Smart Demand Side Management: Storing energy or storing consumption – it is not the same!

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***Abstract*— Energy storage and demand response (DR) are options for coping with the rising share of intermittent renewable generation in countries attempting to reduce environmental damage from electricity. So far little is known about the potential and the impact of DR on the system and on the markets. In this research, it is shown how electricity demand can be derived rationally from reasonable preferences for consumption timing in an environment of load- and price uncertainty. This demand is then aggregated to the market level and a timing market equilibrium is defined. It is then discussed if DR can be considered as a "storage" technology.**

***Index Terms*— Demand Side Management, demand response, electricity storage, electricity demand, electricity market equilibrium**

Nomenclature

$VoLL$	Value of lost load	B	Stopping set
ω	indifference threshold	E_t	originary demand quantities
$f(\omega)$	Distribution of indifference thresholds	$C(\lambda,t\|t_0)$	Aggregated cost to shift load share λ
λ	Share of load to be shifted	θ	Diffusion parameter
$\varpi(\lambda)$	Marginal indifference threshold involved in shifting load share λ	μ_p	Long term mean of an Ornstein-Uhlenbeck (price) process
$c(\omega,t\|t_0)$	Individual cost to shift load	c	Cost parameter
T	Maximal shifting time	$S(p)$	Market supply
A_t	residual load		

I. INTRODUCTION

Energy storage and demand side management are options for coping with the rising share of intermittent renewable generation in countries attempting to reduce environmental damage from electricity generation. Variations in renewable (particularly wind and solar) output result in long- and short-term fluctuations in the residual load of the power system. Their safe and efficient handling can be ensured by supply-side technical options such as renewable curtailment, the improvement of generation flexibility and the introduction of storage technologies. On the demand side, demand side management (DSM) consisting of measures to improve energy efficiency and load shifts have considerable potential in an energy system with high proportions of renewables [18], [19]. Load shifting is referred to as demand response (DR)[1].

State-of-the-art information and data processing technology will allow to control and shift loads specifically and comfortably in industrial and private applications in a deregulated market environment [18]. Some already applied DR business models[2] can be classified along the organisation of the load shifting [20]. While for "direct load control" (DLC) an external demand side manager selects favorable shifts under system aspects among preselected devices, under the "dispatchable load regime" shifted load can be traded on energy markets and finally under "non-dispatchable real time pricing" (RTP) customers select time varying tariffs. Each model has advantages and disadvantages with respect to the potential and the transaction cost.

In any case, these models reflect preferences of the consumers. So, the question arises as autonomous demand side managers (prosumers) and companies deal with the tradeoff between (uncertain) remuneration, amenity and costs of load shifting[3] and as the possibilities of load control and programming are almost unlimited: Which load is selected and shifted for how long? The answer to this question has an impact on the potential of the technology and its interpretation in the system context.

[1] Extensive Reviews and seminal contributions include [4], [7], [8], [9], [14] and [16].
[2] A comprehensive review of business models can be found in [18].
[3] Furthermore, reliability questions are addressed in [21].

Two common answers/approaches for the determination of DRs can be identified: First, time-indifferences of consumers are introduced as constraints in technical optimization models (e.g. [22] as “time window”, [16] and [5]); second, preferences are used to value deviations from a preferred load path[4] (e.g. [21], [23] and [24]). The second approach is very intuitive as it is known (e.g. [3]) that complete power outages – even expected ones – are costly and similar opportunity costs of load shifting can be expected. Nevertheless, it is also reasonable to exploit consumer indifferences that might be described by load shifting constraints. The interrelation between these concepts has not yet been explored.

The first result of our paper sheds light on this interrelation. We design a model of the electricity demand profile of responsive consumers, considering their timing preferences from a microeconomic optimization calculus. We interpret the DR technology as an enabler to exploit load-specific indifference intervals to achieve an - uncertain – remuneration for real time pricing. It can be shown that in this model the aggregate cost function for DR is a mixture of an indifference area depending on time and volume of the shift and a cost function. Both approaches can then be interpreted as simplifying approximations to the “true” valuation function.

We then aggregate this cost function to the system level and thus offer an integrated rational economic theory of DR. For selected load profiles, we examine whether the technology can be interpreted as storage as in [5]. This interpretation is not as straightforward as it seems. The opportunity cost of switching off a refrigerator might be close to zero for few hours but afterwards the probability of spoiling food will increase and raise the cost of time shifting. Thereafter the fridge must be turned on again and the system will be stressed. Suddenly released demand will then increase prices and possibly undermine the DR business model. Intermittent renewables might further tighten this problem. The operator of a conventional low-self-discharge battery, in contrast, would not be exposed to a similar pressure and limit losses simply by waiting for a favourable time to recharge.

