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Published in:
Applied Energy

Link to article, DOI:
10.1016/j.apenergy.2018.05.037

Publication date:
2018

Document Version
Publisher's PDF, also known as Version of record

Applied Energy 225 (2018) 175–182

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Characterizing the energy flexibility of buildings and districts

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HIGHLIGHTS

- Energy Flexibility is defined as a dynamic function suitable for control.
- This definition leads to important and useful characteristics which are discussed.
- Furthermore, it defines a Flexibility Index both on individual and aggregated level.
- Based on this index a standardized method for labelling can be deduced.

ARTICLE INFO

Keywords:
Energy flexibility
Demand response
Flexibility function
Smart building
Flexibility index
Smartness

ABSTRACT

The large penetration rate of renewable energy sources leads to challenges in planning and controlling the energy production, transmission, and distribution in power systems. A potential solution is found in a paradigm shift from traditional supply control to demand control. To address such changes, a first step lays in a formal and robust characterization of the energy flexibility on the demand side. The most common way to characterize the energy flexibility is by considering it as a static function at every time instant. The validity of this approach is questionable because energy-based systems are never at steady-state. Therefore, in this paper, a novel methodology to characterize the energy flexibility as a dynamic function is proposed, which is titled as the *Flexibility Function*. The Flexibility Function brings new possibilities for enabling the grid operators or other operators to control the demand through the use of penalty signals (e.g., price, CO_2, etc.). For instance, CO_2-based controllers can be used to accelerate the transition to a fossil-free society. Contrary to previous static approaches to quantify Energy Flexibility, the dynamic nature of the Flexibility Function enables a Flexibility Index, which describes to which extent a building is able to respond to the grid's need for flexibility. In order to validate the proposed methodologies, a case study is presented, demonstrating how different Flexibility Functions enable the utilization of the flexibility in different types of buildings, which are integrated with renewable energies.

1. Introduction

The sustainable transition to a fossil-free energy system with a high penetration of energy conversion technologies based on fluctuating renewable energy resources, like wind and solar, calls for a paradigm shift in power systems [1,2]. Traditionally, power systems have been designed with centrally-situated large power generation units that are operated to meet the demand. However, to support the transition to a renewable energy system with intermittent and fluctuating power generation, a change is commonly suggested, where demand is adjusted to the available generated power [3,4]. Moreover, renewable energy generation is often locally situated, changing the present system from a unidirectional centralized system towards a bi-directional decentralized system with smaller units and multiple prosumers [5]. Such disruptive changes imply increased utilization of advanced control systems to enable flexible demand through demand response technologies and proper system integration [6]. The flexibility potential is already present (e.g., through heat storage [7]), and is further enhanced by advances and increased utilization of batteries [8]. Today, the use of model predictive control in buildings is seen as a strong opportunity to

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https://doi.org/10.1016/j.apenergy.2018.05.037
Received 15 February 2018; Received in revised form 13 April 2018; Accepted 6 May 2018

minimize costs, while still meeting the comfort requirements [9]. This control can be done either centralized by e.g., a grid operator (direct control), or decentralized by each building owner [10]. In this paper, the focus is on the latter type. The strategies used for defining the optimal controller can take a variety of parameters into account. For buildings the focus can be on energy efficiency, CO_2 efficiency, or minimizing the total cost [11], where trade-offs arise as a part of selecting the strategy. For example, a controller that is energy-efficient is typically not price-optimal given the energy markets and the energy-related taxes that exist today [12].

The building sector plays a key role in the future smart energy system as buildings account for approximately 40% of the global energy consumption [13]. Flexible buildings can provide grid services and thereby accelerate the transition to a low carbon energy system. The potential for using a building for demand response is defined as its energy flexibility [14]. The buildings' ability to provide energy flexibility is influenced by several factors [15]: (1) its physical characteristics such as thermal mass, insulation, and architectural layout, (2) its technologies such as ventilation, heating, and storage equipment, (3) its control system that enables user interactions; the possibility to respond and react to external signals such as electricity price or CO_2 factors, and (4) the occupants' behaviour and comfort requirements.

The energy flexibility potential can be found either by building *simulation* tools, i.e., deductively, or by use of experimental data, i.e., inductively by statistical *time series analysis*. Similar to a prediction of the energy consumption of a building, predicting the energy flexibility requires detailed dynamic modeling of a building's energy systems, including technical constraints, occupancy behaviour, and boundary conditions; see e.g., [16–18]. Using experimental data for estimating the energy flexibility of households with a price-responsive load was first suggested as a part of the FlexPower project [19]. However, the concept of controlling the energy balance in power systems using prices is not new, since it was first presented in [20]. In [21], the authors suggested the use of time series analysis tools to quantify the flexibility of buildings as a response to time-varying prices for the electricity using data from the Olympic Peninsula Project [22]. Similarly, in [23], a method based on inverse optimization was used to estimate the flexibility using real data. It was shown by [21] how the variations in penalties could be used to shift the load from peak hours to off-peak hours. The authors in [6,12] went a step further and demonstrated that the frequency and voltage in power grids could also be controlled by this method. However, they failed to specify which systems (e.g., buildings, districts, pools, etc.) are suitable for this approach.

