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Designing Individual Penalty Signals for Improved Energy Flexibility Utilisation^{*}

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Abstract: The energy flexibility associated with energy consumption must be exploited to accommodate more fluctuating renewable energy. The only solution that enables this without violating privacy concerns is penalty-based control, where penalty signals are designed to give incentives for the consumers to adjust their demand according to the needs of the grid. Designing the penalty signals is a challenging task due to different flexibility potential offered by various energy consuming systems. In this paper, it is shown that the best utilisation of energy flexibility requires individual penalty signals tuned towards the energy flexibility of each consumer. Here, we present a very simple yet novel approach for designing such individual penalty signals for each consumer, such that the value of the energy flexibility is increased, for both the grid operators and the consumers.

Keywords: Renewable Energy, Energy Flexibility, Flexibility Function, Step Response, Discrete Fourier Transformation.

1. INTRODUCTION

The ever-increasing share of renewable energy is helping to reduce the share of the electricity produced by fossil fuel based plants in electrical grids, but at the same time it is giving rise to new challenges related to operation of the grids. According to a recent study, approximately 40% of the global energy consumption is due to energy consumed by buildings (Lindberg (2017)). There are many sources which offer a great potential to provide demand response, defined as their energy flexibility. Perhaps the most obvious source for energy flexibility is batteries (Kneiske and Braun (2017)), that are explicitly designed to store energy. Batteries can act in a fast and efficient manner but they are very expensive (Lund et al. (2016)).

It is economically and environmentally much more viable to use already existing sources of energy flexibility (Dominković et al. (2018)), such as thermal mass of buildings (Dréau and Heiselberg (2016)); bodies of water such as domestic hot water tanks (Halvgaard et al. (2012)), district heating networks (Madsen et al. (1996)), or swimming pools (Zemtsov et al. (2017)). It is very attractive to use the energy flexibility offered by buildings in the design of future smart energy systems (Østergaard Jensen et al. (2017)). The main challenge in the design of the future smart energy systems is the proper utilisation of the energy flexibility. This is due to the varying nature of the energy flexibility offered by different types of buildings (Reynders et al. (2018)). For example, buildings differ in their thermal properties such as insulation and location of thermal mass; the energy consuming processes like ventilation and

heating; the behaviour of occupants and their willingness to be flexible; and most importantly the installation of the automatic controllers which enable the activation of the demand response (Oldewurtel et al. (2013); Stinner et al. (2016); Coninck and Helsen (2016)). Moreover, the energy flexibility offered by different sources in buildings is available for different time-scales.

Additionally, some other challenges associated with the integration of renewable energy resources include frequency, ramping and grid balancing problems due to the fact that the availability of the electricity from renewable energy sources is dictated by weather conditions. Similarly, voltage problems are caused by prosumers injecting power into the grid and increased utilisation of the electricity is also causing problems, such as congestion, when many Electrical Vehicles (EVs) have to be charged at the same time in Distribution System Operator (DSO) grids.

To solve these problems and ultimately enable higher shares of renewable energy, energy demand response has been suggested in the literature. Within the field of energy demand response two main approaches exist; the direct control (Tahersima et al. (2013)) and indirect control (Corradi et al. (2013); Zhou et al. (2017)). The direct control approach consists of controlling electric appliances directly, while the indirect approach utilises incentives. The incentives can be formulated in terms of penalty signals, where the consumers should minimise their accumulated penalty. The most obvious kind of penalty is price, so that consumers minimise their total cost. Furthermore, in the indirect approach the demand response depends on grid location, if one wants to solve voltage problems and do congestion management.

For the current market structure usually the Balance Responsible Party (BRP) controls the prices received by

^{*} The authors would like to thank the Centre for IT-Intelligent Energy Systems (CITIES) project supported by Innovation Fund Denmark for the financial support needed to conduct the research reported in this paper.

the consumers, and thus they should design the penalty signals. However, the grid-problems are the responsibility of the Transmission System Operators (TSOs) and the DSOs. Therefore the communication would either have to be fast between the BRPs and these two parties, or the market structure would have to be changed such as to allow the TSOs and the DSOs to directly modify the penalty signals. In any case, the approach presented in this paper can help tailor the penalty signals regardless of the entities designing them.

