Economical Regulation Power Through Load Shifting With Smart Energy Appliances

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***Abstract*—This paper considers the technical and economical feasibility of the introduction of automated demand response from domestic smart appliances in a European setting as a means to create a significant amount of regulating power. Simplified power-time flexibility models for appliances are introduced on which generic economic simulations can be based. These simulations permit a good indication of the economic value that can be attained as a function of model parameters. This shows that classical load shifting of washing appliances creates sufficient value in the day-ahead market to justify investments in smart energy control services. Cooling appliances create significant value on the balance market and while full scale deployment would lead to significant price erosion in today's market, it could accommodate additional unbalance caused future sustainable generation. The scale of domestic demand response resources can be quantified in two simple parameters: regulation power and storage capacity. For the Dutch situation these are 700 MW, equivalent to 5% of average national power consumption and 5 GWh storage: around 20 minutes of average national power consumption. Smart appliances can deliver a 100% efficient and CO_2 friendly complement to the unpredictability of e.g., large scale wind power as planned in large parts of Europe in 10 to 15 years.**

***Index Terms*—Balance power, balance power market, day-ahead market, demand response, domestic appliances, load management, power system economics, smart grid, wind energy.**

I. Introduction

A. Background

DOMESTIC Demand Response has been studied intensively over several decades [1]–[3]. Early interest was driven mostly by the need to reduce peak power to avoid overloads of the power network and generation capacity, typically on hot days. On first sight the value of peak reduction is quite high due to avoided investments in peak generation power. However, the manual approaches deployed in the USA in particular were difficult to keep operational except when significant economic interests were involved as found in very power-intensive industries [1]. From the year 2000 onwards driven by interest in improving demand elasticity significant initiatives in the USA developed to stimulate demand response [1]. Progress is made and is monitored [4], but so far domestic application has proven to be difficult to sustain, mainly because active customer participation is required for a relatively modest financial return. Automated forms of domestic demand response show specific promise [5], indicating the need for minimal user interaction and maximum user comfort where relatively modest economic incentives are in play.

In contrast to the USA Europe has focused more on a generic introduction of smart grid technology with demand response being one component [2]. Except for interruptible load contracts with power-intensive industries, demand response has not been deployed [6]. However, the need to more actively manage unpredictability of sustainable energy sources creates interest in the potential of demand response.

B. Scope

This paper concentrates on load shifting (LS): a specific form of demand response where no net reduction of load is achieved, but where load is merely rescheduled over time. It is further limited to the domestic market, and to appliances that have a substantial market penetration and which could viably shift power consumption. It does not consider local generation on the basis that this will unlikely achieve significant penetration within 10 years—with exception of PV. PV has a non shift nature however.

Domestic power consumption represents around 30% of overall Dutch power consumption [7], and washing and cooling appliances represent 40% of Dutch domestic power consumption [8]. For these appliances there is significant opportunity to perform load shifting depending on user acceptance to have the appliances task at hand shifted in time.

This study focuses on a market introduction in the 2015 time frame and does not rely on a specific in-home infrastructure for smart grids nor on smart metering.

Since the introduction of demand response is only practical in newly marketed appliances and the EC, in collaboration with industry, is driving a program of steady reduction of white goods power consumption with significant effect through energy labeling programs [8], it is important to consider the forthcoming power consumption reductions in domestic appliances when establishing the benefits of demand response. Therefore, for 2015 average appliances carrying energy label A++ [9] have been assumed representing best in class equipment today and a 40% reduction over today's appliances sold.

Section II defines the control architecture for a quick market introduction scenario in terms of Smart Energy Appliances

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TABLE I
KEY DOMESTIC APPLIANCE PARAMETERS

Appliance	LS Model	Market (%hh)	$\overline{P_a}$ (kWh/a)	D_a/ $T_{a\,on}$ (h)	$T_{a\,max}$/ $T_{a\,off}$ (h)
dish washer	BLS	59%	195	0.5	12
washing machine	BLS	98%	198	0.4	12
tumble dryer	ILS	70%	356	1.0	12
refrigerator	CS	70%	105	0.17	3.0
freezer	CS	30%	292	0.25	2.0
refrig.+freezer	CS	55%	287	0.25	1.8
close in boiler	CS	11%	237	0.03	3.9
ventilation 1 way	CS	45%	262	3.0	1.5
ventilation 2 way	CS	2%	580	3.0	1.5

hh = house holds

(SEAs) and complementary Smart Energy Services (SESs). It also identifies the domestic appliances of interest. Section III defines simple models for the load shifting appliances under consideration, identifies the properties of larger aggregations of SEAs and the equivalence with power storage. Section IV presents the value of load shifting, based on the existing Dutch energy markets, reduction of network investment, reduction of grid losses and as longer term complement to wind generation. Section V considers the business case for introduction and the overall impact on the power grid and power markets. Section VI presents the conclusions.