We formalize this intuition in a rational dynamic electricity consumption- and market model considering electricity prices and the opportunity cost of load shifting. We can show that this managed electricity demand is equivalent to the demand generated by a rationally operated constrained storage device (DR storage model). This “micro founded” DR storage model differs from the commonly applied ad hoc DR storage models with respect to its constraints - but remains sufficiently simple to be applicable.

II. DR TECHNOLOGY

DR refers to the changes in electricity consumption patterns of end-use customers in response to time varying electricity prices or incentive payments from aggregators to improve the reliability and provide flexibility to power system. DR can be classified into two categories: price- and control-based response. Consumers involved in price-based DR use home energy management systems to 1. receive actual electricity prices and 2. control the status of the electric appliances. Consumers, however, involved in control-based DR sign a contract with aggregators so that the aggregator can directly control the electric appliances of the consumer for a certain time according to the contract.

For residential customers, typical electric appliances that are suitable for DR include HVAC (heating, ventilation and air conditioning), refrigerators, washing machines, clothes dryers and dishwashers. For industrial customers, the implementation of DR is more demanding because there are various constraints on the production process, the required production target, inventory restrictions etc. Different types of industrial customers can be expected to implement different DR programs. Especially electric vehicles and data centres offer very promising prospects for DR. Both can adjust their load profiles flexibly and have great potential in DR.

Even though the direct cost of DR is much lower and is viewed as the most economical way to provide flexibility for the power system with high shares of renewables, there are still challenges to tackle. For example, from the engineering perspective a reliable controlling seems questionable as demand elasticity of consumers is difficult to quantify in price-based DR, while incentive-based DR on the other side strongly relies on the real-time communication between consumers and aggregators. This makes DR “unreliable” and "failures” may occur.

More recent advances in the technical implementation of DR include the development of control devices with storage, renewable generation and load shifting [28]. These devices respect reference technical standards and have been tested under laboratory conditions and in the field. Also, the application of energy storage systems for time of use tariffs can be shown to be profitable for sufficient volatile electricity prices [27]. In [22] a theoretical optimization model is developed to study the economic performance of a residential microgrid managing distributed energy sources, storage units, ICT elements and loads.

This technology review makes it clear that modern information technology and infrastructure enables a time- and device-sharp control of electrical loads. Regardless which of the two concepts is applied, the preferences behind the control commands are decisive for the DR and its effect on the system. For this reason, we first deal with the costs of a controlled load shift.

[4] The consumption path that would have been chosen without DR technology ([25]) is referred to as pre-shift load in [22] or as customer baselines [21]. We will use the term “originary consumption“.

III. COST OF LOAD SHIFTING

DR enables the electricity consumer to select specific devices to shift load. The avoidance of subjective shifting cost can serve as selection criterion. We consider a continuum of electrical devices with equal power consumption and an associated indifference threshold ω[5]. The indifference threshold (time) ω is the point in time such that for all t with $t\text{-}t_0 \leq \omega$ a consumer suffers no cost from delaying the application of the electric device by $t\text{-}t_0$ and for all t with $t\text{-}t_0 > \omega$ there is constant marginal cost at the value of lost load ($VoLL$). Aggregating over the indifference threshold delivers a distribution $f(\omega)$ and the shifting costs

$$c(\omega, t|t_0) = \max[0, VoLL\ (t - t_0 - \omega)] \qquad (1)$$

Assume that a share λ of the electricity consumption planned for t_0 should be postponed by $t\text{-}t_0$ units of time. The controlling technology of DR makes it possible to select devices, with low shifting cost first or - because of the monotonicity of $c(\omega,t|t_0)$ with respect to ω – with high indifference threshold first. In this sense, the cost minimizing indifference threshold $\varpi(\lambda)$ can be defined as:

$$\lambda = \int_{\varpi}^{\omega o} f(\omega)\, d\omega \qquad (2)$$

ωo is the maximum threshold corresponding to the maximum shift of T. To achieve the savings share λ all devices with a sufficient indifference threshold $\omega \geq \varpi(\lambda)$ will be selected for postponing load by t units of time. In doing so the aggregated costs sum up to

$$C(\lambda, t|t_0) = \int_{\varpi(\lambda)}^{\omega o} f(\omega) c(\omega, t|t_0)\, d\omega \qquad (3)$$

For all t satisfying $(1\text{-}\lambda)(T\text{-}(t\text{-}t_0)) < 0$ the total shifting cost is zero. This might be considered as rationale for the acceptability of an allocation resulting from the application of constraints to DR optimization analysis.

