mass and domestic hot water tank. Therefore, as discussed in Section 4.2, two scenarios are considered where the final state (T_{end}) is either free or fixed. Secondly, Methodologies D, E and F are compared.

The analysis for the results is shown here for the period of February 25 to March 1. Although the values for the obtained indicators will vary over time - depending on the boundary conditions – this short period suffices to illustrate the differences between the methods while limiting the computation time. To improve the interpretability of the results, Fig. 8 shows the temperature and heat demand as well as the boundary conditions for the reference scenarios. More precisely, the results of the optimal control problem formulated in Eq. (5) are shown as used in Methodologies A, B and C. The results for the optimal control problem of Eq. (6) are not shown here but are, given the flat tariff price profile that is assumed, almost identical to those of Fig. 8. Fig. 9 shows the reference results for the domestic hot water (DHW) part. The analysis for DHW is carried out on a single day (February 26). The figure shows the input tab water profile for that day as well as the resulting temperature and heating power profiles for the SOC_{min} and SOC_{max} scenarios following the control problem of Eq. (5).

Methodologies A–C compute the energy flexibility from the minimum and maximum SOC solutions of the optimal control problem given by Eq. (5) (Fig. 9). Thereby, Methodologies A and B quantify energy flexibility directly from the resulting cumulated heating power profiles. Fig. 10 shows the resulting cumulated energy use for heating (E [kWh]) for to earliest start (SOC_{max}) and latest start (SOC_{min}) scenarios. The results are obtained from the time series data for February 26, as shown in Fig. 9, but similar findings can be deduced from other days. Fixing the final states (T_{end}) of the building and the domestic storage tank at the end of the 24 h prediction horizon to the reference values corresponds to the assumption that the flexibility for the next period is not influenced. As shown on the right hand side of Fig. 10, this results in a negligible increase of the heating power for the structural thermal storage, since otherwise the building would not be able to restore its final state T_{end} due to its high time constants. Constraining the end state of the structural thermal storage for Methodologies A and B thus significantly reduces the obtained energy flexibility which is, according to Methodologies A and B, given by the distance between the earliest and latest start curves. In contrast, when this constraint on the final states is not applied (T_{end} free), the energy content of the building (i.e. the heat stored in the different capaci-

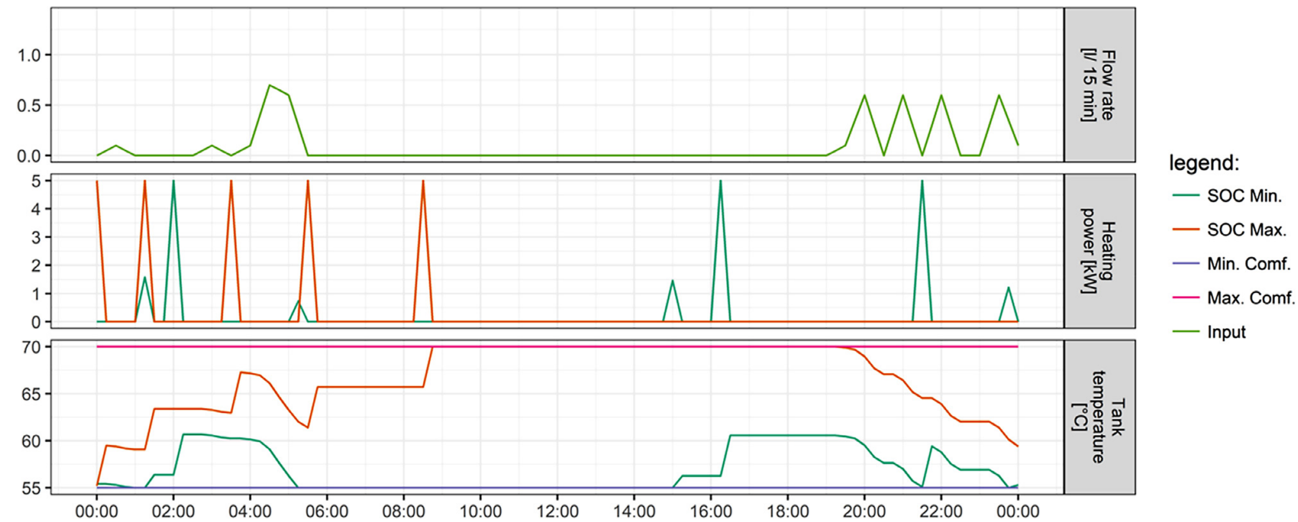


Fig. 9. Time series of the reference profiles for the domestic hot water consumption, showing the reference tab water profile for the analyzed day (February 26), heating power and tank temperature for the SOC_{min} and SOC_{max} scenarios and the minimum and maximum comfort temperature. The latter are denoted as Min. Comf. and Max. Comf. respectively.