II. Starting Points & Control Architecture

A. Smart Energy Appliances

In order to realize the low involvement and highly automated approach needed this paper assumes a concept of domestic smart energy appliances (SEAs). SEAs are domestic appliances with significant power consumption and with the flexibility to shift the time of power use with minimal or no discomfort to the end user via a network control interface. New communication and IT technologies and very low cost network intelligence for domestic equipment can create practical means for large scale control of domestic appliances in the very near future. Control over the appliance is assumed to be exercised by a suitable mix of local intelligence in the appliance and network based computing. This permits the user to conveniently set up presets, e.g., via a web based interface, and select the desired program, e.g., directly on the appliance, in an almost effortless manner so as to overcome known consumer's inertia to deploy demand response applications.

The list of potential SEAs and their annual power consumption is presented in Table I.

LS application of ventilation units is complicated due to the highly non-linear relation between air flow and motor energy: concentrating power consumption in shorter bursts (when energy is cheap) would increase the overall power consumption needed for ventilation. Also there can be a non-desirable increase of noise. Therefore, such appliances have not been considered further for LS application.

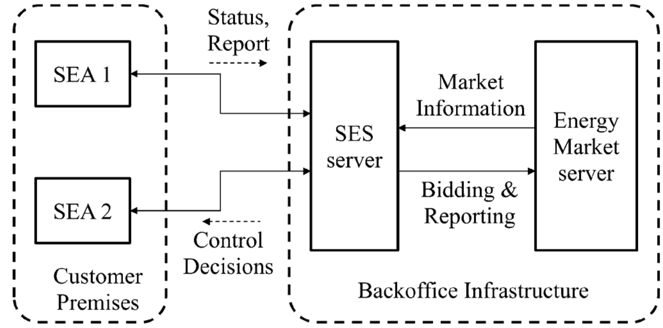

Fig. 1. Smart energy control architecture.

B. Smart Energy Services

Different system concepts are currently promoted to control in home appliances. Some use a home controller, others use pricing information directly to the appliance. This paper assumes that SEAs are autonomous but guided remotely by a Smart Energy Service (SES). The SES contains most of the "intelligence": i.e., strategies to use economic information and predictions and information about the behavior of aggregated energy use and scheduling of larger populations of SEAs. The SES receives status information, e.g., key user actions, and energy usage reports from the SEA. The conceptual control architecture with partitioning of functionality and information exchange has been sketched in Fig. 1.

The SES can use LS flexibility on existing energy markets to create economic value [10], and can be adapted easily to changing market circumstance, regulations and local power network constraints which is key to the introduction of SEAs on the market. The value created on the energy markets can be used to recover investments in the SES and provide incentives to SEA users.

The SES may also allow users to set up their SEA control preferences, provide feedback to end users regarding the performance of their smart appliances and aggregated economic incentives.

III. Load Shift Models

A. Appliance Models

The appliances listed in Table I can be modeled in either of three abstract time-shift models.

The *Basic Load Shift model (BLSm)* permits time shifting of the load-run by a flexible but limited amount. This typically applies to washing machines, dryers and dish washers that are started manually. With $P_a(t)$ being the power consumption of the appliance over time, P_{a_0} the power consumption in on-state and $S(t, D)$ a step function of duration D starting at $t = 0$, and $Shift(f, \Delta)$ denoting the time shifted version of function $f(t)$ by Δ

$$P_a(t) = P_{a_0} S(t, D_a), \tag{1}$$

$$Shift(P_a, \Delta)(t) = P_{a_0} S(t - \Delta, D_a), \quad \text{with } 0 < \Delta < T_{a\,max} \tag{2}$$

Using $E_a = P_{a_0} D_a$ as the energy used for a single run the SEA is characterized by three parameters: the appliances

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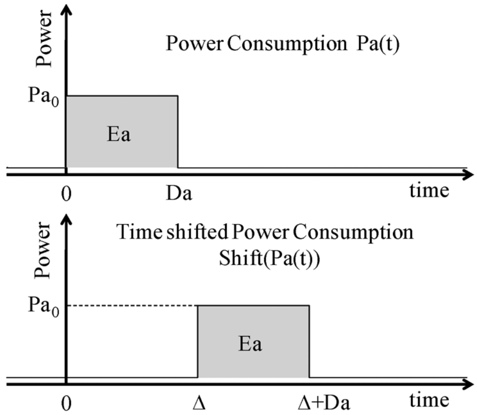

Fig. 2. Basic load shift model.