To keep the analysis simple by avoiding volume considerations we are using all devices for shifting altogether and set $\lambda = 1$. For equally distributed indifference thresholds on $[0,T]$ it can be shown that:

$$C(1, t|t_0) = \begin{cases} \frac{VoLL^2}{2T}(t - t_0)^2 & t - t_0 \leq \frac{T}{VoLL} \\ VoLL\ (t - t_0) - \frac{T}{2} & else \end{cases} \qquad (4)$$

Assuming that $(t\text{-}t_0)\ VoLL < T$ we will go on with the analysis using $C(1,t|t_0) = c\ (t\text{-}t_0)^2$. The opening parameter of the parable is thus closely connected to the $VoLL$. We also assume that the same quantitative relation is true for pulling consumption ahead. One might interpret this case as the foundation for the analysis with quadratic costs.

IV. OPTIMAL TIMING OF THE DEMAND OF AN ORIGINARY ENERGY "PACKAGE"

Given the cost function (4), a rational decision model of power consumption under price uncertainty is now described. In detail, it is assumed that for each consumer there is a "most convenient" price-inelastic electricity consumption path – the "originary" consumption.

Shifting consumption and deviating from this path causes costs modelled with the cost function (4). Electricity is bought at the real-time price to maximize utility net of these losses. In this setting with mean-reverting price processes uncertainty induces incentives to postpone consumption in the case of high prices – as there is a chance of decreasing prices – and pulling consumption ahead in times of low prices – as there is a risk of rising prices. We thus consider the option value of load shifting.[6]

[5] The extension for device specific energy consumption is not straightforward, because devices have been aggregated by their resilience time. But their weight could be included in the distribution f.

[6] A different approach to the option value of load shifting can be found in [15].

This optimization calculus can be interpreted as a problem of optimal stopping. Starting from time zero, the time τ is sought at which the purchase of a certain quantity of electricity at the price p causes the least cost. The costs consist of the expected expenses for electricity and the expected sum of the waiting costs causing each period of length dt the cost $C'(\tau)$ dt.

$$\sup_{0\le\tau<\infty} E\left[-p_\tau - \sum_{n=0}^{\tau-1} C'(\tau)dt \,|p_0 = p\right], p \in S \qquad (5)$$

The price develops according a discretised mean-reverting Ito process. The optimal policy of such problems is the one-step look ahead (OSLA, [17]) policy. It can be specified by the state set adapted to our problem

$$B = \{p_t \in S; p_t \ge E(p_{t+dt}|p_t) + C'(t)dt\} \qquad (6)$$

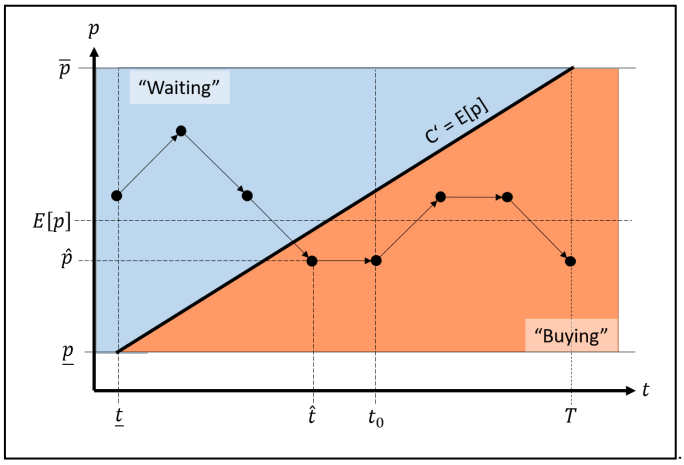


Figure 1. The stopping set B ("Buying") and a discrete price path

If this set is closed, then the policy: "stop at the first time reaching B" is optimal. As can be seen easily, the optimization problem described above does not fulfil this requirement with the Ito price process, since the price, once it has reached a point in B, can rise so sharply that further waiting is again advantageous from the state reached – i.e. the state jumps out of the set B. However, this becomes unlikely the smaller the diffusion of the price process and the higher the waiting cost are. We will therefore assume that the parameters are in a suitable range so that the OSLA policy is a sufficient approximation of the optimal policy. We have verified the validity in numerical examples (see Figure 2).