As mentioned before, batteries provide short-term energy flexibility, while the thermal mass of swimming pools and district heating systems provide long-term flexibility. Some work has already gone into utilising this, by having several control loops, operating in different time resolutions, where the low resolutions are utilised for the balancing market and high resolutions for the regulation market (Fabiatti et al. (2018)). However, while this approach does improve the utilisation of energy flexibility, it requires, for each device, a decision, in which market it should participate. Moreover, it only deals with differences in time scales, while ignoring other, potentially important Flexibility Characteristics (FC) such as the maximum effect and size of the rebound effect (Junker et al. (2018)). Therefore, in this paper, it is shown with a simple yet novel approach, how the penalty signals can be individually designed for different sources to improve utilisation of their energy flexibility while taking into account all the FCs.

The paper continues by introducing the methodology and evaluation criteria in Section 2. Then, Section 3 explains the novel algorithm to tailor penalty signals towards a specific kind of energy flexibility. An online version of this algorithm is introduced in Section 4. In Section 5 the designed penalty signals are evaluated, and conclusions are summarised in Section 6.

2. METHODOLOGY

In this section, we first explain briefly the methodology followed to design the individual penalty signals. Before proceeding towards the explanation of the methodology all the assumptions are stated explicitly below.

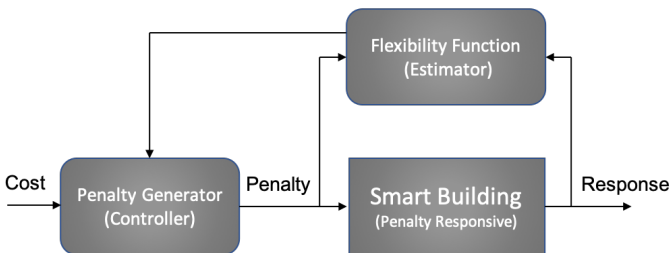


Fig. 1. A smart building is able to respond to a penalty or external control signal.

Assumption 1. *The systems under consideration (buildings) are assumed to be penalty-responsive energy systems as shown in Figure 1.*

Remark 1. *This implies that all consumers receive penalty signals that vary in time, that they respond to, such as to move their consumption away from periods with large penalties.*

Assumption 2. *The output response of the system to penalty signals is linear.*

Remark 2. *This implies that such systems can be characterised using their step-response function and that only the frequencies present in the input will be present in the output.*

Assumption 3. *All grid problems such as demand ramps, frequency/voltage deviations, demand-supply balance, etc. for each point in time, can be collected in a total cost, that quantifies all costs associated with consumed electricity.*

Remark 3. *One cost makes univariate control of the energy flexibility possible, which is much simpler and faster to implement in real-time than multivariate control for all grid problems.*

Remark 4. *Throughout the paper, signals will be referred to without subscripts, while the value at a specific point in time, is referred to using subscripts, i.e. if u is a signal then u_n is the value at time n .*

The objective of the grid operators is to design penalty signals that make consumers impose the least total cost on the grid. As already discussed, the cost depends not only on time, but on the consumers location on the grid as well. This can easily be incorporated by first adjusting the cost function for spatial differences, and then considering one location at a time. It was demonstrated in (Junker et al. (2018)) that the value of energy flexibility can be quantified as the magnitude of the savings obtained by utilising the flexibility, i.e. the so-called Flexibility Index (FI). When utilising energy flexibility, it is important to keep in mind that the grid operators and consumers have different goals. Grid operators want to minimise grid costs, whereas consumers want to minimise their expenses. To evaluate the value of flexibility for both grid operators and consumers the FIs must be computed for both parties.