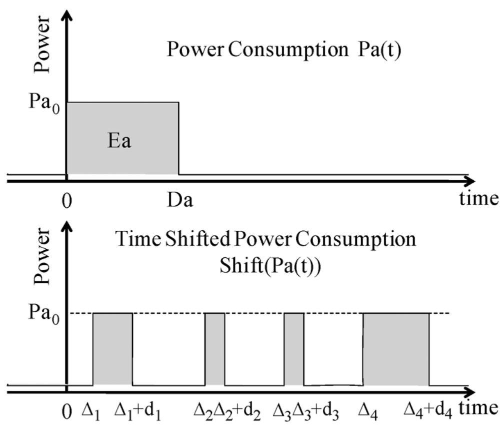

Fig. 3. Interruptible load shift model.

on-state energy consumption E_a, the duration of the power consumption D_a, and the maximum delay of the power consumption the appliance or its user can permit $T_{a\ max}$. The model and its parameters are further clarified in Fig. 2.

The *Interruptible Load Shift model (ILSm)* adds additional power-time scheduling freedom to the BLSm by allowing the interruption of the actual load run, thus creating a more fine-grained control over the timing of load. So rather than a single delay a series of delays $\bar{\Delta}$ (vector) is needed and durations $\bar{d}$ (vector) to model the shifting function. Assuming (1) as the original load function

$$
\begin{aligned}
&Shift(P_a\bar{\Delta},\bar{d}) = \sum_{i=1}^{n} P_{a_0} S(t-\Delta_i, d_i),\\
&\text{with } \Delta_i + d_i < \Delta_{i+1}, \qquad \Delta_n + d_n < T_{a_{max}}\\
&\text{and } \sum_{i=1}^{n} d_i = D_a, \quad \bar{\Delta} = \begin{pmatrix} \Delta_1 \\ \Delta_2 \\ \dots \\ \Delta_n \end{pmatrix}, \quad \bar{d} = \begin{pmatrix} d_1 \\ d_2 \\ \dots \\ d_n \end{pmatrix}, \quad (3)
\end{aligned}
$$

Typically there is an under limit on the duration: $d_i \geq d_{a_{min}}$. Note that $E_a = \sum_{i=1}^{n} P_{a_0} d_i = P_{a_0} \sum_{i=1}^{n} d_i = P_{a_0} D_a$. The ILSm has one additional parameter over those for the BLSm to characterize the appliance: the minimum load duration $d_{a_{min}}$. The model's characteristics have been sketched in Fig. 3.

Finally the *Continuous Switching model (CSm)* captures appliances with periodic power use that can be retimed as long as

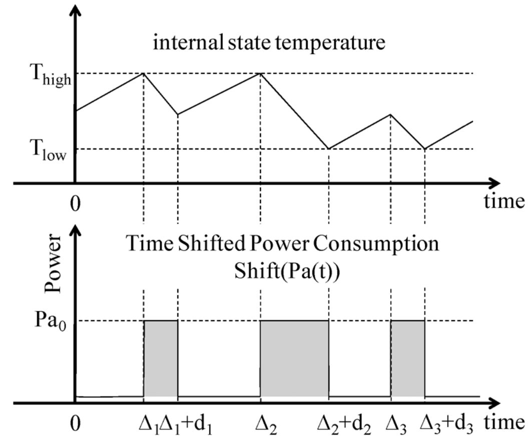

Fig. 4. Continuous switching model example.

constraints (e.g., low and high temperature set points in cooling appliances) are observed. Any disturbances of this periodic behavior by external influences (e.g., opening the freezer) are assumed to be an additional uncontrollable load, possibly negative, that is added to the periodic schedule. A normal on/off regulator will switch the cooling on at the higher set point and switch it off at the lower set point. Hereafter heat will leak from the environment.