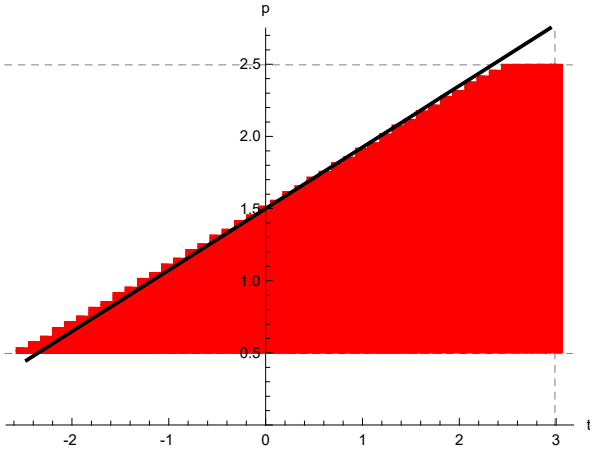


Figure 2. Optimal consumption timing with stochastic prices: numerically solved discretized problem and OSLA policy as black line.

A continuous time version of the indifference condition (6) can be specified as:

$$\lim_{h\to 0} \frac{d}{dt}(p_t - E[p_{t+h}|p_t]) = C'(t) \tag{7}$$

For mean reverting (electricity price) processes like the Ornstein-Uhlenbeck- or the Jacobi-Process it can be shown [1] that $E[p_{t+dt}|p_t] = \mu_p + (p_t - \mu_p)e^{-\theta\, dt}$ respectively,

$$\begin{aligned}\lim_{h\to 0} &\frac{dp_t - E[p_{t+h}|p_t]}{dt} \\ &= \lim_{h\to 0} \frac{d}{dt} - (p_t - \mu_p)(1 - e^{-\theta h}) \\ &= (p_t - \mu_p)\theta\end{aligned} \tag{8}$$

μ_p is the long term mean and θ the diffusion parameter of the according processes. With the cost function $C'(t) = 2ct$ and the introduction of the reference point t_0 (3) becomes:

$$p_t - \mu_p = \frac{2c}{\theta}(t - t_0) \tag{9}$$

For $p_t = \mu_p$ and $t = t_0$ immediately buying is optimal. The acceptable waiting time increases with c and p and decreases with θ. The latter means the less persistent the process, the longer the acceptable waiting time.

V. Equilibrium on the Electricity Market with Endogenous Timing

The OSLA policy provides a link between the current price, the expected price and the waiting times for mean reverting price processes. Figure 3 shows how this relationship - specified in (9) - can be applied to define a stochastic electricity market equilibrium.[7]

The representative demand for electricity is given as the time series of originary demand quantities E_t. This assumption takes account of the good predictability of electricity demand. The residual load A_t follows a stochastic process. This reflects the uncertainty of renewable generation. Its volume is known in t and its execution is mandatory in t. A market demand can be constructed from the price-inelastic residual load and the unexecuted originary demand. To this end, for every demand that has not yet been executed, based on equation (9) and the respective waiting times, a reservation price is determined for the immediate purchase of electricity. Demand quantities are ordered and accumulated according to the reservation prices. Using a linear market supply curve $S(p) = p$, a market equilibrium can be determined.

The equilibrium is the demand point, at which the aggregated quantity of demand is just served by supply. The electricity demanded at the equilibrium price is executed. This includes the shift of load - originary demand - from different points in time, potentially including past and future. It is then determined which originary demand has not yet been executed and the same steps are carried out in the next period, and so on. In this way, a backward analysis, which is frequently required in the case of dynamic optimization problems, can be avoided.

[7] An equilibrium model is developed in [26]. Existence is proved in the deterministic case.

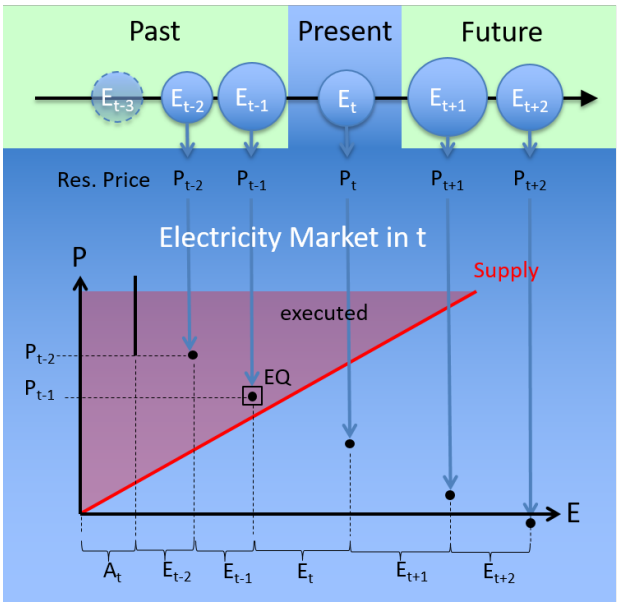


Figure 3. Stochastic dynamic electricity market equilibrium.