It is straight forward to do this for the consumers, if we assume that u^i is the penalty signal received by the i^{th} consumer and $y_n^i(u^i)$ is the power consumption of the same consumer at time step n , then the accumulated penalty \mathcal{P}_{ac} at time $T > n$, which translates into the total cost for the i^{th} consumer, is given by

$$\mathcal{P}_{ac} = \sum_{n=0}^T u_n^i y_n^i(u^i). \quad (1)$$

The relative value of the flexibility is given by comparing \mathcal{P}_{ac} to the normal operation \mathcal{P}_0 , where penalty is not taken into account:

$$FI_i = 1 - \frac{\mathcal{P}_{ac}}{\mathcal{P}_0}. \quad (2)$$

For the grid operators, the cost is not related to the penalty signal, but to the grid cost. Thus, assume that λ_n^i is the cost imposed on the grid by the i^{th} consumer, when consuming energy at time step n . If there is a total of I consumers, then the FI for the grid is given by

$$FI_G = \frac{\sum_{i=1}^I \sum_{n=0}^T \lambda_n^i y_n^i(u^i)}{\sum_{i=1}^I \sum_{n=0}^T \lambda_n^i y_n^i(0)}. \quad (3)$$

It is worth mentioning that in this paper, both measures will be taken into account when evaluating flexibility.

3. DESIGNING INDIVIDUAL PENALTY SIGNALS

In (Junker et al. (2018)), it was also shown that the FI heavily depends on the penalty signal, meaning that a system might be considered very flexible in some scenarios, while not being particularly flexible in others. This fact is exploited here in a novel way to tailor penalty signals for each system. The key is to design penalty signals with time domain characteristics similar to the cost signal and with the same energy. This ensures that the signal is modified in such a way that each system is able to react more to it, but the energy flexibility is still utilised to solve the real problems such as the grid or consumer costs etc.

Suppose, that the consumption of building i at time n is given by the baseline consumption, μ_n , plus the effect of the penalty signal, u^i , as

$$y_n^i(u^i) = \mu_n + \sum_{k=0}^{N-1} h_k^i u_{n-k}^i. \quad (4)$$

Then the Flexibility Function (FF) (also called step-response function in time series analysis - see e.g. (Madsen (2008))) can be expressed in terms of the impulse response coefficients, $\{h_n\}_0^{N-1}$ by,

$$F(n) = \sum_{k=0}^n h_k, \quad \forall n \in \{0, 1, \dots, N-1\}, \quad (5)$$

where N is the length of the impulse response of the system under consideration. The frequency response function can be simply obtained through the Discrete-time Fourier Transformation (DFT) of the impulse response coefficients:

$$\mathcal{H}(\omega) = \sum_{k=0}^{N-1} h_k e^{-\frac{ik}{N}\omega}, \quad (6)$$

where ω is the angular frequency. In short notation, this can be written as $\mathcal{H} = \mathcal{F}(h)$. It is important to note that the frequency-domain representation is equivalent to the time-domain representation, and time-domain representation can be obtained via the Inverse Discrete-time Fourier Transformation (IDFT), $h = \mathcal{F}^{-1}(\mathcal{H})$ given by

$$h_n = \frac{1}{N} \sum_{k=0}^{N-1} \mathcal{H} \left(2\pi \frac{k}{N} \right) e^{\frac{2\pi ik}{N}n}. \quad (7)$$

Similarly, if we define $Y = \mathcal{F}(y)$ and $U = \mathcal{F}(u)$, then

$$Y(\omega) = \mathcal{H}(\omega)U(\omega). \quad (8)$$

Equivalently this can be written as,

$$Y(\omega) = |\mathcal{H}(\omega)||U(\omega)|e^{i\angle\mathcal{H}(\omega)\angle U(\omega)}. \quad (9)$$

From this representation it is clearly seen that $|Y(\omega)| = |\mathcal{H}(\omega)||U(\omega)|$. This implies that the amplitude of the output signal at frequency ω is the amplitude of the same frequency in the input signal, scaled by $|\mathcal{H}|$. Thus, if we wish to increase the amplitude of the output, the power of the input should be focused around frequencies where $|\mathcal{H}|$ is large. The second part of (9) shows that the phase change from input to output at frequency ω is given by $\angle\mathcal{H}(\omega)$, where in this paper it is assumed that the phase has been unwrapped (Smith (2007)). So if the output signal should not be too delayed compared to the input signal, then the energy of the input signal should be concentrated around places where $\angle\mathcal{H}(\omega)$ is close to zero. Hence for each energy flexible system under consideration