This leads to a steady duty cycle with $T_{a\ on}$ in on state and $T_{a\ off}$ in off state. With P_{a_0} the on-state power consumption and $\overline{P_a}$ the average power consumption, the power time function is

$$P_a(t) = P_{a_0} \sum_{i=-\infty}^{\infty} S\left(t - i(T_{a\ on} + T_{a\ off}), T_{a\ on}\right) \quad (4)$$

$$\overline{P_a} = P_{a_0} \frac{T_{a\ on}}{T_{a\ on} + T_{a\ off}} \quad (5)$$

The shifted version takes a complex form with many shift parameters, which is not represented here. However the characterizing parameters for the model are: the on-state power consumption P_{a_0}, cycle on and off time $t_{a\ on}$ and $t_{a\ off}$ and the minimum on and off durations $d_{a_{\min\ on}}$ and $d_{a_{\min\ off}}$. Fig. 4 sketches the time shifting operation of CSms.

Some appliances, most notably freezers have options to provide additional load-time flexibility by using "super cooling" type techniques. The application to LS is economically complex however, since appliance power efficiency typically reduces significantly which significantly impacts the economics of the application.

The relevant appliances and their respective key quantitative and model parameters are listed in Table I. Market penetrations and average power consumption figures are based on [8]. Timing parameters are estimates or averages for larger groups of individual types.

B. Appliance Aggregation

In many power markets it is important to deliver the pre-agreed load in a time interval. In day-ahead markets deviations from the pre-agreed plan are typically resolved using a balance market of some form, which can involve high penalties. When

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offering LS as capacity on the balance market predictability of the balance resource is a crucial contract parameter.

The load shift capability of a large group of SEAs offers significant flexibility in time and in load. Loads may be switched on and off to create a very precise load characteristic over time. This permits these use of SEAs through SESs as highly accurate regulation power. However the dynamic LS properties of an appliance are directly reflected in the aggregation.

Let $g(t,\bar{c})$ be a power-wise normalized model function for any of the above models, with $\bar{c}$ the smart energy control parameters excluding an overall delay, $G(\omega,\bar{c})$ it's Fourier transform, $\bar{P}_a$ the power of a model instance, $Aggr(t)$, be the aggregation, and it's Fourier transform $F\{Aggr(t)\}(\omega)$ denoted as $aggr(\omega)$

$$Aggr(t) = \sum_{i=-\infty}^{\infty} \overline{P}_{a_i} g(t-\Delta_i, \overline{C}_i) = \tag{6}$$

$$aggr(\omega) = \sum_{i=-\infty}^{\infty} G(\omega, \overline{C}_i) \overline{P}_{a_i} e^{j\omega\Delta_i} \tag{7}$$

(7) Shows that the spectral controllability of the aggregated load is a linear weighted sum of $G(\omega,\bar{c}_i)$, which is identical for loads of the same type. I.e. a poor excitability of G for some frequency implies a poor excitability of the aggregate.

This implies that "slow" SEAs application to fast varying load control is ineffient, and specifically for the BLSm step function that any control close to or beyond $\omega = \pi/D_a$ is problematic. Similar considerations apply to higher frequency behavior of aggregated ILSm and CSm SEAs when considering constraints on shortest duration switching. Combinations of different appliance types could be used to realize complex dynamic LS profiles, though this has not been elaborated in this paper.

C. Storage Equivalence

Qualification of load shifting in terms of equivalent storage capacity creates a unified metric, permits comparison to physical storage and aids to understand its limits as regulating power.

When considering a single BLSm SEA it is hard to consider the time shifting capability of load it represents as a storage capacity. The storage capacity it may represent has a transitional nature: it expires as the maximum load delay $T_{a_{max}}$ approaches.

However, when considering larger aggregations of BLSm SEAs that start their model cycle on a more time-continuous basis a continuous storage representation is appropriate. This is the equivalent of the next SEA starting to delay its power use as the previous one approaches its maximum delay. Under the assumption of a uniformly distributed start time for the model cycle, the maximum "charged" state of the SEA aggregation is represented by all SEAs starting their load as early as possible, and the maximum discharged state is represented by all SEAs delaying their load cycle as much as possible. I.e. the SEA aggregation can be regarded as providing an storage capacity of the average load during $T_{a\ max}$. For an individual SEA this implies

$$S_a = \overline{P_a}\, T_{a\ max}. \tag{8}$$

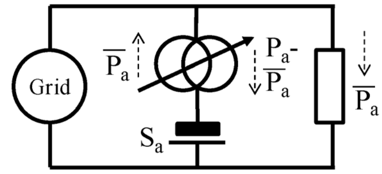

Fig. 5. Electrical equivalent of CSm SEAs using storage.