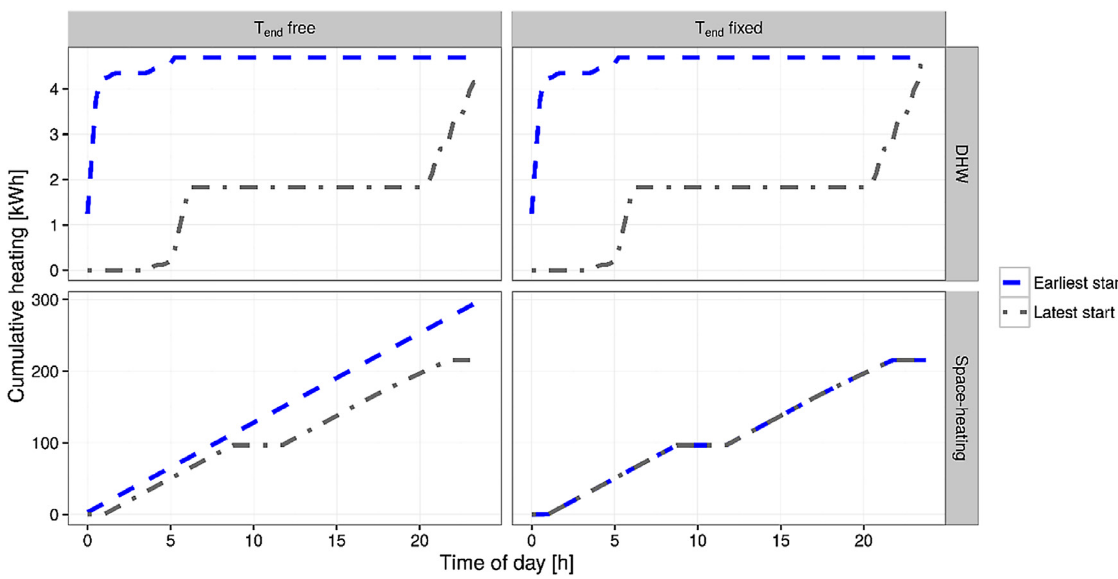


Fig. 10. Cumulative energy use for heating of domestic hot water tank (DHW) and space heating obtained by the optimal control problems formulated in Methodologies A and B assuming the final state of the system is fixed (Tend fixed) or free (Tend free).

ties) increased significantly, resulting in a large difference observed between E_{max}(24 h) and E_{min}(24 h). Additionally, this difference between E_{max}(24 h) and E_{min}(24 h) is caused by the increased energy losses when the thermal capacity is charged to its maximum temperature. These storage losses were not included in the original work of Nuytten et al. [45] and D' hulst et al. [46] and limit the application and interpretability of these methodologies in practice. The inclusion of storage losses results in a continuous increase of the difference between E_{max}(24 h) and E_{min}(24 h) even when the energy content of the storage capacity does not change.

Figs. 11 and 12 show respectively the results the flexibility indicators $\tau_{delayed}$ and τ_{forced} (Methodology A) and P_{inc} and P_{dec} (Methodology B), as derived from the flexibility profiles in Fig. 10. According to Methodology A, $\tau_{delayed}(t)$ represents the time during which the heating can be switched off following the E_{max} profile from $t = [0{:}t]$. Therefore, the forced delay ($\tau_{delayed}$) has been limited to the time it takes to reach the end of the prediction horizon, (here 24 h). Fig. 11 (left) shows how it is possible to postpone reheating the storage tank until the end of the prediction horizon once the storage tank has been heated to its maximum SOC. At the same time, the results for τ_{forced} (Fig. 12(right)) show how the limited heat capacity of the tank (~4 kWh) in relation to the high thermal power of the heat pump (12.5 kW) results in a forced operation of about 15 min. In both cases, slight differences are found between the scenarios with free and fixed T_{end}, since for the cases where T_{end} is fixed, the amount of heat stored in the tank for the E_{max} scenario is lower. The impact of fixing T_{end} is found to be limited and is mainly visible in $\tau_{delayed}$ where in the scenario with free T_{end} more energy can be stored within the storage tank, resulting in higher values for $\tau_{delayed}$.