A time series of equilibria from a given set of resolved residual impulses is now derived and discussed. In this example, the originary demand over the simulation horizon from 0 to 16π with a period length of $\pi/12$ is $\mu/2$ ($\mu = \pi/8$). The residual load follows the impulse-giving curve $\mu + \frac{1}{2} \sin t$. The equilibrium quantities are shown in Figure 4 and the equilibrium prices in Figure 5.

In the case of shifting costs $2c/\theta = 0.5$, the market equilibrium quantities follow a periodic course, which corresponds from 0 to almost π the pulse phase and is continuous. Afterwards, the market equilibrium is not monotone and slightly positively phase-shifted. The peak pulse levels are no longer reached after load shifting. Thus, the curve can be characterized as smoothed by demand response. This can also be seen in the cumulative difference between impulses and equilibrium demand - "stored" energy in Figure 5. The stored energy increases until just before the time π. Thus, the height of the peak is reduced by the load shifting and the valley is also "filled".

Economically, a rise in the residual demand leads to a price increase, which induces a positive demand response: the expected price decline makes waiting profitable. The load is shifted, which reduces the demand pressure of the residual load on the price, so that it does not rise as much as without load shifting. After the peak, the demand decreases, the price also decreases, so the incentive to wait suddenly disappears and demand postponed is realized very quickly. This can also be deduced from the rapid decrease of the maximum delayed periods in Figure 7 after the peak (light red curve).

At first, a slight fall in prices can release very long-"waiting" demand. Therefore, the price initially falls sharply. Then less long postponed demand "requires" a higher reservation price due to shorter waiting times. The market is consolidating, the price increases slightly. This back and forth can repeat several times, until the stored energy is released. As soon as the market price has fallen short of the long-term average price, a rising price can be expected. In this case pulling demand ahead is advantageous and stabilizes the price also in the demand valley.

Figure 4. Market volume response (dashed red curve) to sinus residual impulse (blue curve). First values have been omitted to exclude the system adjustment

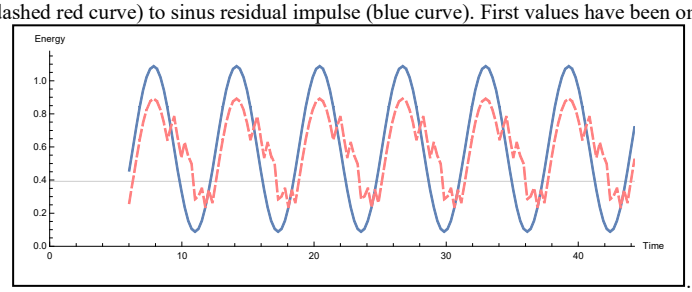
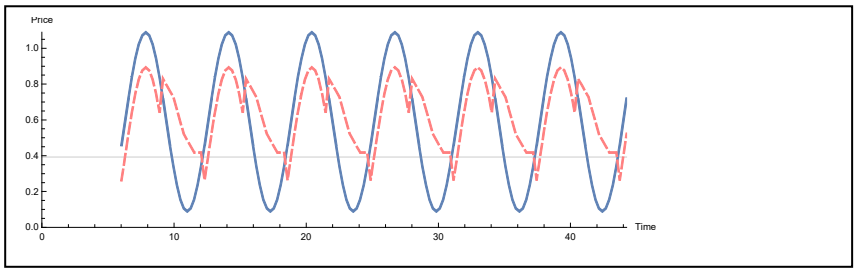


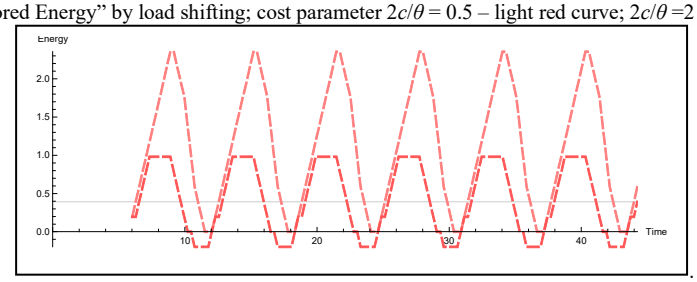
Figure 5. Market price response (dashed red curve) to sinus residual impulse (blue curve).