The complementary maximum charge $P_{a\ ch}$ and discharge $P_{a\ dc}$ power flows are

$$P_{a\ ch} = \frac{S_a}{D_a} - \overline{P_a} = \overline{P_a}\frac{T_{a\ max} - D_a}{D_a}, \tag{9}$$

$$P_{a\ dc} = \frac{S_a}{T_{a\ max}} = \overline{P_a}. \tag{10}$$

Following similar principles the storage capacity represented by a CSm SEA and its equivalent are provided in Fig. 5.

By introducing the average load of a BLSm and ILSm SEAa being $\overline{P_a}$, the average storage capacity S_a represented by the SEA is

$$S_a = \overline{P_a}\, T_{a\ max}. \tag{11}$$

For these appliances the maximum equivalent charge and discharge power are

$$S_a = \overline{P_a}\,(T_{a\ on} + T_{a\ off}) \tag{12}$$

$$P_{a\ ch} = \frac{S_a}{T_{a\ on}} \qquad P_{a\ dc} = \frac{S_a}{T_{a\ off}}. \tag{13}$$

Both power and capacity have significance in the qualifications for LS applications, their relation being defined by charge and discharge speed. Typical SEAs have a a much higher charge than discharge power, which impacts their economic application.

IV. Economic Value

A. Power Markets

In defining the value of LS the total value created for society is taken as a starting point. Consideration regarding the re-division of such benefits among participants to create a business chain is not directly addressed. The most obvious means of monetizing LS resources are the power markets: the day-ahead market (APX in the Netherlands) and balance market (as run by the Dutch ISO TenneT). Some caution is needed however to use electricity markets as a value metric since a complex relation exists between long term investments and market yields, leading to capacity markets in some regions [11], [12].

In discussions on defining the value of LS and distributed generation resources less conventional value arguments are sometimes promoted. One example is the value of stand-alone operation: self-reliance as a primary principle or the ability handle grid outages. Other possible value can be associated

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e.g., to using locally generated sustainable energy to run the local appliances or to be able to run a virtual sustainable grid. If appreciated by customers or governments such arguments can greatly boost the value of SEAs. However, such valuation may not necessarily lead to the most economically efficient and short term CO_2 lenient way to use energy resource. On the counter side it should be noted that the price of CO_2 today does not adequately reflect an economic incentives needed to curb CO_2 level rise.

In view of the above and the fact that this article focuses on fast introduction of SEAs on a full market scale it is most suitable to use the conventional energy markets as the basis for valuation.

Many countries have day-ahead markets: the Dutch day-ahead market is the APX, which uses 1 hour time units for pricing. Since there is substantial international transmission capacity the prices on the Dutch market are a good average of Nordig, German, UK and Belgium energy prices.

Balance markets have a more varying nature [13] and have a purely national nature. The Dutch balance market has some characteristics which make it interesting as a tool to determined LS value for more agile LS loads [14], [15]. It uses 1/4 hour pricing, is totally neutral to generation and load resources and over the 7 years has awarded the same price to demand (unbalance creators) as to supply (reserve capacity resources). The market is not suited well for operating with short haul storage type resources however; for value evaluation it has been assumed that this restriction is not a practical obstacle. There is a clear price relation between the balance and day-ahead market which permits easier analysis of cross-market applications (e.g., for ILSm SEAs).

The economic value of the above load shifting applications is derived from economic simulation using historic data series of the energy markets in the Netherlands.

B. Day-Ahead Market Value

The predictability of the day-ahead market is very good. Even without regular predictions day-ahead pricing is quite stable. There are even more sophisticated tools to improve beyond this [16], [17]. Therefore, for simulation using "foresight" of the forthcoming price provides a straightforward result. In addition to the models above the assumption is made that $t_{a\ max} = 12$ h for all BLSm and ILSm SEAs as per Table I, and that start times are uniformly distributed between 7 am and 10 pm. CSm model appliances are assumed to be running continuously but be interrupted due to manual intervention. Variation of these latter assumptions shows some dependence of the resulting economic value but does not change the results in a major way. The economic value is the day-ahead price at the time of start minus the minimum that can be achieved when postponing the start by a maximum of $T_{a\ max}$. The results are graphically presented in Fig. 6, using the price per MWh for both value and day-ahead market for the BLSM and ILSm appliances. The results show a strong dependence on the value of $T_{a\ max}$ and the time series of the day-ahead market. The final LS value per SEA is listed in Table II.

