A Dynamic Household Appliance Stock Model for Load Management Introduction Strategies

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***Abstract*—In this paper, the dynamics of market introduction of new electric household appliances and their gradual propagation into the existing appliance stock is investigated. The study is focussed on the release of appliances that possess a certain new property, in the present case a communication interface for "Smart Grid" applications such as sophisticated load management methods. Understanding the introduction dynamics is particularly relevant for estimating the amount of installed load management compatible household appliances and the available control potential in a given year in the future, which is essential for "Smart Grid" business model development. Due to the relatively long life span of household appliances, it can be shown that it takes up to several decades to achieve a complete replacement of the conventional appliance stock in the absence of additional measures. The focus of the paper is on methodology and application of stock models describing the number of appliances "in the field" over time. Different approaches depending on the availability of input data are illustrated and the effect of additional measures, such as replacement incentives, is evaluated. Results are given for the Swiss market of refrigerators, freezers, and heat pumps.**

I. Introduction

An increasing part of today's energy production originates from intermittent renewable energy sources such as wind and solar power, which poses new challenges for maintaining the active power balance in the grid due to their limited controllability and predictability. Flexibility of both generation and load has a high value in systems with large amounts of renewable energy sources. Consequently, a significant amount of research is being devoted to the field of load management (LM), also known as Demand Side Management or Demand Response, in order to turn previously uncontrollable loads into controllable resources [1], [2], [3], [4].

The connection of a highly dispersed population of appliances to a load control system is a non-trivial task. Depending on the type of appliance and desired control functionality in the power system, it may be possible to retrofit existing appliances with a certain communication capability (e.g. through "smart" power plugs). Some functionalities, such as the controlled increase of consumption in a population of refrigerators, will require a device-integrated communication interface. A crucial question for the design of future "Smart Grid" business models is the quantity of such units in the existing stock of appliances in the years after their market introduction.

Efforts to describe the evolution of the existing stock of certain consumer goods have been made before, mainly in order to gain an understanding of the overall number and age structure of installed appliances. Stock models are applied for assessing the impact of energy efficiency strategies [5], [6], [7], forecasting of domestic energy consumption [8], policy making for lower domestic energy carbon emissions [9] or evaluating recycling policy performance [10]. The main contribution of this paper lies in the specific study of "Smart Grid" communication interface availability over time, as well as the effect of replacement incentives and retrofit of existing appliances with such interfaces.

This paper is structured as follows: Section II presents the basic methodology for modelling the stock of existing appliances over time, including the effects of limited service lifetime and the sales of new appliances. In Section III, the modelling of incentive-based additional purchases and retrofit of existing appliances is discussed. Section IV presents a case study considering the Swiss market of refrigerators, freezers, and heat pumps. Conclusions are drawn in Section V.

II. Modelling the appliance stock

This section explains the methodology of modelling stock, survival, and sales of a household appliance type.

A. Basic Stock Model

To model the stock of appliances, a vintage stock model as proposed in [11] is applied. According to the kind of statistical data available, three modelling approaches are considered:

1) Sales data available: In the case of sufficient statistical data for appliance sales, the stock is modelled by the sales data $S(t)$ and a survival function $L(t)$ describing the relative evolution of remaining appliances. The survival function is discussed in detail in II-B. Consistent with [12],

$$stock(k) = \sum_{i=k_0}^{k} S(i) \cdot L(k-i) \tag{1}$$

yields the number of appliances in the stock for year k, considering all appliances purchased between the years k_0 and k. The survival function gives the relative fraction of appliances bought in year i and still remaining in the stock in year k. Each vintage $S(i)$ is multiplied by its "survival fraction" in the year k, yielding the absolute numbers of appliances of each vintage in year k, the sum of which results in the total number of appliances in the stock.

