On the Value of Device Flexibility in Smart Grid Applications

Marco E. T. Gerards and Johann L. Hurink
Department of EEMCS
University of Twente
Enschede, the Netherlands

***Abstract*—Demand-side management and demand response are proposed as a means to solve different objectives in smart grids, such as, e.g., maximizing self-consumption of a house or peak shaving. Crucial components in these approaches are load shiftable/steerable devices, so-called smart appliances. Although several studies already use these devices and determine how to use their flexibility, their impact on—or value for—the overall system is not studied. This paper provides a methodology to calculate the value of flexibility of smart devices. The methodology makes it possible to quantitatively compare the impact of these devices for different kinds of objectives.**

The developed methodology is applied in a case study to compare the flexibility of white goods, home batteries and electric vehicles. The results indicate among others that smart white goods may not always be that important for smart grids.

***Index Terms*—Demand side management, device flexibility, load management, optimization, smart devices.**

I. Introduction

The share of renewable electricity is steeply growing. Due to this, some countries give incentives to customers for self-consumption. As an example, in the Netherlands household tariffs are based on annual net energy demand. As a response to this, an electrification of heat supply (e.g., CHPs and heat pumps) and transportation (e.g., electric vehicles) takes place. Unfortunately, the times of production of renewable energy and consumption by these new appliances do not always match. Furthermore, charging times of electric vehicles (EVs) are typically synchronized [1] and this may lead to overloaded low voltage grids in the future.

Lately, a lot of research efforts aim at resolving these issues. Demand-side management (e.g., [2], [3]) and demand-response programs [4] provide incentives to domestic customers to adapt their behavior, or directly control their appliances. Commonly in these programs, customers have so-called smart appliances that can be steered within such a framework. Typical examples are electric vehicles, heat pumps, batteries, white goods and HVACs systems. Next to controlling the appliances, even the curtailment of PV is considered as an option in some situations.

In previous research, some focus has been on the availability of flexibility in terms of *when* devices are available (e.g., how often and when washing machines are used) and the amount of flexibility customers are willing to offer [5] (e.g., the delay for EV charging). Furthermore, some test sites already use such devices in domestic situations (e.g., [6]). However, these studies do not introduce a quantitative measure to characterize the *potential value* of these devices for the objective of these test sites. More precisely, we are not aware of approaches to quantify the impact of a single device on a local objective in a way that makes it easy to compare its value to that of other devices.

The value of flexibility depends on the given objective (e.g., peak shaving, maximization of self-consumption) and the context (e.g., shape of the overall load profile, amount of available PV). For example, when there is no local energy production present, the value of flexibility for self-consumption is zero. Furthermore, the typical usage patterns of appliances and the allowed flexibility have a significant impact. E.g., a washing machine has a low flexibility value when 1) it is used only a few times per week, 2) it is already on at favorable times, or 3) its owner only offers a limited time window wherein its operation can be shifted.

To express the value of flexibility for different settings, we present a structural approach that allows us to compare different appliances under different circumstances (Section II). This approach assigns a single *flexibility value* to each appliance in the given context, which then can be used to compare the value of this appliance to that of other appliances.

Since the value of flexibility depends on its context, Section III contains an extensive case study that gives quantitative results for some typical situations that are encountered in practice. For this, we calculate the value of several important devices, namely different white goods, electric vehicles and home batteries in the context of different types of house load profiles (with and without PV). Based on these values we show that, for example, white goods such as washing machines, dryers and dishwashers provide low flexibility (in almost every context) compared to electric vehicles or even quite small batteries. Section IV concludes the paper.

II. Approach

To assign a value to the flexibility of a device, we build on the optimization objective of the given (demand side management) setting. This optimization objective, which is often called the cost function, is a function that expresses the cost dependent on the decisions and decreases when the objective is better (i.e., lower "costs"). In most settings this cost function depends in some way on the load profile of the house (i.e., load over the day).