Characterizing energy flexibility in a structural way is challenging as it involves many aspects [24]. A characterization of the energy flexibility and structural thermal energy storage is made in [25]. Here, the authors propose three characteristics: (1) available storage capacity, (2) storage efficiency, and (3) power shifting capability that reflects the relation between the aspects of power, duration and comfort constraints. Authors in [26], on the other hand, investigate the flexibility of a heat pump pool, and propose some characteristics; one example being the time until the electricity has returned to the baseline load. The drawback of the characterization methods in [25,26] is that they focus on specific characteristic numbers independently of each other. Furthermore, communicating the values of all these characteristics is complicated, and thus, there is a need for a simplified characterization that can take the dynamics of the system into account. The fact that these methods refer to a baseline load also makes them difficult to use in practice, where there is no baseline.

In this paper we propose a method to characterize the energy flexibility as a dynamic function, titled the Flexibility Function (FF). Unlike the bidding-based approaches that assume constant flexibility as described in [27,28], the dynamic nature of the FF enables the description of energy flexibility transients. Thus, it is useful even when the system is not in steady state, which is the case whenever energy flexibility has recently been utilized. The suggested method does not need any calculation of a baseline load. The FF can be determined either by simulation or by analyzing time series data. In situations where the FF is based on experimental data, it indirectly considers other factors such as heating equipment, usage, comfort and controllability. This generic energy flexibility characterization enables a comparison between systems with vastly different characteristics (e.g., an office building and a sewer system). It also enables the computation of the total flexibility when combining several systems. The suggested methodology for a dynamic characterization of the flexibility of e.g., a building, is designed such that it can be used for providing the energy system and the grid with ancillary services. Such services are given a high priority in the EU Winter Package [29]. In the linear case, the flexibility can be characterized using impulse response functions, step response functions, frequency response, and transfer functions - see also [30,31]. Consequently, the flexibility can easily be described using different approaches and characterized either in time or frequency domain. Since the intermittent energy sources may only partly be predictable, methodologies for energy demand management for dynamic systems under uncertainty must be established. It will be argued that the suggested dynamic description of the energy flexibility is designed such that it facilitates methods for providing grid services such as voltage control, load balancing, and other ancillary services. In this paper, we will focus on buildings, but the technology can be used for other types of flexible responses like waste water treatment plants [32] and supermarket cooling [33,34].

Based on the FF, a method for calculating a Flexibility Index (FI), which measures the reaction of a building or cluster of buildings to penalty signals like CO_2 intensity or control signals imposed by the grid, is also proposed. For instance, a FI of zero indicates that the building does not react at all, whereas a FI equal to 0.2 denotes that 20% of the penalty-related cost can be saved due to the smartness and flexibility of the building. This generic characterization of energy flexibility assumes that the system under consideration either contains a penalty-aware controller [6,11,35] or a manual response to variations in penalty signals like electricity price or CO_2 intensity (hereinafter referred as penalties) as described in [36]. The FI holds the essential information for particular applications of flexibility, and can be understood and communicated without technical insight in energy flexibility.

The paper is structured as follows: In Section 2 the novel idea of a FF is introduced along with the requirements for using it. Then, in Section 3 three applications of the FF is presented: (1) Quantitative description of energy flexibility, (2) Computing FIs, (3) Performing ancillary services. Next, Section 4 illustrates the concepts in a case study. Finally, Section 5 is a short summary and outlines plans for the future work.

2. Characterizing flexibility of penalty-aware buildings

This section introduces the novel idea of characterizing energy flexibility through a dynamic function, the FF, and the prerequisites for applying it. In this paper, we consider the building level. However, the methodologies can be applied to any energy-consuming system, e.g., a sewing system, a group of buildings, or a district. In many cases, it would actually be more optimal to consider a group of buildings, a smart district or a smart city, since the large scale offers solutions for energy production and storage, which may not be economically or practically suitable in the case of a single building. In fact, the district heating network in Denmark is a key element for the operation of the Danish power system that consists of more than 40% fluctuating wind energy [37].

2.1. Penalty-aware control and smart buildings

The methodology for characterizing energy flexibility presented in this paper are based on the general assumption that the system providing the flexibility is *smart* in a manner that it is able to respond to an external *penalty* signal. Penalty signals express the importance of a local

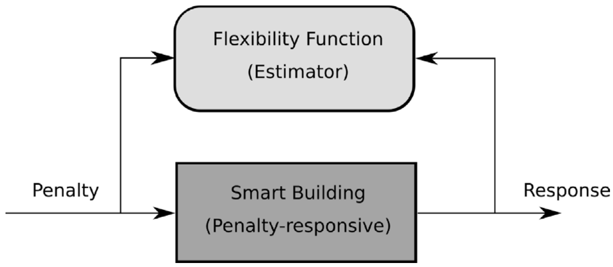

Fig. 1. A smart building is able to respond to a penalty or external control signal.

and temporal adaption of the power consumption. Therefore, in this context, a smart building is an energy-flexible building, which is equipped with penalty-aware controllers responding to external penalty or control signals, as illustrated in Fig. 1. The choice of control methodology for reacting to penalty signals is independent of the characterization of the energy flexibility. However, in this paper, we utilize an economic model predictive control methodology [6,11,35].