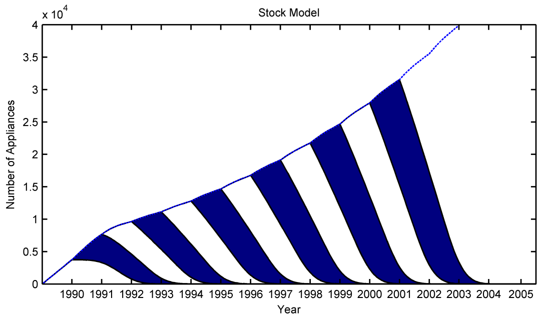

Fig. 1. Example of a vintage stock model

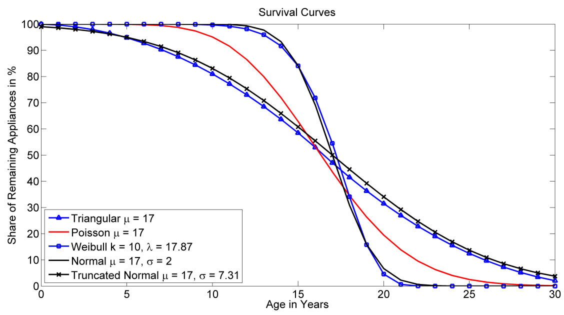

Fig. 2. Exemplary survival models

2) Sales data not available – Ownership approach: If no sales data can be retrieved from statistics, but ownership levels and number of households are known, the stock is computed by the product of ownership level and number of households as shown in [11]:

$$\mathit{stock}(k) = \mathit{households}(k) \cdot \mathit{ownership}(k) \quad . \tag{2}$$

The variable $ownership(k)$ is the household ownership proportion of a certain appliance type, i.e. the percentage of households that possess it.

3) Sales data not available – Electricity consumption approach: This approach for modelling the stock uses the annual total energy consumption of all appliances of the considered type and the unit electricity consumption (UEC) according to [11]:

$$\mathit{stock}(k) = \frac{\mathit{total\ electricity\ consumption}(k)}{\mathit{UEC}(k)} \quad . \tag{3}$$

The missing sales data is estimated by:

$$S_{\text{estimated}}(k) = \frac{1}{L(0)} \cdot (\mathit{stock}(k) - \sum_{i=k_0}^{k-1} S_{\text{estimated}}(i) \cdot L(k-i)) \quad , \tag{4}$$

where the term $L(0)$ is the initial failure rate of the appliances. If it is assumed that no appliances are withdrawn from the stock during the first year after purchase, $L(0)$ is equal to 1.

Figure 1 depicts an example of a vintage model with 12 vintages sold between 1989 and 2000. It can be seen how the individual vintages diminish due to the decreasing fraction of survival. At every point in time, the new sales and the remaining appliances from earlier vintages are summed up and form the stock.

B. Survival Model

The survival function $L(k, i)$ describes the fraction of appliances purchased in year i and still remaining in the stock in year k. The time span between the purchase of a product (its entry into the stock) and its withdrawal is named the service lifetime T. If the annual number of failures or replacements of the product is described by the probability density function (PDF) $f(T)$, and its corresponding cumulative distribution function (CDF) is

$$F(t) = \int_t^\infty f(T)dT \quad , \tag{5}$$

then the survival function is defined by

$$L(t) = 1 - F(t) \quad . \tag{6}$$

To model the replacement $f(T)$ and its resulting survival function, the major causes of withdrawal have to be considered, as listed in [13]: aging, defects, breakage, socio-economic reasons (e.g. higher income) and improved technology.

A significant number of different mathematical models for the replacement process can be found in the literature. The service lifetime T is assumed to be a random variable with expected value $\mathrm{E}(T)$ and variance $\mathrm{Var}(T)$. The probability density function $f(T)$ can either be a single parameter function or a two parameter function. Exemplary survival functions are depicted in Fig. 2. Some of the survival models described in [13] are summarised in the following list:

- The simplest model is a **symmetric, triangular distribution** with lower bound 0, mode μ and upper bound $2 \cdot \mu$. This model assumes a constant annual increase of withdrawn appliances until the average service lifetime and the same constant decrease afterwards (symmetric distribution). Triangular distributions are usually applied in case of scarce data.
- Another simple model is the **Poisson distribution**. It is a discrete distribution with a single parameter $\mu = \mathrm{E}(T) = \mathrm{Var}(T)$.
- The **Weibull distribution** is widely used in survival analysis. It features a shape parameter k and a scale parameter λ. A value of $k < 1$ indicates a decreasing failure rate, whereas for $k = 1$ the failure rate is constant over time and values $k > 1$ show an increasing failure rate.
- The **Normal distribution** was used in [11]. The number of failed appliances is normally distributed around the expected value μ with standard deviation σ.
- The **Truncated Normal distribution** is applied to model normalised service lifetimes with initial failure rate unequal to zero. Unlike the other distributions mentioned before, the truncated normal distribution assumes that a certain number of appliances is withdrawn right after purchase.