In the following we study the ability of a device to influence the load profile of a house in a way that improves the objective. The load profile of the house is denoted by a vector $\vec{p}$, which specifies the average power for N consecutive time intervals (e.g., time intervals of 5 minutes length). For our analysis, two different house profiles are considered in this paper, namely the profile wherein the device is used without smart control / optimization (denoted by $\vec{p}$) and the profile wherein the device is used in its best way w.r.t. the given objective (denoted by $\vec{p^*}$).

In this paper we consider two specific objectives, namely peak shaving (Section II-A) and self-consumption (Section II-B). For both we give a method to calculate the value of flexibility of a device. These values are absolute measures of flexibility that make it possible to compare the flexibility between devices. Furthermore, we generalize these methods to a more general class of objectives (Section II-C).

A. *Peak shaving*

For peak shaving (or load flattening), we study the influence of a given device on the ability to smoothen the load of a given house over a certain period. A commonly used objective for peak shaving (or load flattening) is the 2-norm of the load vector $\vec{p}$:

$$\|\vec{p}\|_2 := \sqrt{\sum_{n=1}^{N} p_n^2}.$$

By using this, the highest peaks receive the highest costs, hence in the optimization process a reduction of the highest peaks is favorable.

While this 2-norm serves well for optimization, it cannot be used directly as a flexibility measure since the number of intervals (i.e., the granularity of the discretization of the planning period) influences its outcome. Instead, we prefer a flexibility value calculation independent of the number of intervals. To achieve this, we use the root mean square (RMS) as measure, since it introduces a scaling factor to compensate for the number of intervals. It is defined by

$$M_2(\vec{p}) := \sqrt{\frac{1}{N}\sum_{n=1}^{N} p_n^2}.$$

To calculate the value of flexibility, we study the improvement that results from using the device in the mode that leads to the lowest value of $M_2\left(\vec{p^*}\right)$ compared to its default mode of operation leading to profile $\vec{p}$. For example, the default mode for a washing machine may be the customer preferred starting time, while for a battery it may be defined as not using the battery at all. More formally, the value of the peak-shaving flexibility of a device is given by:

$$\nu_{\text{peak}} := M_2\left(\vec{p}\right) - M_2\left(\vec{p^*}\right).$$

B. *Self-consumption*

If maximizing self-consumption is the goal, the objective has to express the consumption of self-produced energy. This can be done by minimizing the import from the grid

$$\sum_{n \in \{n|p_n>0\}} p_n.$$

However, when we calculate the flexibility value later on we prefer an alternative notation leading to the same result:

$$\|\vec{p}\|_1 := \sum_{n=1}^{N} |p_n|,$$

which is commonly referred to as the 1-norm. To obtain a measure independent of the number of intervals, we again divide by this number and get

$$M_1\left(\vec{p}\right) := \frac{1}{N}\sum_{n=1}^{N} |p_n|.$$

The value of the self-consumption flexibility of a device is the improvement made with respect to the default mode of operation, i.e.,

$$\nu_{\text{self}} := M_1\left(\vec{p}\right) - M_1\left(\vec{p^*}\right).$$

C. *Generalization*

The underlying function $M\left(\vec{p}\right)$, which is used to determine the value of flexibility, can be generalized using the *generalized mean* (also called power mean or Hölder mean), which is given by:

$$\overline{M_m}\left(\vec{p}\right) := \left(\frac{1}{N}\sum_{n=1}^{N} p_n^m\right)^{\frac{1}{m}}.$$

Since for our application mainly the load is important (i.e., the size of the peak but not its sign) we slightly adapt this to:

$$M_m\left(\vec{p}\right) := \left(\frac{1}{N}\sum_{n=1}^{N} |p_n|^m\right)^{\frac{1}{m}}.$$

Using this function, the generalized value of flexibility for a device can be expressed by:

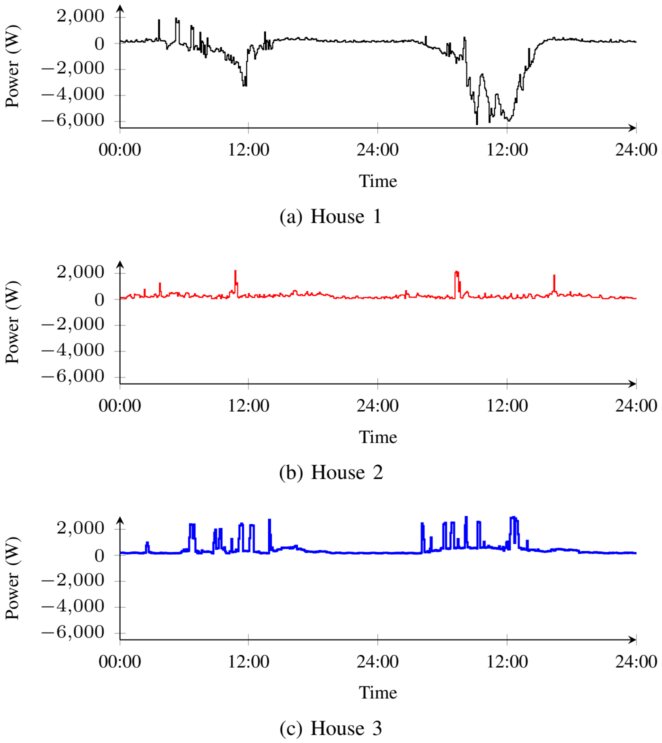
$$\nu_m := M_m\left(\vec{p}\right) - M_m\left(\vec{p^*}\right).$$

This generalizes the method of calculating the value of flexibility of the previous two subsections to different objectives. As presented, for peak shaving and self-consumption we can use m=2 and m=1 respectively. Also for other values of m, relevant measures can be obtained. E.g., the limiting cases $m \to -\infty$ and $m \to \infty$ lead to reducing the minimum and maximum loads.

III. Evaluation

The value of flexibility ν_m can be used to compare the impact of the flexibility of different devices. For example, when either a washing machine or a battery is used to improve the self-consumption objective, their values ν_{self} can be used to compare which device offers the most flexibility to support this objective.

Section III-A presents the set up of an evaluation that uses the presented methodology and is based on a representative case. This case is used in the sections that follow to study the value of flexibility of batteries (Section III-B), white goods (Section III-C) and electric vehicles (Section III-D) respectively.



(a) House 1

(b) House 2

(c) House 3

Fig. 1. First two days (01-04-2016 and 02-04-2016) of the house profiles used in the evaluation.

A. Case study

For the case study, we consider (five minute interval) measurements from three houses, all situated in southern Germany. The house profiles of these houses for two specific consecutive days are given in Fig. 1. To avoid influence of variation within a week, we consider all days of a four week period (weeks from 01-04-2016 to 28-04-2016). Furthermore, evaluation of self-consumption is only relevant in case of PV, hence it is only done for House 1.

B. Battery flexibility

To evaluate the battery flexibility, we take for $\vec{p}$ the measured house profile and for $\vec{p^*}$ the profile after optimization. Two optimization objectives are considered, namely self-consumption and peak shaving.

For self-consumption, a simple greedy algorithm can be used to steer the battery. It charges when there is a production surplus, and it discharges the battery to prevent import from the grid that would otherwise be needed. The value for flexibility ν_{self} is calculated for batteries ranging from 0 to $4\,\text{kWh}$, all assumed initially to be empty and having a maximum (dis)charging power of $3\,\text{kW}$. The result of the evaluation is shown in Fig. 2. It shows that this specific house obtains only marginal benefits from a battery larger than $3\,\text{kWh}$.

For the second objective, peak shaving, we use a tailored battery planning algorithm from [7] to calculate the optimal (dis)charging settings for peak shaving. The amount of flattening that can be achieved depends on the variation within the profile and the size of the battery. To study the influence of the variation, we consider the three different house profiles, while for the influence of battery sizes we again used capacities ranging from 0 to $4\,\text{kWh}$. We assume that the state-of-charge (SoC) is $50\,\%$ before the first day, and added a constraint to ensure that the SoC is again $50\,\%$ after the last day. The resulting values for flexibility ν_{peak} are presented in Fig. 3. This shows that for a house without PV, a relatively small battery can already achieve good flattening. For the house with PV, larger batteries still have some additional use, since they can shift abundant PV energy from one day to another.