(in this case different buildings, see Section 5 for details), we can combine the amplification and the phase change to make a scaling function as described below:

$$S^i(\omega) = \frac{|\mathcal{H}^i(\omega)|}{c + \angle\mathcal{H}^i(\omega)}, \quad (10)$$

where c is a constant that determines how much weight is put on the amplification and on the phase change. As c goes to infinity all the weight is put on the amplification, while having c close to $\min_{\omega} \angle\mathcal{H}^i(\omega)$ puts all weight on having a small phase change. Using this scaling function, a penalty signal for system i can be designed by multiplying it unto the DFT of the cost signal, $\Lambda = \mathcal{F}(\lambda)$:

$$U^i(\omega) = S^i(\omega)\Lambda^i(\omega),$$

which can then be transformed back into the time-domain as $u^{i'} = F^{-1}(U^i)$.

Finally, the mean and the energy of the penalty signal is adjusted to match the original signal, so that it is only the shape that differs:

$$u^i = \frac{u^{i'} - a}{b}, \quad (11)$$

where a and b are chosen so that the

mean: (12)

$$\frac{1}{T} \sum_{n=0}^{T-1} u_n^i = \frac{1}{T} \sum_{n=0}^{T-1} \lambda_n^i, \quad (13)$$

and energy: (14)

$$\frac{1}{T} \sum_{n=0}^{T-1} (u_n^i - \bar{\lambda}^i)^2 = \frac{1}{T} \sum_{n=0}^{T-1} (\lambda_n^i - \bar{\lambda}^i)^2, \quad (15)$$

remains constant. The steps used to design a penalty signal for system i based on the grid-cost signal λ^i are summarised in Algorithm 1:

Algorithm 1 How to design individual penalties.

- (1) Compute $\mathcal{H}^i = \mathcal{F}(h^i)$,
 - (2) Compute $S^i = \frac{|\mathcal{H}^i(\omega)|}{c + \angle\mathcal{H}^i(\omega)}$,
 - (3) Compute $u^i = \mathcal{F}^{-1}(\mathcal{F}(\lambda^i)S^i)$,
 - (4) Find a and b so that $u^i = \frac{u^{i'} - a}{b}$ has mean and energy equal to λ^i .
-

Notice how λ^i was already adjusted to the location of consumer i (indicated by the superscript). The location-based penalty was then tailored towards the flexibility of the consumer, making a penalty signal that is ideal for both the flexibility *and* location of the consumer.

4. ONLINE IMPLEMENTATION

In the previous section, it was assumed that a full cost signal can be split into different penalty signals at once, but in reality we want to design penalty signals online, without knowing the future grid costs. Here, we address this issue and a simple solution using a sliding window is proposed. Results of this online approach are compared to the offline solution and discussed in Section 5.

In the previous section, we designed penalty signals from time 0 to time T , by using the original cost signal in the

same time interval. This means that u_n^i depends on λ_k for all $0 \leq k \leq T$, even if $n < T$. This violates the condition of causality, and means that in reality such penalty signals can only be designed for historical data. If the proposed approach needs to be useful for control, then the relation between u^i and λ^i must be made causal. Notice, how this is already the case for u_T^i , so the last value of the designed penalty signal could be useful in practice.

We can build on this fact, by designing the penalty signals for an interval of R time steps, $(n - R + 1, n)$, but only use the last value of the designed signal, to get a penalty for time step n . The interval can then be moved one time step to $(n - R + 2, n + 1)$, to compute a new penalty signal, from which again only the last value is used. Now each value of the designed penalty signal only depends on the present and the last $R - 1$ time steps. Compared to the previous approach, we only get one new value at a time, and thus will have to iteratively go through all time steps. The steps involved in the procedure for causal design of individual penalties, starting from time step $n = 0$ are summarised below in Algorithm 2:

Algorithm 2 Causal design of individual penalties.