The economic value is good for appliances with coarse but large time shifts like washing machines, but poor for appliances

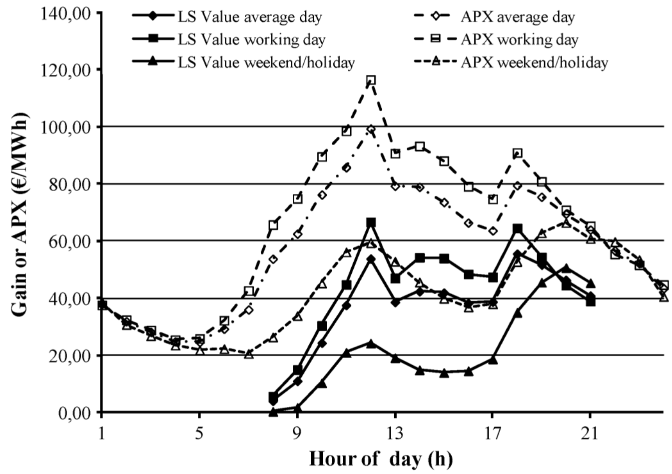

Fig. 6. Day-ahead price and LS value and as function of start time.

TABLE II
ANNUAL VALUE FOR APX, BALANCE AND NETWORK LOSS

Appliance	APX Value (€/a)	Balance Value (€/a)	Network Loss (€/a)
dish washer	5.70		0.19
washing machine	5.80		0.20
tumble dryer	10.30	14.53	0.35
refrigerator	0.70	1.80	
freezer	1,30	4.80	
refrigerator + freezer	1.43	4.70	

with agile but modest time shift capabilities like freezers. It should be noted that the result is sensitive on the assumption on $T_{a\ max}$. It may be possible to improve on these assumptions using specific human behavior statistics. In the Netherlands, the regional DSO Enexis has initiated two pilots [18] specifically designed and developed to increase insights in "*How, and to what extent, can flexibility be mobilised effectively from electricity consumers*?"

C. Balance Market Value

Balance market unpredictability requires deployment of forward looking strategies to extract value from the balance market: i.e., making decisions on load shifting without full knowledge of the near future. Four strategies are compared. These all operate within the constraints of the lower and upper temperature boundary that needs to be maintained by the appliance: i.e., the appliance is always switched on or off regardless of the economic strategy at the temperature limit, though possibly only for a short duration. The strategies are: (a) switch on below a fixed market price (price set point is optimized for one year), (b) switch on in case the market requires generation decrease at market price, (c) switch on below a certain fixed level below APX (level optimized for one year) and (d) an optimal strategy using foresight. Fig. 7 shows the results; demonstrating that for the shorter $T_{a\ off}$ periods under consideration the realistic strategies a, b and c have comparable results, but only 50% of the optimum obtained with foresight.

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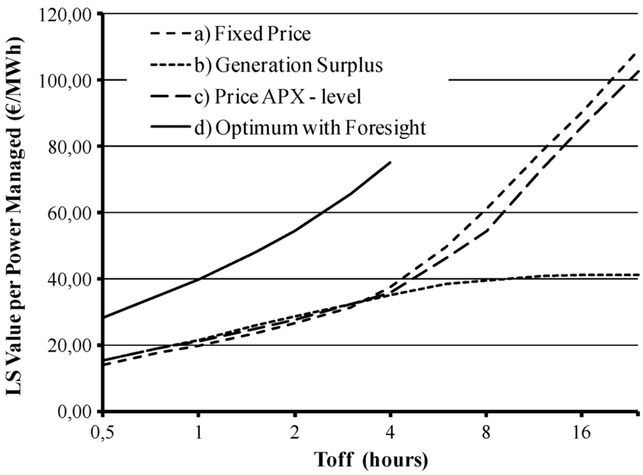

Fig. 7. Balance market value as function of $T_{a\ off}$ for short $T_{a\ on}$.

This implies that it may be possible to further improve results using some form of adequate forecasting for the balance market. The results also show that there is significant value to be obtained even with small time shifts: i.e., high agility versus "depth" of shifting is rewarded.