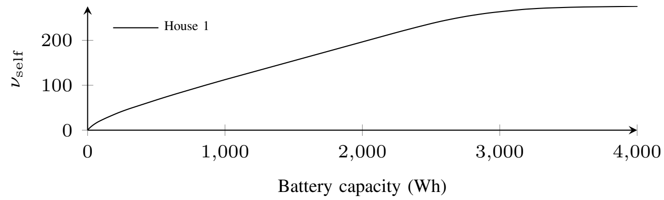


Fig. 2. Self-consumption value of batteries.

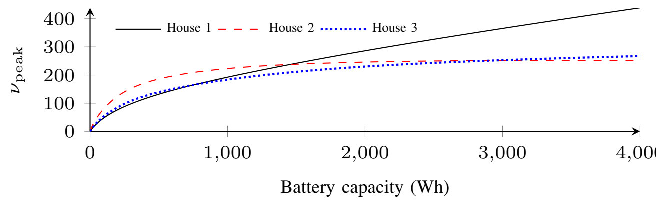


Fig. 3. Peak-shaving value of a battery.

C. White good flexibility

To study the flexibility of white good devices we consider a few specific devices: a Siemens XL 1462 Festival washing machine (SF WM), an old model Bosch Silence dishwasher (BS DW), an LG WM2016CW (LG WM) and an LG DLE2516W dryer (LG DR), where the latter two are from a public data set [8]. For all devices, the user enables the device each day at the *enable time* t_e and sets a relative activation deadline d, which means that the device must be started in the interval $[t_e, t_e{+}d]$. In the analysis below we assumed that the preferred starting time is as late as possible within the interval $[t_e, t_e{+}d]$, i.e., at $t_e{+}d$.

The value of flexibility largely depends on this enable time and the relative deadline: if the device would normally be started just after the PV peak and can be shifted to the PV peak, the value of flexibility is high. However, when the device is normally started at a favorable time (e.g., when there is much PV production), the value of the flexibility is low.

For self-consumption, the value of flexibility is depicted in Fig. 4. When the relative deadline is set to three hours, the peak of the value for flexibility is around noon. This implies that the device would normally be assumed to start at $3\,\text{pm}$ (after the PV peak), but the interval gives enough flexibility to shift its operation to the PV peak (noon).

Fig. 5 shows the value of peak shaving flexibility as a function of the enable time for three different relative deadlines

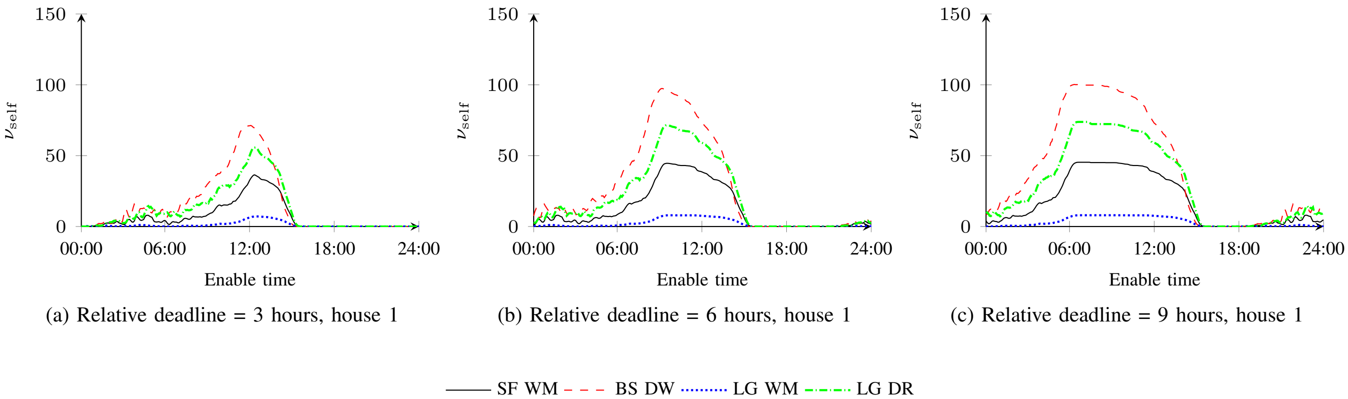


Fig. 4. Self-consumption values of time-shiftable devices (house 1).