As a typical example, consider a building that needs to be heated and let the penalty be the energy-price. In this case, the penalty-aware controller will try to keep the building within thermal comfort boundaries at the lowest possible cost. This is illustrated in Fig. 2, where the top plot shows temperature in a building using both a penalty-aware controller that minimizes costs (green, dashed), and a regular one that minimizes energy usage (red, solid). The middle plot shows the penalties (black columns) and the heating operation of the controllers. It is seen that in general the regular controller keeps the temperature just above the minimum required value. On the other hand, the penalty-aware controller tends to heat when the penalty is low, which results in the temperature varying more. The lower plot shows the accumulated penalty, and as expected, the regular controller accumulates more penalty than the penalty-aware controller. This principle of penalty-aware control for diverse flexible systems and for a variety of penalty signals has been applied in many studies [12,32,35,38].

Depending on the context of application, e.g., local energy mix, energy system constraints, or even societal ambitions, different penalty signals can be constructed to tailor the optimal energy demand. Let us consider three different penalty signals:

- **Real time CO_2.** If the real time (marginal) CO_2 emission related to the actual electricity production is used as penalty, then, a smart building will minimize the total carbon emission related to the power consumption. Hence, the building will be *emission efficient*.
- **Real time price.** If a real time price is used as penalty, the objective is to minimize the total cost. Hence, the building is *cost efficient*.
- **Constant.** If a constant penalty is used, then, the controllers will simply minimize the total energy consumption. The smart building is, then, *energy efficient*.

It is clear that smart buildings with controllers with the objective of minimizing the total emission will in general use more energy, but this happens at periods with, for instance, a large wind power production. Thus, the alternative might be to stop some wind turbines.

2.2. The flexibility function

The principles described in this paper can be used for any power-related flexibility. However, we will consider heating as an important example of a flexible power load. It is clear that a heating system can be turned off for some periods (minutes to hours) without any remarkable consequences on the thermal comfort. As flexibility is a dynamic phenomenon, the relationship between the penalty signal and the response must be described using a dynamic function. For simplicity, we assume

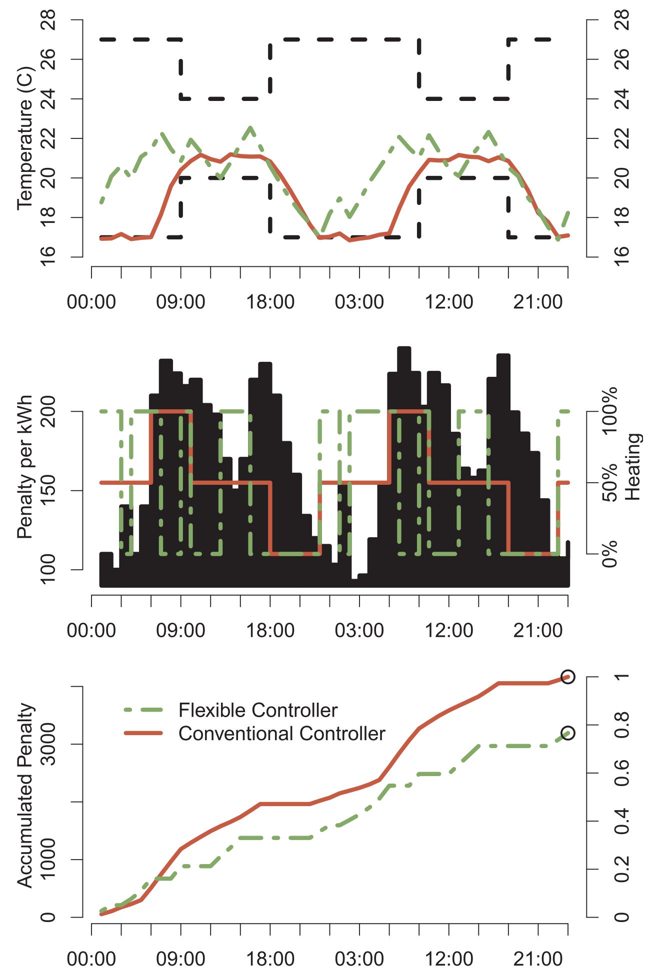

Fig. 2. Top plot: An example of the temperature in a building controlled by a penalty-aware controller (green, dashed) and a conventional controller (red, solid). Both controllers are restricted to stay within the dashed lines. Middle plot: The black shading gives the penalties, while the green and red lines show when the two controllers heat, respectively. Bottom plot: These graphs illustrate the accumulated penalty for each of the controllers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

that the building and the response to the penalty signal can be considered *linear and time-invariant*. Furthermore, we assume that the resulting load when exposed to a penalty signal can be separated into two parts; the load that responds to the penalty, and the non-responsive load R_t. In this case, the load (i.e., the response) Y_t at time t can be described as