Sensitivity analyses were performed to identify the impact of the parameters. At a cost parameter of $2c/\theta = 2$, the maximum energy stored decreases (Figure 6, dark red curve). This is due to the lower maximum delay (figure 7, dark red curve). Thus, a similarity of storage capacity and the cost parameter $2c/\theta$ can be found. This is intuitive as the reservation price increases faster as the shifting costs are higher. At a given price peak, a further postponing is then dispensed earlier. Possibly, so early that the peak has not yet been reached.

The asymmetry between load postponing and load-pulling is noticeable. While during a residual load increase load is postponed by up to 9 (4, $2c/\theta = 2$) periods, pulling ahead never exceeds 4 (or 2) periods (Figure 6). This asymmetry only vanishes at far lower costs.

Figure 6. "Stored Energy" by load shifting; cost parameter $2c/\theta = 0.5$ – light red curve; $2c/\theta = 2$ – dark red curve



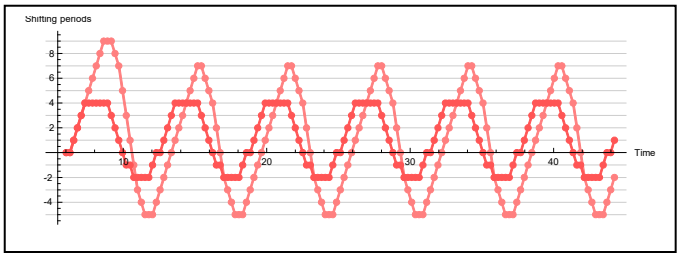


Figure 7. Number of shifting periods

VI. DSR "EQUIVALENT" STORAGE MODEL

It is now possible to discuss the common approach to interpret DR as storage – viewed as best practice by [5]. As previously indicated, the equilibrium volumes under rational DR are highly like equilibrium volumes generated by a rationally operated storage of limited capacity [2]. Here the cost factor $2c/\theta$ has a similar impact as the storage capacity, however, only caused by the temporal extent of the shifting, with constant shiftable energy. The additional impact of variations in the shiftable volume – e.g. by a consumption pattern – has not been analysed.

Nevertheless, these results can be interpreted as if the DR is a storage-equivalent technology whose modelling makes a deeper temporal structuring dispensable. However, it has also been shown that the temporal tracing of the postponed consumption reveals a first-in first-out storage model in the DR, which can lead to inhomogeneous discharges up to non-monotone price developments. The unequal number of periods in the pulling ahead and postponing and the different gradients of the storage discharge also indicate characteristics of the DR, which cannot be described in a conventional storage model without a temporal substructure or additional restrictions.

VII. CONCLUSION

Modern communication and information technologies allow real-time electricity price signals to be used to control electricity demand, which is delegated according to the temporal preferences of the consumers, creating a short-term price elasticity of demand. In the system, this can lead to considerable efficiency gains through increased flexibility. We interpret DR as a

technology that reduces consumer's effort of participating in real time electricity markets, thereby inducing load shifting and introducing demand elasticity.

We develop a general model of individual electricity consumption timing (DR) that combines two common technical modelling approaches: 1. The exploitation of individual timing indifference by restrictions and 2. The individual valuation of consumption shifting by penalties. These approaches appear as simplified special cases of the general model.

Considering the opportunity cost we derive DR enabled rational consumption paths and their impact on energy markets under uncertainty. This analysis extends the understanding of the incentives to apply DR, including its option values and the value of its integration into the system, likely to rise with renewable penetration. Thus, the analysis of DR is raised to a new level and the quality of its economic evaluation is considerably deepened.

Our next step is to quantify the load and price processes to estimate the equivalent storage potential of DR and to evaluate its significance for the system. If a significant storage potential arises, the load duration could be smoothed and peak load capacity reduced as shown in [2].

So far the market simulation has been running partially unsteady. This may be caused by the very simplistic assumption of a representative originary demand, which is always shifted in undividable blocks between the periods. A microsimulation, better adapted to the heterogeneity of the market participants, with distributions of electricity consumption and subjective costs, should make the market reaction more realistic and smooth.

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