For space heating, there is a larger difference between both scenarios for T_{end} resulting from the underlying assumption in Methodologies A and B, that the storage capacity is represented by a single time-constant. While this is found to be an acceptable assumption for the storage tank, this assumption does not hold for a building where dynamics are governed by both the low time con-

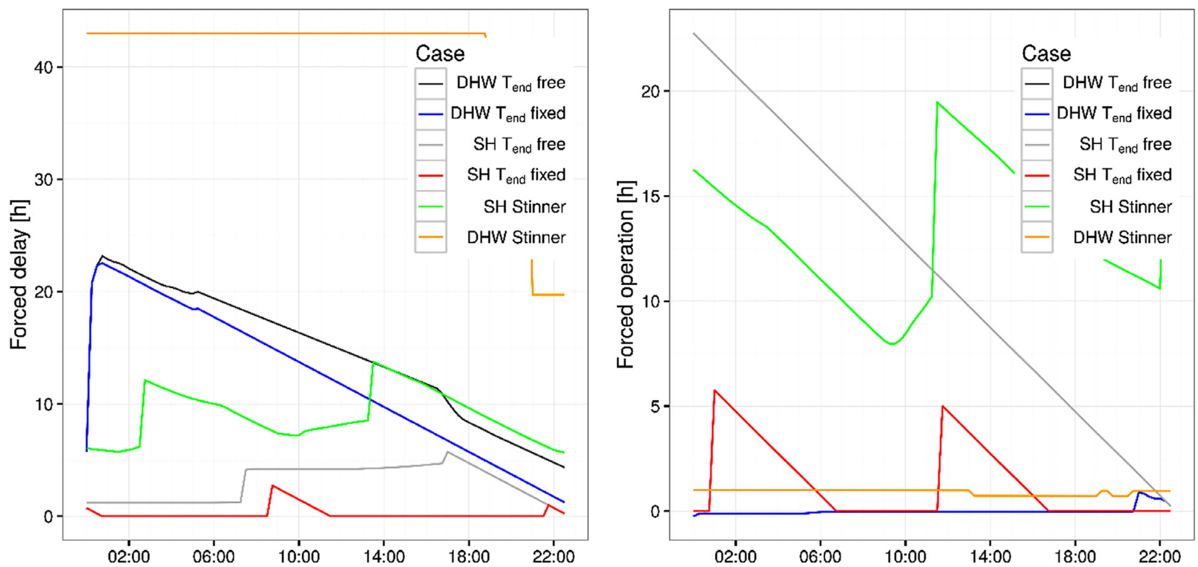


Fig. 11. Forced delay (left) and forced operation (right) according to Methodology A for space heating (SH) and domestic hot water (DHW) under the assumptions of fixed (T_{end} fixed) or free (T_{end} free) final states.