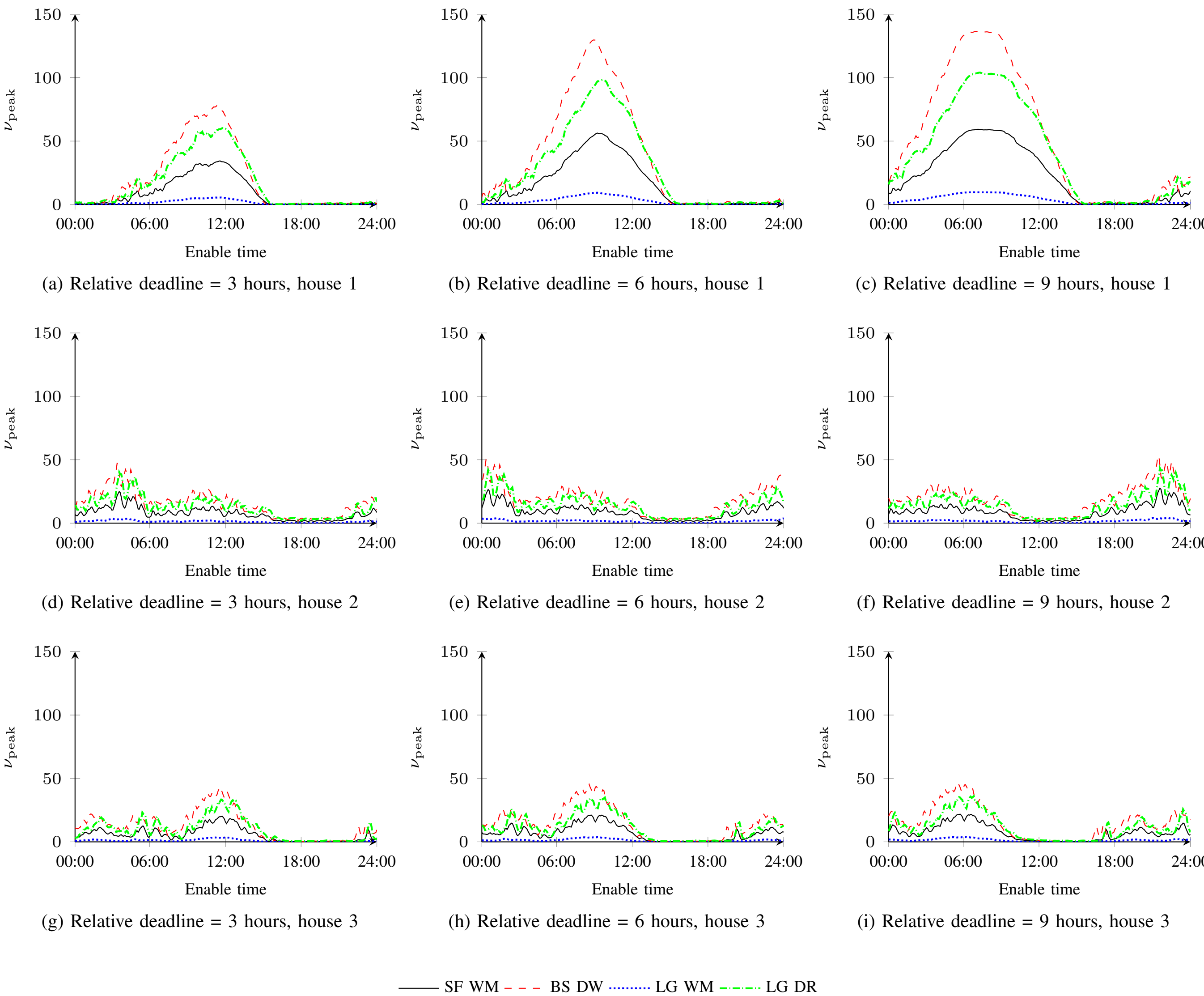


Fig. 5. Peak-shaving value of time-shiftable devices.