- (1) Compute $\mathcal{H}^i = \mathcal{F}(h^i)$,
 - (2) Compute $S^i = \frac{|\mathcal{H}^i(\omega)|}{c + \mathcal{L}\mathcal{H}^i(\omega)}$,
 - (3) Compute $v^i = \mathcal{F}^{-1}(\mathcal{F}(\lambda_{n-R+1 \dots n}^i)S^i)$,
 - (4) Find a and b so that $v^i = \frac{v^i - a}{b}$ has mean and energy equal to $\lambda_{n-R+1 \dots n}^i$,
 - (5) Assign $u_n^i = v_R^i$,
 - (6) Increase n to $n = n + 1$,
 - (7) Repeat from step (3).
-

5. RESULTS AND DISCUSSION

The case-study conducted in this paper is performed for the same three conceptual buildings, with vastly different FCs, as described in (Junker et al. (2018)). The FFs of the buildings are shown in Figure 2. It is clearly seen, how Building 1 is slow to respond to a step increase in the penalty, but is able to sustain the response for a long time, while Building 3 responds very quickly, but only for a short amount of time. Building 2 is somewhat in the middle.

Furthermore, the data used for the comparison is identical to that used in (Junker et al. (2018)), where penalty signals are constructed based on wind and solar production in Denmark and consumption ramps in Norway. However, here the time frame is extended to include all data from 10/11–2015 to 17/09–2018. Moreover, the penalty signals are combined to form a cost signal that weighs each of the three signals equally, and for this study it is assumed to represent the cost that consumption imposes on the grid. A part of these signals can be seen in Figure 3, where the morning and afternoon ramps in the Norwegian grid are apparent along with the diurnal cycle for the Photovoltaic (PV) production and the very slow varying nature of the wind power production. These penalty signals will collectively be referred to as the natural penalty signals.

For the sake of simplicity, in this paper, it is assumed that the grid cost signal is equal for each of the buildings

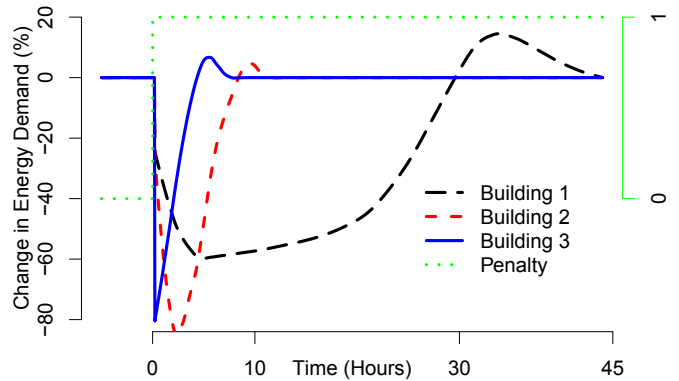


Fig. 2. The Flexibility function (FF) or step-response function for three different idealised buildings, with vastly different flexibility characteristics (FC).

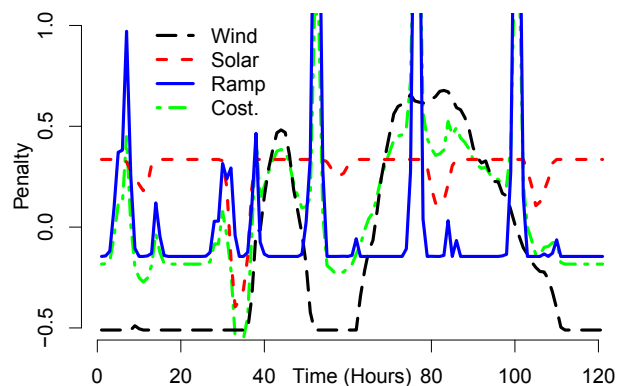


Fig. 3. Penalty signals based on wind production, solar production and consumption ramps are shown in black, red and blue respectively. The total grid cost signal is shown in green.