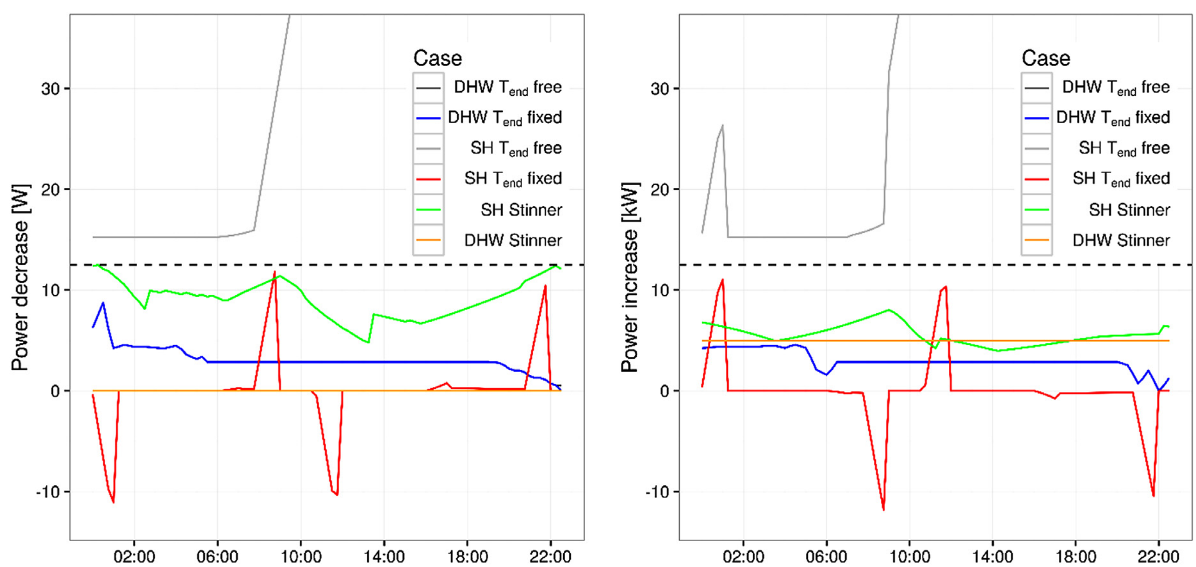


Fig. 12. P_{dec} (left) and P_{inc} (right) according to Methodology B for space heating (SH) and domestic hot water (DHW) under the assumptions that T_{end} is free or fixed. The dotted line shows the nominal power of the heat pump (12.5 kW).

stant of the indoor air and the high time constants of the structural thermal mass. Since Methodologies A and B calculate short-term (∼minutes to hours) flexibility indicators from the results of long-term (∼day) optimal control solutions, the single state assumption is found to be inaccurate in the case of space heating. This may even result in a loss of interpretability of the results when T_{end} is free. According to Methodology A, $\tau_{delayed}$ varies between 3 and 6 h when T_{end} is free. At the same time, τ_{forced} shows that the heating could operate at maximum power until the end of the prediction horizon without jeopardizing comfort. However, simulation of the temperature response (Fig. 13) shows that when the building cools down from SOC_{max}, T_{min} (here 21 °C) is reached after only 1 h instead of the predicted $\tau_{delayed}$ of 3 h.

To overcome this loss of interpretability, Methodology C does not calculate the energy flexibility directly from the cumulated heating power profiles but simulates, for each point in time, a forced and delayed operation event. For these events, the initial conditions correspond to the state obtained for the minimum and maximum SOC solutions of Eq. (5), respectively. Moreover, Methodology C does not imply a specific end time for the event. Compared to Methodology A, Methodology C results in higher values for $\tau_{delayed}$ (Fig. 11(left)) with values between 6 and 13 h. These values for $\tau_{delayed}$ are significantly longer than the cool-down periods that were found in Fig. 13 because the initial state of the thermal mass is based on the results of SOC_{max}. This means that the entire thermal mass of the building was preheated before the start of the cooling down period. The forced operation time obtained for space heating associated to Methodology C is 20% lower during the first half of the day than the value for Methodology A with free T_{end}. The higher values for Methodology A are due to the computation of $\tau_{delayed}$ without considering the storage losses in the cumulated heating profiles.

In the analysis of the power flexibility for Methodology C, P_{dec} and P_{inc} are obtained by comparing the average power during the delayed and forced operation periods to the power for the maximum and minimum SOC reference results, respectively. Since the