$$Y_t = \sum_{k=0}^{\infty} h_k \lambda_{t-k} + R_t, \tag{1}$$

where $\{\lambda_t\}$ is the penalty signal, and R_t is the non-responsive consumption. Here, it is assumed that the penalty is constant between time steps. The length of the time steps can vary between a second and whole days, depending on the problem being solved. In the example illustrated by Fig. 2, the penalty changes once every hour, and thus, in this case, it makes sense to let the time steps be equal to one hour. In continuous time, the convolution sum in Eq. (1) is simply the convolution integral. In linear systems theory, see e.g., [31], the function $\{h_k\}$ is called the impulse response function. It reflects the effect of penalty on demand response after k time-steps. However, it is more appropriate to find the step response function, since it contains information about important characteristics of the system related to flexibility, as will be explained in Section 3.1. Thus, we define the FF as the step response function, i.e., by

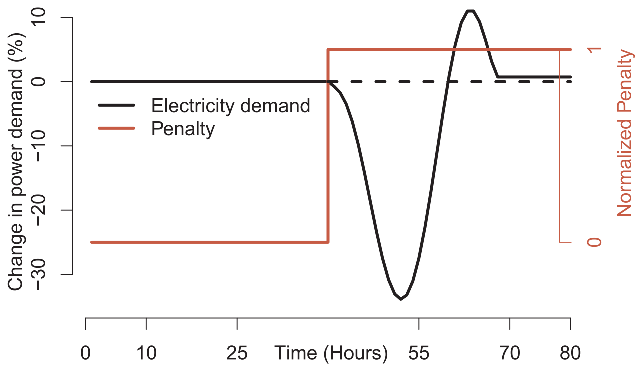

Fig. 3. The expected change in energy consumption due to an increase in penalty for an indoor swimming pool. The red line shows the penalty while the black line shows the expected change in energy consumption. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

finding the expectation at time t when $\lambda_k = 0$ for $k < 0$ and $\lambda_k = 1$ for $k \geqslant 0$:

$$FF(t) = \sum_{k=0}^{t} h_k. \tag{2}$$

Fig. 3 shows the estimated FF of a summer house with an indoor swimming pool located in Denmark. The swimming pool is being controlled using CO_2 intensity in the Danish power grid as penalty signal. The set-up is described in [39]. It is seen how the energy demand drops shortly after the penalty increases, since heating of the swimming pool, in this case, will usually be turned off. After a while, the energy demand starts increasing, since as time continues, to avoid the temperature dropping too low, the heating has to be resumed. At some point in time, the energy demand exceeds the initial level prior to the increase in penalty to bring the temperature back to the initial state. Later, the energy demand comes to rest at the energy demand prior to the increase in penalty. Notice that the response is extremely slow due to occasional technical issues in the control setup resulting in occasional unresponsiveness of the heating system.

In this example the FF is estimated based on time series data consisting of penalties and the penalty responsive load. A similar result was obtained in [21] for residential buildings. Alternatively, the FF can be found from first principles by setting up a detailed model of the systems, its constraints, occupancy behaviour, controllers and boundary conditions. Such a simulation-based approach has been used in e.g., [16–18]. In general, we might need to consider varying coefficient models where the flexibility depends on external variables like the ambient air temperature. Varying coefficient models can be written as

$$Y_t = \sum_{k=0}^{\infty} h_k(\theta)\lambda_{t-k} + R_t, \tag{3}$$

where θ is given by the external variables. As an example the ambient temperature has a large impact on the flexibility, since the heating/cooling system can only provide flexibility when the respective need is verified. The relationship can be estimated through e.g., non-parametric kernel estimation [40,41]. Using Eq. (2), it is straightforward to define the FF in the nonlinear and time-varying cases as well. It is also to be expected that the FF, due to physical changes in e.g., buildings and electrical grid, changes over time. Thus, the models should also be adaptive as described in [31,42].

3. Applications of the flexibility function

In this section it is shown how characterizing the FF can be used to differentiate between different kinds of flexibility. It is, then, described how the FIs, that quantify usefulness of flexible systems in different settings, can be computed based on the FF. Lastly, a brief description of how the FF can be used to perform ancillary services is presented.

3.1. Characterizing the energy flexibility

Most commonly, the time constants constitute the main part of characterizing the energy flexibility [34,43,44]. Indeed, this is an important parameter. For instance, the illumination of a room has a very small time constant, since the full effect of illumination from turning light-bulbs on or off happens almost immediately. On the contrary, the heating of a swimming pool, due to its thermal dynamics, has a large time constant. However, only the information about the time constants of a system is not sufficient to fully characterize and quantify its energy flexibility. Again, referring back to the swimming pool, it is not particularly flexible if the heating equipment is sized in such a way that it needs to run all the time, since in this case it can never be switched off to provide flexibility. However, as heating systems are usually sized to cover the maximum load on the coldest day, the swimming pool has excess heating power throughout most of the year. This excess heat pump capacity, then, is able to provide all the heat the swimming pool needs in a short time span. Thus, the heating time can, to some degree, be chosen to match when it is most beneficial to do so.