(i.e. $\lambda^i = \lambda^j$ for all i and j), so that only the combined consumption is of importance.

Initially the non-causal design introduced in Section 3 is considered, but before comparing it to the other method, the parameter c , must be tuned. The savings shown in Figure 4 are based on the grid costs and consumer costs for varying sizes of c . The dashed lines show the results for when only $|\mathcal{H}|$ is used, which corresponds to letting $c \rightarrow \infty$. On the y-axis the savings compared to having constant consumption are shown, which implies that larger values are better. It is clear that larger values of c lead to larger savings for both the grid and the consumers. Moreover, the savings seem to converge to that obtained for $c \rightarrow \infty$.

This observation implies that, when seen both from the perspective of consumers and grid operators, it is not useful to consider the delay at least for the simple models used here for the simulation. The delay is therefore disregarded, mathematically corresponding to letting $c \rightarrow \infty$ and practically obtained by replacing (10) and step (2), for both the offline and online algorithms, by the simpler expression

$$S^i(\omega) = |\mathcal{H}^i(\omega)|. \quad (16)$$

With this scaling function, the tailored penalty signals shown in Figure 5 are obtained. The penalty signal de-

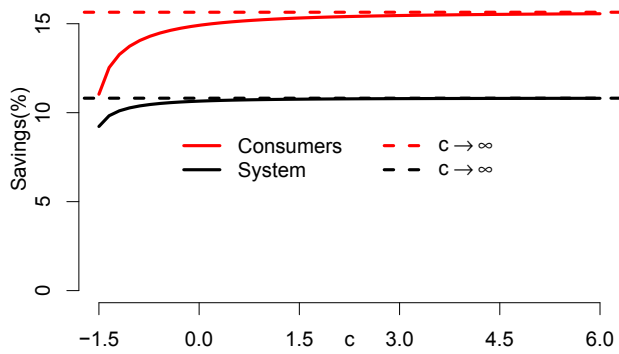


Fig. 4. Grid savings (equation (3)) and consumer savings (equation (1)), when using penalty signals designed according to algorithm 1, with varying sizes of c .

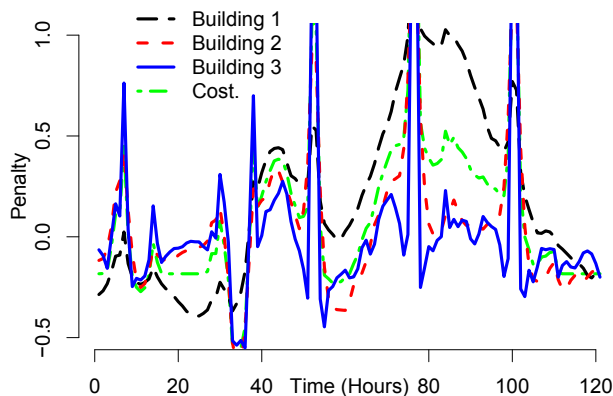


Fig. 5. Penalty signals, based on the cost signal shown in Figure 3, but tailored towards building 1, 2 and 3, using Algorithm 1.

signed for Building 1 is quite similar to the wind penalty, while that designed for Building 3 resembles the ramp penalty a lot. This fits with the findings reported in (Junker et al. (2018)), where it was shown that the largest savings are obtained when exposing Building 1 to the wind penalty, Building 2 the solar penalty and Building 3 to the ramp penalty.

Now that we have tailored penalty signals specifically to each of the buildings they should outperform the natural penalty signals from Figure 3, so we include these in the comparison. Table 1 shows the savings for both consumers and the grid for each combination of penalty signals. The cost when using the designed signals is the same as what was shown by the dashed line in Figure 4. Most importantly, we see that the designed individual penalties yield the largest savings for both consumers and the grid. This means that there is no conflict of interest between consumers and grid operators. Moreover, each consumer is receiving the penalties yielding him/her the largest savings. It is worth noticing how the savings are equal for consumers and the grid, when the original cost signal is used as the penalty signal, since in this case the consumers are faced with the exact same cost as the grid. For the natural penalty signals, consumers save more than from the original cost signal, but the grid saves less.