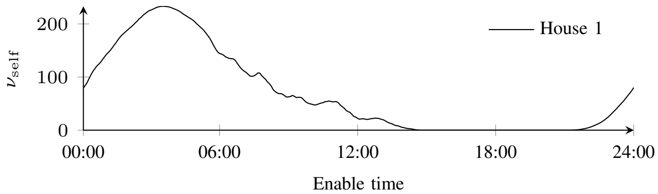
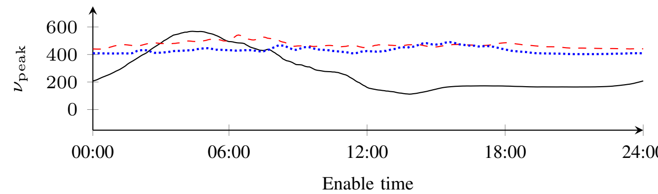
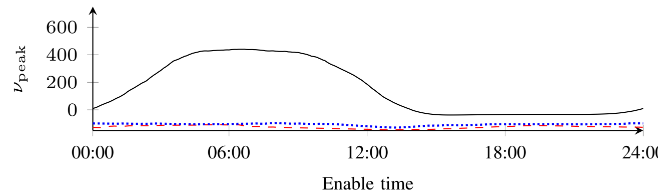


Fig. 6. Self-consumption value of an electric vehicle at house 1 (relative deadline: 6 hours).



(a) Compared to charging upon arrival.



(b) Compared to no EV

House 1 House 2 House 3

Fig. 7. Peak-shaving value of an electric vehicle (relative deadline: 6 hours).

(3, 6 and 9 hours). Note, that the best start times for both self-consumption and peak shaving mostly coincides. In both cases, it can be noted that devices with a high load (e.g., an old dishwasher) offers more flexibility. The value of flexibility decreases when white goods become more energy efficient.

Whereas this study assumes that the devices are used each day, in practice they are not and the value of peak shaving should be scaled accordingly. Since the scaling value is typically in the range 0.2–0.5 (i.e., used every 5–2 days), the deployable flexibility is quite small for both objectives. For example, for peak shaving, in the best case (scaling of 0.5) the value for peak shaving is comparable with a 180 Wh battery. This best case is not representative and requires strong assumptions, namely: the device is used every other day (scaling of 0.5), can be shifted to a relatively good start time (e.g., away from a consumption peak to a PV peak), high energy consumption, etc.

Another reason why the flexibility in practice is lower than indicated here is imperfect information. In this evaluation the time shiftable device is turned on at the optimal time, but to determine this time a look-ahead future is needed (i.e., is there PV production for the duration of the washing machine program?). In practice, such information is hard to obtain, hence the start times cannot be chosen optimally and the value of flexibility decreases. Some other devices, e.g., EVs [9], suffer less from this problem since they can respond faster to changing circumstances.

Note, that the absolute height of the graphs in Fig. 5 for the three different houses cannot be used as a criterion for comparing how good these house perform. We can only compare flexibility of different appliances based on the same base house profile $\vec{p}$.

D. Electric vehicles

To study the flexibility of an electric vehicle (EV), we assume that it must be charged with 4 kWh every day, has an enable time t_e and a relative deadline d of 6 hours, i.e., it is charged within the charging window $[t_e, t_e + d]$. For charging, any charging power in the range 0 to 6 kW can be used and varied over time. Note, that fewer charging options decreases the value of flexibility.

For self-consumption, the optimal charging settings $\vec{p^*}$ can be calculated by a greedy algorithm that charges at full power in the intervals with the lowest load. This optimal case is compared with a base case $\vec{p}$ that assumes charging at full power from t_e until the EV is fully charged. Remarkably, Fig. 6 shows that the EV offers almost the same flexibility for self-consumption as a battery (also of 4 kWh) when it is offered at night, but otherwise this flexibility declines steeply. The reason for this is that when the charging window starts around noon, default charging already coincides with the PV peak, while when the EV can charge from 04:00 (to 10:00), the EV charging can be postponed to a period with PV production (instead of charging at night) and the value of flexibility is higher.