Six characteristics for the FF, termed hereinafter as the Flexibility Characteristics (FC) as shown in Fig. 4, are identified as follows:

- τ (Time): The delay from adjusting the energy price and seeing an

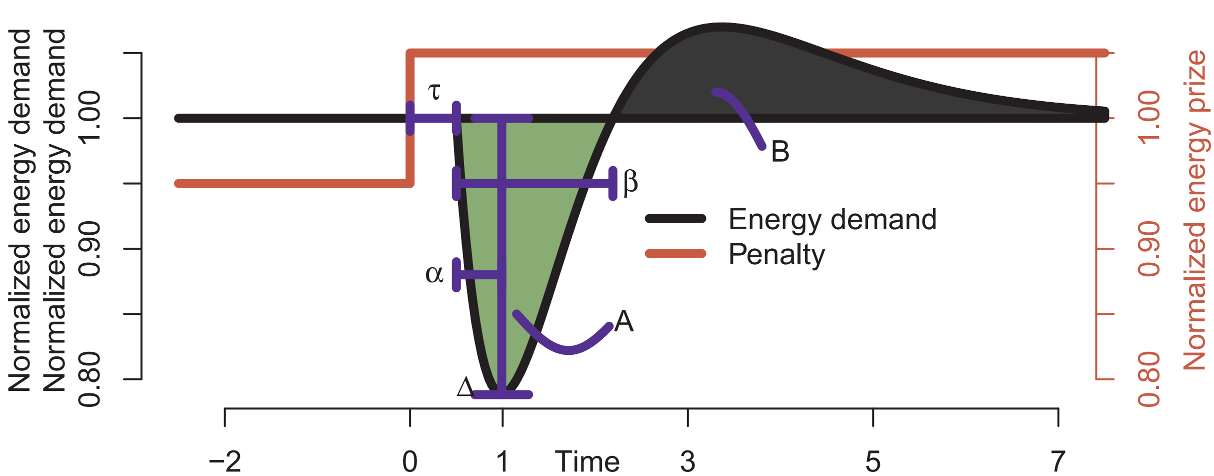

Fig. 4. Flexibility characteristics.

effect on the energy demand. 0.5 in the example.

- Δ (Power): The maximum change in demand following the penalty change. 0.2 in the example.
- α (Time): The time it takes from the start in change in demand until it reaches the lowest level. 0.6 in the example.
- β (Time): The total time of decreased energy demand. 2 in the example.
- A (Energy): The total amount of decreased energy demand.
- B (Energy): The total amount of increased energy demand.

These FC describe how feasible control strategies can be constructed. For example, Δ has to be larger than the adjustment that one wants to make, while β has to be greater than the amount of time that one wants to adjust the demand. If the effect of the control needs to happen quickly, then, it is important to have a small τ and α. Similarly, it is of great interest to consider **A** since it gives how much demand one can move in total. The size of **B** is related to the loss in efficiency that one can expect when utilizing flexibility. These characteristics are useful for determining what kind of renewable energy sources can be used to integrate, as shown through a case study in Section 4. The FC also gives the feasibility of participating in different energy markets. For example small values of τ and α enable participating in balancing markets while **A** is more important for participating in day ahead markets. However, currently participation in these markets requires much more than one building. A proposed solution to this problem is to aggregate buildings in a district or buildings connected to a district heating network [45]. One of the advantages of this characterization is that the aggregated flexibility of several buildings is given by estimating the FF from their combined energy usage. Alternatively the additivity of the FF, allows the aggregated FF to be found by summing the individual FFs. The FC are readily obtained from the aggregated FF. This means that the exact same methodology can be used for the individual buildings and districts of buildings alike. Notice that the time constants of the individual buildings are not assumed to be equal. Indeed, a district of buildings can consist of a mix of well-insulated buildings with large time constants and poorly-insulated buildings with smaller time constants. If a district of buildings is provided with the same penalty signal, then the aggregated FF is of interest. In general, the grid operator requires FFs in the same or higher spatial resolution as that of the penalty signals. If penalty signals are constant within districts of buildings, then, it is the accumulated energy demand and flexibility that is of interest, and thus it makes sense to estimate the aggregated FF.

3.2. Flexibility indexes for buildings

This section introduces the concept of a FI, which combines the penalty signals from Section 2.1 and the building's FF from Section 2.2. The motivation for introducing a FI is that it communicates the *value* of utilizing the flexibility dependent on its purpose, e.g., cost minimization or CO_2 minimization. Moreover, while the FC defined in Section 2.2 have clear value for engineers and researchers in a design and control context, this FI is expected to be easier to interpret for a wider audience, such as end-users and legislative bodies.

Seen from the building owners' perspective, their benefit of utilizing buildings' flexibility is determined by the cost savings that is achieved by utilizing it. This leads to the Expected Flexibility Savings Index (EFSI). On the other hand, from the grid operators' point of view, their benefit of utilizing buildings' flexible resources is to know how much of their request/need for demand response can be activated. In this case, the penalty signal could be linked to wind availability, peak load reduction, or balancing of the electrical grid, etc., yielding the FI.