Table 1. Flexibility Index (FI) for each of the buildings and the grid, when exposed to either the cost signal, the original penalty signals or the designed penalty signals.

	Original	Natural	Designed	Causal
Consumers	8.3 %	11.6 %	15.6 %	13.9 %
Grid	8.3 %	7.5 %	10.8 %	9.3 %

Up-till now it is shown that the designed signals offer great promise, but it is worth mentioning that these are designed in a non-causal way, and thus it is not possible to implement them in practice. The performance of the causally designed signals for FI for varying bandwidths, i.e. R is shown in Figure 6. The maximum savings are found for $R = 2$ years, with a local maximum at $R = 1$ year, which is no coincidence. The DFT results in spectral leakage when the length of the transformed data does not coincide with the periods of the signals (Proakis and Manolakis (2007); Pintelon and Schoukens (2012)). That is why the spectral leakage is minimised when the period is an integer amount of years, since renewable electricity production follows a seasonal pattern, mainly due to varying weather conditions. A hamming window was used for the shown results, to reduce spectral leakage.

For the consumers, it is not of particular interest to avoid spectral leakage, since it is of less relevance to consumers whether the designed individual signals are similar to the original cost signal or not. On the contrary, for the grid, if the penalty signals are not similar to the cost signal, then the consumers are not trying to minimise their consumption at the time of high grid costs. Thus, it is of high importance to the grid that the penalty signals are similar to the cost signal, so that the flexibility is used to solve the grid problems. For small values of R the savings are very sensitive to changes in R , and so, it would make sense to stay away from this region.

Figure 6 also shows the FI found for the original cost, natural and non-causal designed signals, and as it is clearly seen the causally designed signals do not result in quite as large FIs as the non-causal signals. On the other hand, using the causally designed penalty signals still result in larger savings than when using either the original cost signal or the natural penalty signals. Hence, for an online application, the causally designed signals should be used.

The last column of Table 1 shows the FIs for the causally designed signals using a window of $R = 2$ years, where an improvement of 5.6 % and 1 % can be seen for the consumers and system respectively, as compared to using the original cost signal.

6. CONCLUSION

Penalty-based control design of smart grids not only offers a good possibility to exploit the energy flexibility offered by various sources in full capacity but also helps in accommodating more fluctuating renewable energy sources in the grid. Design of the penalty signals for such a control-loop is a challenging task. In this paper, we have proposed a novel yet very simple frequency domain method for tailoring the penalty signals towards consumers. This, in turn facilitates each grid problem being solved by the consumers with the most appropriate kind of energy flexibility. It was shown

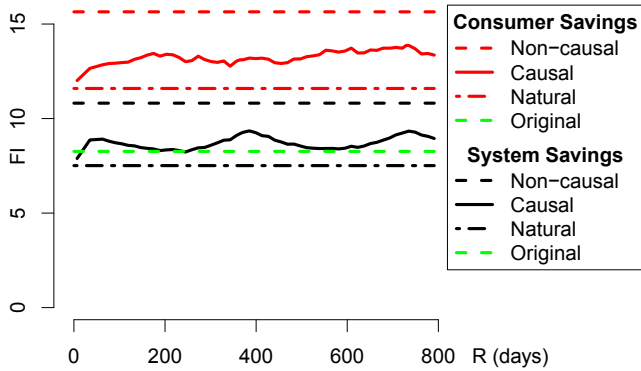


Fig. 6. Grid Savings (equation (3)) and consumer savings (equation (1)) for different penalty signals. For the causally designed penalties the bandwidth, R is varied.

that this tailoring of penalty signals towards the flexibility of consumers increases the savings from 8.3 % to 13.9 % for the consumers and 8.3 % to 9.3 % for the grid respectively. Finally, it was demonstrated how this simple approach can be combined with location-based penalties, so that the utilisation of energy flexibility can be maximised for grid specific problems. The other major advantage of the proposed approach is that it is computationally inexpensive, and can thus be used in real-time without any major modification.

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