To calculate optimal charging settings $\vec{p^*}$ for peak shaving, we use the algorithm from [10]. Two different base cases $\vec{p}$ are considered. The first base case is again charging at full power starting at t_e, resulting in the value for flexibility depicted in Fig. 7a. Although the enable times that allow shifting the charging to coincide with PV production gives the highest values, smart EV charging has also a high value of flexibility over the remainder of the day because it prevents the charging peak. Since this smart charging can both prevent a charging peak and a PV peak, the EV potentially has a higher impact than a battery with the same capacity. The second base case assumes no EV at all, as depicted in Fig. 7b, and indicates the gain of adding an EV to achieve peak shaving. The graph matches the intuition that acquiring an EV for peak shaving is only useful when PV is available. In the other situations it even leads to larger peaks.

E. Discussion

Whereas the previous sections studied the value of flexibility for individual devices, this section focuses on comparing the flexibility of the different devices. For self-consumption, the different devices are compared with different enable times and a relative deadline of 6 hours. For the battery and EV, a capacity of 4 kWh is assumed. The value of flexibility for all devices with these parameters is given in Fig. 8. Clearly, the EV and battery offer high flexibility, while the flexibility of the studied white goods is modest and will in practice be lower than illustrated here, as discussed before.

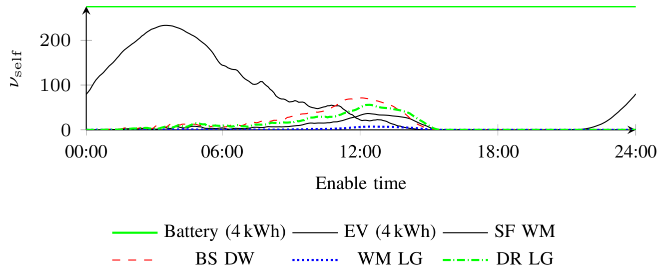


Fig. 8. Self-consumption value of several devices at house 1 (relative deadline: 6 hours).

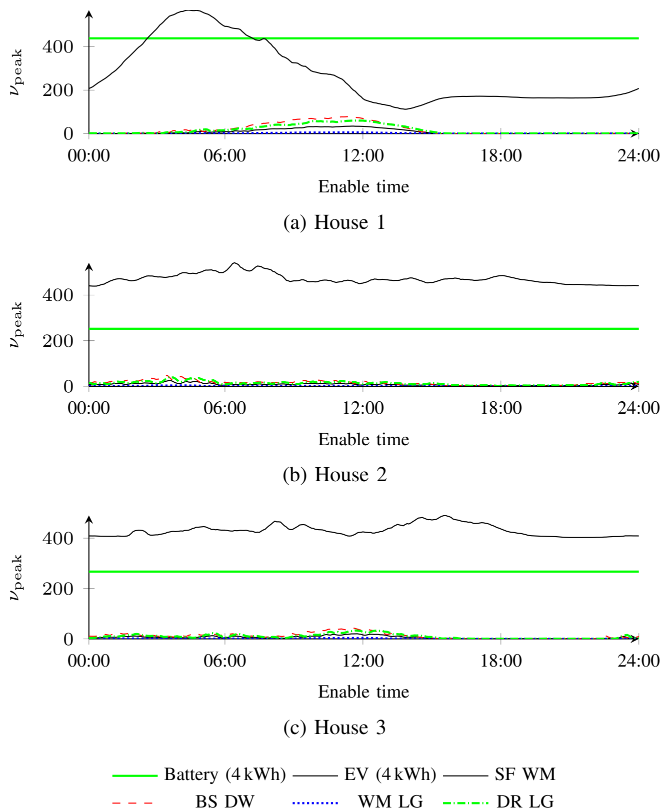


Fig. 9. Peak-shaving value of several devices (relative deadline: 6 hours).