The most accurate way to identify a FI is to have two identical buildings with identical usage behavior; for one performing the control based on penalties while letting the other be penalty-ignorant. The ratio between the accumulated penalties would then tell us how large the relative savings would be. This is, however, not feasible in practice. Instead, we propose that the FI for buildings can be assessed by simulating its operation by using the FF with both penalty-aware and penalty-ignorant controllers, and comparing the accumulated penalty of the two. If, for instance, the penalty is the real time electricity cost, then the index will show how large savings one would be able to achieve. What the test really shows is how much the smart building (thermal mass, controllers, etc.) is able to react to the penalty signal.

In summary, two different FIs are suggested. The first index is related to the actual penalty, and hence to the actual costs. The second index is based on a reference penalty designed to test certain characteristics. The FIs are:

- *Expected Flexibility Savings Index*: This index is related to actual costs, meaning that an EFSI equal to 0.10 implies that the expected savings for the actual smart building is 10%. A drawback of this definition is that it depends on the actual level of the penalties, and it might be difficult to get an EFSI larger than, say, 0.25.
- *Flexibility Index*: This index is related to reference penalties and these reference penalties will be designed such that the FI will be able to take values between zero and one. If, for instance, we are focusing on a flexibility for peak shaving, then this alternative definition could lead to a FI equal to 1 if power consumption in the peak periods is avoided completely.

Both indexes are calculated using the same procedure which is described in the following, exemplified by the FI. The FI uses the reference penalty signal, λ, and consists of the following steps:

1. Let λ_t be the penalty on the energy consumption at time t.
2. Simulate the control of the building *without considering* the penalty, and let u_t^0 be the energy consumption at time t.
3. Simulate the control of the building *considering* the penalty, and let u_t^1 be the energy consumption at time t.
4. The total operational cost of the penalty-ignorant control is given by $C^0 = \sum_{t=0}^{N} \lambda_t u_t^0$.
5. Similarly the operational cost of the penalty-aware control is given by $C^1 = \sum_{t=0}^{N} \lambda_t u_t^1$.
6. Then the quantity

$$FI = 1 - \frac{C^1}{C^0} \tag{4}$$

gives us the fractional amount of saved weighted cost, and this is the suggested FI.

If the penalty signal, λ, is the actual cost (like real-time price or CO_2), the calculation procedure leads to the EFSI instead of the FI. The controller in a smart building must be able to respond to the external penalty signal. If the controller is unable to do so, then $FI = 0$. An example of the procedure can be seen at the bottom of Fig. 2, where the accumulated cost is shown. The flexible controller accumulates around 80% of the regular controller cost, and thus for this particular building and penalty signal $EFSI = 0.2$. Indeed, it is seen that the ability to estimate the long-term expected savings is due to the transient behavior being included in the FF. Static flexibility representations lack this quality, which means that the same approach is not applicable for them.

The penalty signal for calculating the FI should be long enough to include relevant seasonal effects. Most renewable energy resources includes yearly variations, and to capture this, the time period chosen for the case study is one year. The penalty signals can be designed as typical scenarios for e.g., the CO_2 variability for the considered area, as done in Section 4. In Denmark, a typical scenario should be related to the variability of wind power, and wind might be present or missing for 1–3 days, as shown by Fig. 6. For countries with a lot of solar power, the scenario should be linked to the truncated harmonic variation of solar power, and hence the low penalty should be around say 8 h. For countries like Norway, with a lot of hydro power, but where the typical morning and afternoon peak load is covered by fossil sources, the penalty should be around say 2–3 h. In fact this illustrates that the suggested concept could be used to create a FI for buildings optimized for wind power, solar power or optimized for peak shaving for a couple of hours.

3.3. Ancillary services

Problems related to frequency, voltage, and congestion have historically been solved by the supply side. However, according to [46] recent increases of e.g., PV integration mean that local demand side flexibility is required. In this scenario, traditional transactional solutions are ill-suited for the fast activation of flexibility required for proper grid management and therefore other approaches should be introduced. For instance, it is suggested by [46] to perform ancillary services by adjusting the electricity price for the loads causing the problems. This corresponds to penalty-based control of the load, where the penalty is chosen as the solution to specific problems. For example in case of voltage magnitude regulation, a problem formulation could be

$$\underset{\lambda_t}{\operatorname{argmin}} \left|\left| f\left(\sum_{k=0}^{\infty} h_k \lambda_{t-k}\right) - v_{ref} \right|\right| + \alpha \left|\left| \lambda_t - \lambda_{ref} \right|\right|,$$

where λ_t is the penalty at time t,v_{ref} is the nominal voltage and f is a function mapping the load to voltage. The first term describes the cost of violating the nominal voltage level, while the second term ensures that the penalties do not deviate too much from the nominal level, λ_{ref}. α determines how much weight is put on each of the objectives. The coefficients h_k, used to determine the load as a function of penalty, are given by the FF. Thus, the penalty provided for each area is determined by its FF. Similarly, frequency and congestion problems can be solved the same way. Another major advantage of this method over the transactive energy approaches, is that it only needs one-way communication to send the penalty signals, compared to the two-way communication needed to negotiate prices.