Using data series of different years between 2005 and 2010 show that the balance market value varies by a factor of 2: i.e., market conditions are rather volatile. This is a clear risk when making investments to operate in this market.

Overall the results demonstrate solid values for short but agile time shifting capable SEAs in the Dutch market.

Specific simulations were conducted for the ILSm appliance: the dryer.

Table II shows that using the balance market more value can be created than with the day-ahead market. It was investigated whether a combined strategy on both markets was necessary, but the results on the balance market only yielded virtually identical values.

D. Network Related Value

Other benefits of load shifting include network upgrade investment delays and reduction of network losses. These effects have been quantified using relatively simple approaches.

Network investment has been quantified using the annualized net present value of delayed investment as a result of the reduction of peak load on a network section, assuming MV/LV transformer upgrading is dominating the costs involved. The approach uses known load statistics of one of the distribution network operators in the Netherlands to create a realistic replacement scenario. The results show a value that is a fraction of the value created on the day-ahead market: i.e., network investment cost is a substantially less strong economic driver than day-ahead market fluctuations.

Network loss reduction value has been quantified using a simple quadratic model for technical non-zero losses network losses as a function of load which is a common approach in industry [19], and assuming shifted load has a maximum effect on reducing losses (i.e., is shifted from peak to non-peak hours which have 40% less load) and average technical network losses in the Dutch distribution network of around 2%. Again this represents only a fraction of day-ahead market value as per Table II, so also this does change the economic incentive for LS scheduling the SEAs.

It should be noted however that both of the above value sources arise naturally with day-ahead market optimization, which results in a interesting positive side effect of the deployment of SEAs for distribution network operators. Specifically the network loss reduction is a true energy saving.

E. Environmental Benefits

Load shifting itself does not reduce power consumption and thus environmental effects are not straightforward to assess. Nevertheless there is a significant body of research, e.g., [20]–[22], to show the potential benefit of (agile) regulation power to compensate for unpredictability of large wind power deployments as planned in various European countries: reduced start/stop operation of conventional power plants, improved load factor of running conventional power plants and absorption of excess wind power capacity have both economic and environmental benefits. These effects will become significant in particular when high percentages of wind power will be deployed. Several such plans are now being considered or deployed in various EC countries, e.g., Germany.

The benefits arise in two situations. The first situation arises when committing the dispatch of conventional generation capacity while expecting significant wind power—less excess capacity will be needed to provide regulation power in case there is less wind power than predicted. By dispatching less excess capacity also the efficiency of conventional generation capacity improves.

The second situation arises in case of a wind surplus (more wind power than predicted) where LS resources provided by SEAs can absorb the surplus effectively rather than having to discard it.

It should be noted that SEAs can provide this regulation capacity with close to 100% efficiency; i.e., there is no environmental side effect. As to the scale and storage capacity provided: when SEAs are deployed fully in the market the total equivalent storage capacity is very significant (see below), and certainly sufficient to assist in creating a substantially more efficient dispatch schedule for conventional generation resources.

F. Quantitative Result Summary

Table II summarizes the key economic results. It is to be noted that economic values may change significant over the expected life of an SEA. It is unlikely they are sufficient by themselves to incentivize consumers to purchase SEAs. Considering for instance past experience with improved appliance energy efficiency where additional investment could easily be recovered, yet this did not represent sufficient impetus for industry towards more efficient appliances. So some form of industry promotion like the use of new energy labeling schemes will likely be needed to raise the market awareness needed to successfully introduce SEAs.

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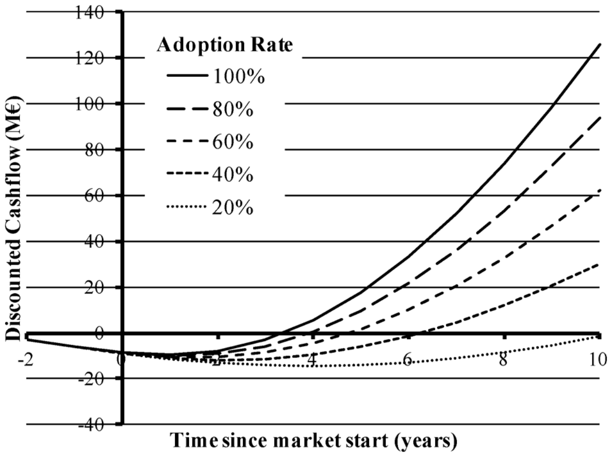

Fig. 8. SES NPV over time as function of customer adoption rate for day-ahead market value of SEA.