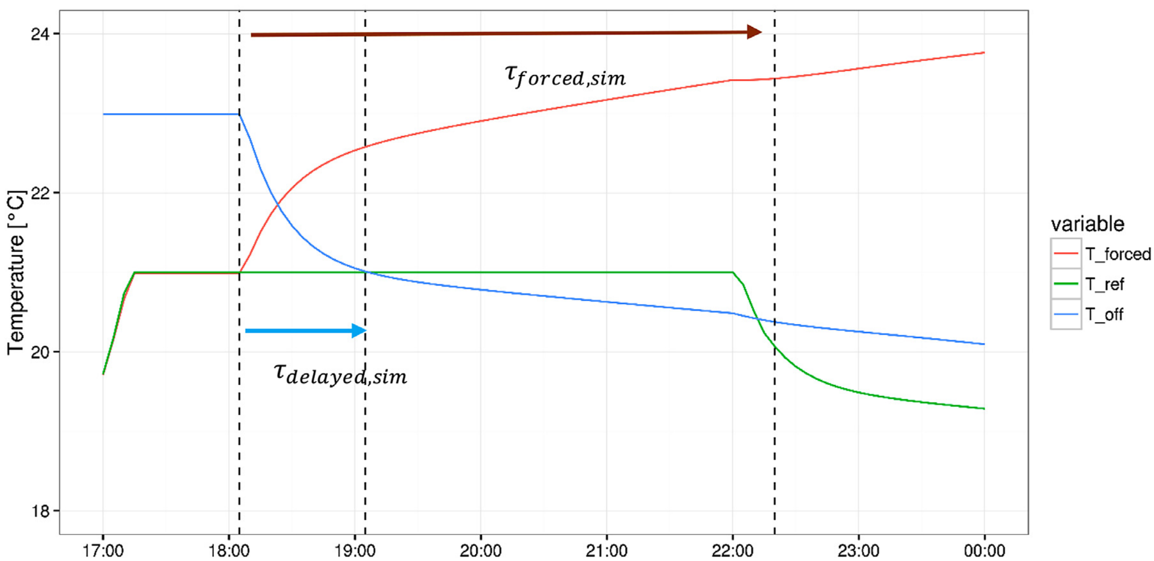


Fig. 13. Simulation results of temperature responses when forcing heating on (red) and off (blue) starting SOC_{min} and SOC_{max} respectively. The reference profile (green) shows the scenario that does not use energy flexibility. $\tau_{delayed,\ sim}$ and $\tau_{forced,\ sim}$ are the simulated forced delay and forced operation, which should be compared to the values from Methodology A. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

power demand for DHW production is 0 during most of the day, the P_{dec} and P_{inc} show values of respectively 0 and 5 kW. The latter is equal to the design power for DHW. For space heating, values for P_{dec} vary between 5 and 12.5 kW (equal to $Q_{Nom,SH}$), while P_{inc} varies between 3 and 8 kW, demonstrating that, due to the relatively high heat demand for this winter week, power flexibility is mostly available for downward shifting. However, due to the limited power increase that is possible, this power increase can be maintained for a long time (Fig. 11), clearly illustrating that the indicators should not be analyzed separately [54].

In contrast to Methodologies A and B, Methodologies D, E and F quantify the (short-term) flexibility indicators by analyzing the change in power or the shift of energy during a short-term event compared to a reference scenario. As such, they provide information over a certain prediction horizon (here 1 day) of the flexibility that can be obtained for such short-term events (here 2 h). Flexibility hence results from a change in power compared to a reference during this pre-defined, short-term period.

Fig. 14 shows the comparison between the upward and downward power shift of Methodologies C and D and the PSC (Methodology F). While the interpretability for Methodology B (Fig. 12) was found to be jeopardized in the case of building thermal mass, the results of Methodology E and F show the potential increase (and decrease) in power for a duration of 2 h as a function of the starting time of the energy flexibility period. The minimum energy use scenario on the building level was used as a reference heating profile for Methodologies D, E and F. Hence, P_{down} for Methodology E is mostly equal to zero since reducing the heating power compared to the minimum energy results would result in thermal comfort problems – which are strongly penalized in the objective function. In contrast, Methodology C uses the SOC_{max} profile as a reference, resulting in potential reductions up to 12.5 kW (equal to Q_{Nom}). P_{up} for Methodologies E and F clearly reflects the influence of the occupancy profile. In the morning (between 6:00 and 10:00) and between 15:00 and 22:00, a reduction of P_{up} is found since part of the heating power is needed to heat up the building and can therefore not be used for flexibility. A comparison between the afternoon reduction of P_{up} on February 26 and 27 also demonstrates how this reduction depends upon the external boundary conditions such as outdoor temperature and solar gains. Specifically, on February 26th, the colder outdoor temperature results in a higher heat demand in the reference scenario and thus less power is available in the afternoon for energy flexibility. A similar dependence on the dynamic boundary conditions is found for Methodology C. However, the profile shows less sharp fluctuations. The latter is explained by the fact that for Methodology C both the power shift and the temporal shift are varying, while these were fixed for Methodologies D and F.