4. Case study

This section demonstrates how different FFs enable the utilization of flexibility toward integrating various types of renewable energies. Three theoretical FFs are shown in Fig. 5. For the sake of simplicity assume that these represent three buildings, having vastly different FC. Building 1 is able to move the largest amount of energy, while Building 3 is able to move the least. On the other hand, Building 3 is able to respond faster than the other two. Building 2 is somewhat in the middle. We can also consider a combination of the buildings, which is easily as the average of the FFs.

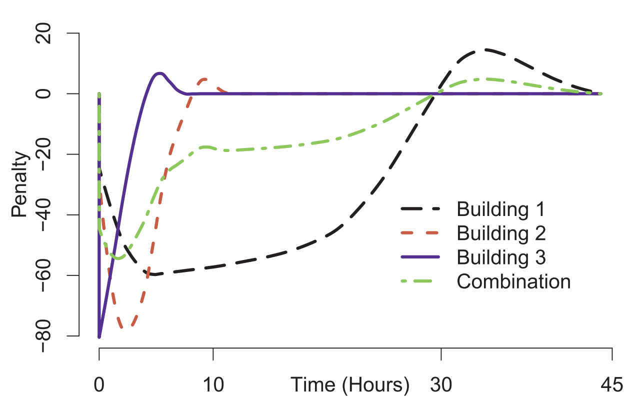

Fig. 5. The Flexibility Function for three different buildings.

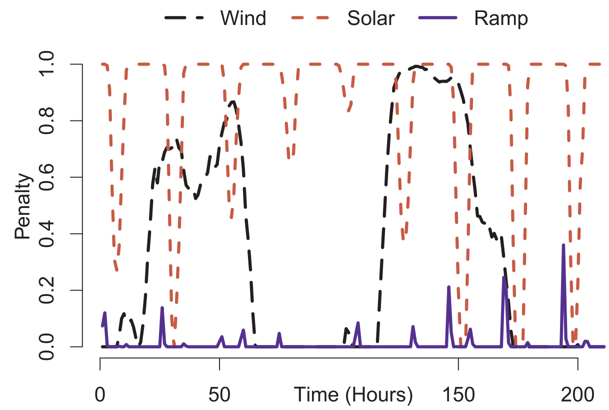

Fig. 6. Penalty signals based on wind and solar power production in Denmark during 2017. Ramp penalty based on Consumption in Norway during the same period.

Let us consider, how well each building performs in environments dominated by different kinds of renewable energy, namely wind, solar, and hydro power. For wind and solar power, we have used the production of 2017 in Denmark to make penalty signals inversely proportional to the amount of produced wind or solar power. Hydro power can be controlled and thus, it does not experience the same kind of problems as wind and solar. The problems still experienced are mainly due to large ramps in demand during the morning and afternoon hours. Therefore, a penalty signal based on these ramps has been constructed from the 2017 data obtained from the Norwegian power grid [47].

A period of the penalty signals can be seen in Fig. 6. The daily variation is seen for the solar penalty, and since the period is during the winter where the solar power production is large only for short periods of the day. The wind penalty starts at zero due to the period starting with windy weather. Then, it changes for a couple of days where apparently the wind power production is small. However, after this period, we see almost three days of zero penalty, which means that there were lots of wind. The ramp penalty remains close to zero with only a few peeks when the ramp in demand was large. This snapshot of the data is representative of the penalty signals in general, where in short: wind is dominated by low frequency variation, solar by 24-h variation, and ramp by few sudden spikes.

Computing the EFSI as described in Section 3.2, Table 1 quantifies how well each of the buildings' flexibility is utilized in the integration of wind power, solar power, and dealing with ramping problems, respectively. It is seen that the EFSI is heavily dependent on the penalty signal, to the extent that for each penalty signal a different building is the most flexible. Building 1 is able to make the most of the wind penalty, since it is the only building that is able to sustain a demand response on a time scale similar to that which the wind penalty changes on. For the solar and ramp penalties it does not matter that Building 1 is able to sustain the demand change for such a long time, since these two penalties change much more frequently. In fact, the response of Building 1 is so slow that usually it is not able to react to the changes in penalty when based on solar or ramp. For these two penalty signals the faster speed at which Building 2 and 3 can react with is critical. In the

Table 1
Expected Flexibility Savings Index (EFSI) for each of the buildings and the swimming pool based on wind, solar and ramp penalty signals.