A similar comparison is done for peak shaving, depicted in Fig. 9. The offered flexibility of white goods is marginal, especially when there is no PV. When there is PV, the value of flexibility of EV charging may be even higher than that of a battery with the same capacity.

IV. Conclusions and Discussion

This paper provides a quantitative methodology to determine the value of flexibility, which is the improvement of a certain objective based on the house profile that is obtained by optimally using flexibility of a device instead of taking some default action for the device (e.g., starting a washing machine when preferred by the customer). We used the so-called generalized average to determine this value for different objectives (e.g., peak shaving and maximization of self-consumption). This measure has been chosen since it is not directly influenced by the resolution and number of time intervals.

In the presented evaluation, this methodology is used to determine the value of flexibility for different white goods, home batteries and electric vehicles. Our evaluation indicates that the value of flexibility for white goods is small compared to a battery or electric vehicle.

For the presented evaluation we assume that flexibility is perfectly used, implying that the future must be predicted quite well. Devices such as batteries and EVs can often be deployed without predictions, or the decisions are robust against prediction errors. More precisely, for maximizing self-consumption they even do not need predictions of the expected house profile since they can apply a greedy strategy: charge when there is abundant PV, otherwise discharge to fully compensate for the house consumption, and for EVs peak shaving algorithms that are robust against prediction errors exist [9]. In contrast, most of the currently existing white goods are uninterruptible, and therefore they cannot use this strategy because after starting the device, this decision cannot be undone and therefore they do need good predictions to make an optimal decision. This gives an additional reason why the value of flexibility of white goods is in practice even lower than shown in this paper.

Within this paper we give the value of flexibility for different enable times. In future work we want to combine this result with occurrence statistics of these enable times (and other statistics) to obtain average values of flexibility for different devices.

References

[1] G. Pasaoglu, C. Thiel, A. Martino, A. Zubaryeva, D. Fiorello, and L. Zani, "Projections for electric vehicle load profiles in Europe based on travel survey data," Joint Research Centre of the European Commission, Tech. Rep. EUR 25993, 2013.

[2] M. E. T. Gerards, H. A. Toersche, G. Hoogsteen, T. van der Klauw, J. L. Hurink, and G. J. M. Smit, "Demand side management using profile steering," in *PowerTech, 2015 IEEE Eindhoven*, June 2015, 6 pages.

[3] A. Molderink, V. Bakker, M. G. C. Bosman, J. L. Hurink, and G. J. M. Smit, "Management and control of domestic smart grid technology," *IEEE Trans. Smart Grid*, vol. 1, no. 2, pp. 109–119, September 2010.

[4] P. Siano, "Demand response and smart grids–a survey," *Renewable and Sustainable Energy Reviews*, vol. 30, pp. 461–478, 2014.

[5] R. Stamminger, G. Broil, C. Pakula, H. Jungbecker, M. Braun, I. Rüdenauer, and C. Wendker, "Synergy potential of smart appliances," Smart-A project, Tech. Rep., November 2008.

[6] E. Klaassen, C. Kobus, J. Frunt, and H. Slootweg, "Load shifting potential of the washing machine and tumble dryer," in *2016 IEEE International Energy Conference (ENERGYCON)*, April 2016, 6 pages.

[7] T. van der Klauw, M. E. T. Gerards, and J. L. Hurink, "Resource allocation problems in decentralized energy management," *OR Spectrum*, 2017, 25 pages.

[8] M. Pipattanasomporn, M. Kuzlu, S. Rahman, and Y. Teklu, "Load profiles of selected major household appliances and their demand response opportunities," *IEEE Transactions on Smart Grid*, vol. 5, no. 2, pp. 742–750, March 2014.

[9] M. E. T. Gerards and J. L. Hurink, "Robust peak-shaving for a neighborhood with electric vehicles," *Energies*, vol. 9, no. 8, p. 594, July 2016.

[10] T. van der Klauw, M. E. T. Gerards, G. J. M. Smit, and J. L. Hurink, "Optimal scheduling of electrical vehicle charging under two types of steering signals," in *IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), Istanbul, Turkey*. USA: IEEE Power & Energy Society, October 2014, pp. 122:1–122:6.