Also, a clear overlap is found between Methodologies E and F. The PSC for an ADR event of 2 h – as defined in Methodology F – is equivalent to the upward shift defined in Methodology E. The only difference is that the PSC is calculated based on a rule based control, involving an iterative process to find the exact value, while the power shifts of Methodology E are directly obtained by solving the optimal control problem. It should however be noted that Reynders [56] acknowledges the possibility of quantifying the proposed indicators by optimal control as well, as the indicators are defined independently of the calculation approach. At the same time, a direct relation between Methodologies D and E was identified. Since both methodologies are based on the same optimal control problems, the amount of flexible energy used in Methodology D is obtained by integration of the power shift in Methodology E over the flexibility horizon.

In addition to the amount of energy or power that is being shifted, Methodologies D and F emphasize how activating a storage capacity for energy flexibility comes at a cost. In Methodology D, this cost is calculated by analyzing the increase in the energy cost over the prediction horizon compared to the reference solution corresponding to the minimum energy (cost) case. Methodology F defines a storage efficiency which expresses the additional energy use in relation to the amount of stored energy use during the flexibility event. Fig. 15 shows both the stored energy and the additional energy use as a function of the starting time of the flexibility event. Fig. 15 clearly demonstrates the strong link between Methodologies D and F. Therefore, it is noted that on average the cost for energy flexibility is lower for Methodology D. This can be assigned to the use of optimal control compared to the thermostatic control in Methodology F. Apart from the building control strategy used to quantify energy flexibility, both methodologies are equivalent.

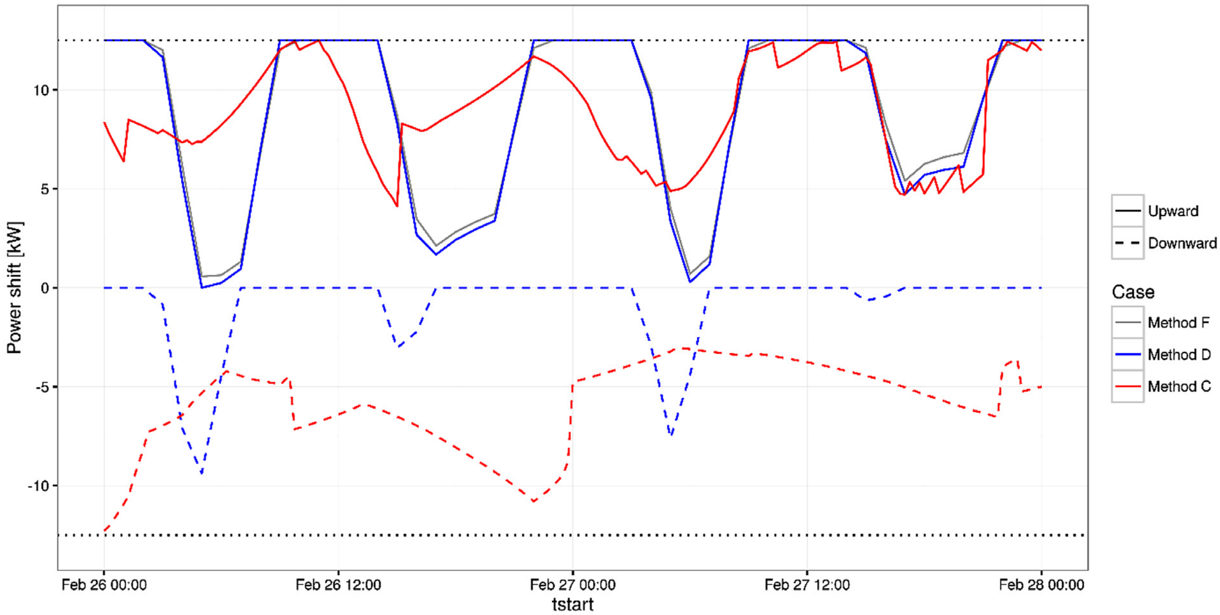


Fig. 14. Comparison Power shifts P_{up} and P_{down} according to Methodologies C, D F for the space heating case. *Note* that Methodology F only quantifies upward shift. The dotted black lines show the nominal heating power (12.5 kW).