	Wind (%)	Solar (%)	Ramp (%)
Building 1	11.8	4.4	6.0
Building 2	3.6	14.5	10.0
Building 3	1.0	5.0	18.4
Combination	5.4	8.0	11.5
Swimming Pool	3.5	2.7	0.6

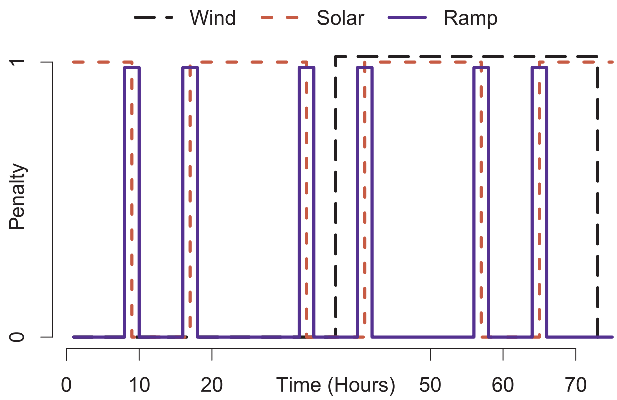

Fig. 7. Reference scenarios of penalty signals related to ramping or peak issues as well as the integration of wind and solar power.

Table 2
FI for each of the buildings and the swimming pool based on reference penalty signals representing wind, solar and ramp problems.

	Wind (%)	Solar (%)	Ramp (%)
Building 1	35.1	7.2	18.9
Building 2	10.3	24.0	37.5
Building 3	4.9	11.1	71.0
Combination	16.8	14.1	42.5
Swimming Pool	8.1	4.0	2.8

end, the solar penalty is slower than the ramp penalty making it better suited for building 2 that can sustain its response for a while, while the very fast variations in the ramp penalty can only be captured by the fast response of Building 3. Due to the linearity of the FF, the combination of each of the buildings simply obtains FIs equal to the average of the buildings. The swimming pool obtains low scores due to the technical issues in the control setup, but is still able to provide some flexibility for the wind-based penalty scenario.

To get the FI we use simple deterministic reference scenarios that represent the issues related to ramps and integration of wind and solar power. Examples of this can be seen in Fig. 7. The wind penalty is constant for 36 h, alternating between 0 and 1. The sun penalty is equal to 0 for 8 consequent hours each day and 1 otherwise, while the ramp penalty is equal to 0 all the time except for two periods of two hours each, every day, where it is equal to 1. These signals are simple, and more sophisticated signals can be developed to better represent reality. However, by repeating these signals and simulating each of the buildings' response, we compute the FI based on these scenarios and obtain Table 2. Comparing with Table 1, the trend is similar except that the numbers are approximately 3 to 4 times larger. This means that even these very simple reference penalty signals are sufficient for testing the energy flexibility. Furthermore, the reference scenarios indicate how close the building is to reaching the limit of what is possible for the given reference scenario. For example, we see that Building 3 achieves a FI of 71% of the maximum amount of possible energy flexibility when it comes to the ramp-based penalty.

5. Summary and future work

Planning and control problems experienced in power systems, when integrating considerable amounts of fluctuating renewable energy resources, call for a paradigm shift to a demand control approach. With buildings accounting for a considerable amount of global energy consumption, the energy flexibility offered by this sector can be used to implement required demand response measures. Taking this into consideration, this paper proposes an energy flexibility characterization methodology based on the presented flexibility function, which describes the reaction of a specific smart building, or cluster of smart buildings, to a penalty signal. The dynamic nature of the flexibility function enables it to be useful even when the system is not in steady state. Assuming linearity and time-invariance, the flexibility function contains all information about the relationship between the penalty signal and the resulting energy demand profile. Several important features of the flexibility function determine what kind of grid problems can be solved by the available energy flexibility, as demonstrated by the presented case study. In particular the flexibility index quantifies the overall effectiveness of utilizing the referred energy flexibility, in different scenarios.

In addition to the technical and operational applicability of the methodology, the flexibility characteristics and flexibility index are also used for labelling of energy flexible systems, such as buildings. This is an important step forward compared to previous static approaches. Flexibility labels can be obtained by defining standardized penalty signals and comfort intervals (for temperature, humidity, etc.). Under those standardized boundary conditions, results can be used for an inter-comparison of technologies, buildings or even districts in their potential energy flexibility. As such, the presented methodology can, for example, contribute to the development of the smart readiness indicator, which is currently being investigated as an amendment to the European Energy Performance of Buildings Directive [48] to assess the level of smartness of buildings.

Within the framework of the International Energy Agencies' Energy in Buildings and Communities Annex 67, the proposed energy flexibility characterization methodology will be further developed and evaluated. Specifically, more data will be collected to assess the described time invariance and linearity assumptions. Nevertheless, as shown in Section 2.2, time varying models are a natural extension. The nature of possible non-linearities will have to be investigated, to decide on appropriate methods to deal with them.

Acknowledgment

The work has been carried out as a part of IEA EBC Annex 67 'Energy Flexible Buildings', CITIES, SmartNet, and the FME ZEN Centre. The authors are thankful to The Danish Energy Agency (EUDP), Innovation Fund Denmark, EU-H2020, and the Norwegian Research Council for the support. Furthermore, the presented work partially receives the support of the European Union, the European Regional Development Fund ERDF, Flanders Innovation & Entrepreneurship and the Province of Limburg. Finally, we acknowledge the members of IEA EBC Annex 67 for a lot of fruitful comments and suggestions.

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