V. Deployment and Impact

A. SES Investment Case

The introduction of SEAs in the market requires the availability of at least one default SES to operate the SEAs. It is assumed the initial investment in the SES is 10 Meuros and the annual operating cost are 50% of its initial investment. It is further assumed 70% of the generated economic value is retained by the SES operator, and 30% is passed to the customer. A typical consumer market penetration scenario is used, starting with 10% in year one, increasing by 20% each year to saturate at 90% after 5 years. Appliance replacement rates are between 9 and 15 years [8]. Investments are assumed to start 2 years ahead of SEA market launch. Using a participation fraction of customers to reflect sensitivity to customer participation in practical SEA deployment and using 5% interest rate (typical for utilities) the NPV versus time diagram in Fig. 8 shows that an investment recovery is possible within 6 years of the start of the investment at the scale of the Dutch nation, dependent on the adoption rate of customers, which is uncertain at this stage.

It can be concluded that at this assumed level of investment it is not easily possible to divide the Dutch national market to create a fully open market approach and recover investments. In case the SES is operated efficiently as a central service center for commercial parties the economics of SES provision may be combined with an open market approach for end customer relations. Also an international approach to SES deployment may be interesting also in view of the scale of SEA development at trans-national level. Such an international SES would need to integration with different national energy markets.

The effect of incremental cost at appliance level for networked intelligence is not easy to assess. Initial cost will be high but will sharply decrease over time to near zero cost as market penetration such functionality increases. The end user value also includes environmental friendliness and other benefits of networked functionality. Nevertheless, this is a key hurdle for adoption by domestic appliance manufacturers.

B. Scale of Regulation Power

Assuming 100% market penetration is reached within 10 to 15 years of market launch, a total capacity of 700 MW of regulation power and 5 GWh of equivalent storage capacity is created for the Netherlands, which has an average power consumption of 13 GW.

The impact of BLSm and ILSm appliances on the day-ahead market is modest even in case of full market deployment and customer participation national peak power consumption is reduced by 5% and off-peak power consumption increased by 12%. It is estimated that as a consequence of market effects the maximum revenue reduction at break-even point (see Fig. 8) is around 10%.

The LS capacity available for the balance market is significantly larger than the present need for balance power: the average balance power requires is around 100 MW, cooling appliances alone can deliver 200 MW regulating power. This clearly demonstrates a significant capability to support the efficient integration of large future wind power deployments in the power grid, though at the same time shows the business case dependency of smart cooling appliances on future increased volume development of the balance market.

This 100% efficient storage/regulation capacity should be regarded as a very valuable resource. Modern IT and communication technology can enable the exploitation of domestic appliances as SEAs and make a contribution to building a sustainable smart grid infrastructure.

Though the deployment in other countries in Europe of SEAs by type and power is slightly different, and power markets—specifically balance markets can vary, the Dutch case study is probably a reasonable starting point to assume the economic viability of a domestic LS concept across most of Europe and to assess the potential in more detail the methodology presented in this paper can be used. It should be noted that a European wide approach is crucial to provide sufficient scale for the appliance industry to incorporate the required technology in appliances.

VI. Conclusions

This paper introduces three simple models to characterize the power time relation and load shifting capabilities of all relevant domestic appliances. When such appliances are considered in larger aggregations they can be shown to be equivalent to a 100% efficient storage capacity with a specific maximum power charge and discharge rate that can be expressed in models parameters.

The models are used to establish the key parameters of all relevant domestic appliances, and economic simulation has been used to establish the value of the appliances on both the Dutch day-ahead and balance markets. The value is significant but probably insufficient to launch SEA in the market without additional promotion or incentive.

The investment case for SES on the day-ahead market shows that investments can be recovered within 7 years after investment start at the Dutch national scale. This implies a centralized approach to a national SES or an international approach is needed. Potential cooling appliance capacity substantially exceeds average demand for the balance market today, creating

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a complex investment case, yet demonstrating the opportunity to compensate future potentially large imbalances from sustainable generation.

The combination of SEA and SES creates a efficient and flexible regulation power with a capacity of 700 MW and with an equivalent of 5 GWh of storage in the Netherlands.

Short term deployment of this SEA and SES matches the time scale of large wind power deployments in Europe, thus forming an economically attractive and environmentally efficient complement to the unpredictability of wind power.

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