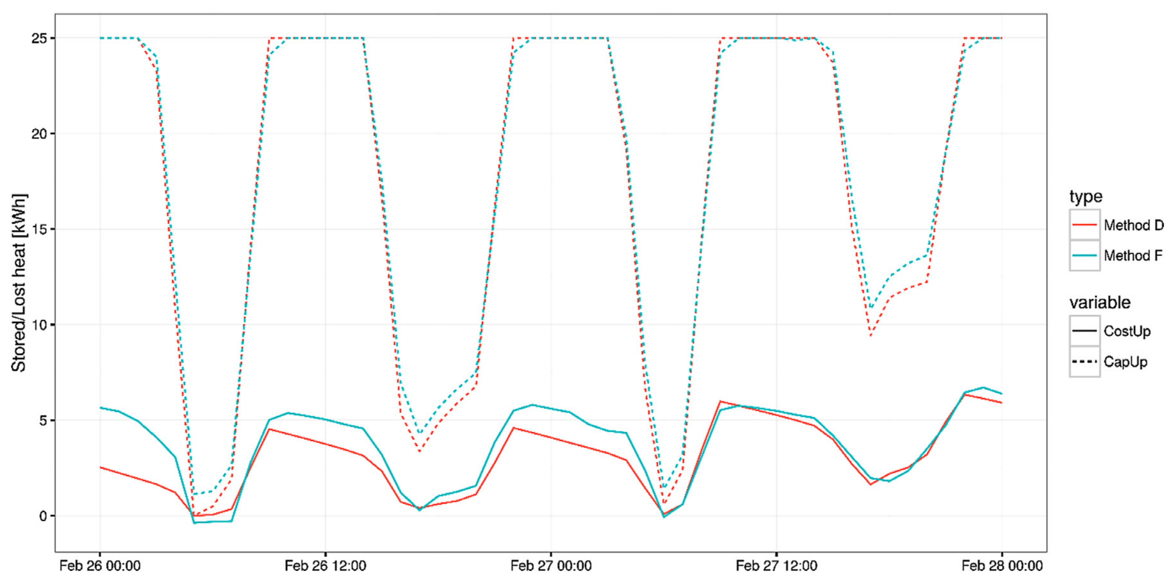


Fig. 15. Activated storage capacity for upward flexibility (CapUp) versus the associated extra energy use (CostUp) obtained for Methodologies D and F.

5. Conclusion

This paper presented a hands-on review of definitions and quantification methodologies for energy flexibility in buildings. First, a review of definitions of energy flexibility was conducted, whereby a large number of studies were identified that tackle the subject. Although these studies mostly start from the concept that energy flexibility implies the ability to shift energy, each of these studies was found to focus on specific aspects or properties of energy flexibility. Based on the review, these different focus points could be grouped into 5 categories: focus on energy infrastructure context, focus on electricity, focus on energy price, focus on possibility of compromising other building performances (e.g. thermal comfort) and focus on systems interacting with building.

Besides definitions for energy flexible buildings, this paper reviewed quantification methodologies that allow the energy flexibility of buildings in a design or operational context to be quantified and predicted. Based on the literature, two general approaches for quantifying energy flexibility were identified. A first approach quantifies energy flexibility indirectly assuming a specific energy system and/or energy market context and using past data. The second approach, directly predicts the energy flexibility that a building can offer to the energy system without considering if this flexibility can or will be used by the system. These quantification methodologies can therefore be interpreted as bidding curves for energy flexibility.

The latter approach was analyzed more extensively whereby proposals for indicators and corresponding quantification methodologies were found. Although these studies have a different focus, three general properties of energy flexibility can be observed: (i) the temporal flexibility; (ii) the amount of energy or power that can be shifted; and (iii) the associated cost of activating this flexibility. In all cases, these three properties are calculated by comparison against a reference scenario where no external demand for energy flexibility is made.

Application of the identified methodologies to the case study revealed that methodologies that quantify energy flexibility by analyzing flexibility events at specific times have clear advantages when dealing with systems with thermal losses and multiple time constants, such as thermal mass of buildings. In contrast, methodologies that relied on cumulated energy profiles lose their interpretability for such systems mainly since they treat a system governed by multiple time constants as a single state system. Moreover, results of Methodologies D, E and F are found to be highly comparable and reflect the dependence of the predicted energy flexibility on dynamic boundary conditions, such as climate and occupancy. Between Methodologies D and E, the only difference was found in the way the final results are communicated. Between Methodologies D and F, limited differences were found as result of using respectively an optimal control based or rule based quantification method. Finally, although Methodology C gave physically interpretable results, a quantitative comparison was not possible as they start from a completely different problem description.

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