C. Sales Model

The total sales data $S(k)$ used to supply the stock model described II-A is composed of sales due to first time purchases

$X(k)$ and replacement sales $R(k)$ as given in

$$S(k) = X(k) + R(k) \quad . \tag{7}$$

1) First Time Purchases $X(k)$: First time purchases $X(k)$ represent the diffusion process of sales. Different approaches to model diffusion can be found in the literature. In [14], a model to describe the diffusion process of new consumer goods as an interaction between new users and potential users is explained. This model, called Bass model, is widely used in the field of marketing to forecast product diffusion into the market, because it offers wide-ranging flexibility and easy interpretation of its parameters. The basic differential equation originally proposed by Bass is:

$$\frac{dN(t)}{dt} = \left(p + q\frac{N(t)}{m(t)}\right) \cdot (m - N(t)) \quad , \tag{8}$$

where $N(t)$ is the cumulative number of units purchased at time t, m is the market potential or market size, p the coefficient of innovation and q the coefficient of imitation. These model coefficients p and q reflect the fraction of all adopters who are "innovators" and "imitators", respectively. Innovators are not influenced by the number of products that have been sold before. They decide to purchase a good independently in an "innovative" manner. The imitators, conversely, rely in their decision on the number of products that have been purchased earlier and "imitate" the previous buyers. It is assumed that the importance of innovators is higher at the beginning and decreasing over time (see [14]).

If the coefficients p and q are time-invariant, the solution of the differential equation (8) is (see [14] and [15]):

$$N(t) = m(t) \cdot \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}} \quad . \tag{9}$$

The overall market potential $m(t)$ is considered time-variant and is explained in further details in II-C4. In order to solve the equation for total sales (7), the first time purchases $X(k)$ are needed, instead of the cumulative sales $N(t)$ derived from the solution of Bass' equation (9). This is achieved by evaluating equation (9) at time k and $k-1$ and building the difference $N(k) - N(k-1)$, resulting in:

$$X(k) = m(k) \cdot \frac{1 - e^{-(p+q)k}}{1 + \frac{q}{p}e^{-(p+q)k}} - m(k-1) \cdot \frac{1 - e^{-(p+q)(k-1)}}{1 + \frac{q}{p}e^{-(p+q)(k-1)}} . \tag{10}$$

2) Replacement Sales $R(k)$: If it is assumed that all appliances are immediately replaced after their withdrawal from stock, the replacement sales $R(k)$ in year k can be modelled by the reduction of stock in the year k. Moreover, if zero initial failure is assumed, the sales vintage of year k has to be omitted. In case of non-zero initial failure, the appliances bought in year k and retired within the year of purchase k have to be respected. Equation (11) is developed for zero initial failure condition $L(0) = 1$:

$$R(k) = \sum_{i=k_0}^{k-1} S(i)\left[L(k-1-i) - L(k-i)\right] \quad . \tag{11}$$

3) Replacement Rate: It may be necessary to model a decreasing stock. Therefore, a *replacement rate* ≤ 1 has to be introduced. The replacement sales are then multiplied by this replacement rate:

$$R^*(k) = \textit{replacement rate} \cdot R(k) \quad . \tag{12}$$

4) Market Potential $m(k)$: In case of the market of domestic appliances, the overall market potential $m(k)$ depends on the number of households and on the potential number of second units, if households usually possess one or two units. A large range of macroeconomic and demographic factors influence the market potential, such as disposable income of households, household size, electrification, urbanisation, and climate factors. In developed countries, it is likely that a household possesses more than one refrigerator, but certainly not every household has a water heater or a heat pump. The sum of households and second units scaled by a certain factor α represents the maximum possible number of cumulative sales. The growth of households and second unit numbers are assumed to follow a logistic curve, resulting in

$$m(k) = \alpha \cdot \left(\frac{m_h}{1 + e^{-(k-\mu_h)/s_h}} + \frac{m_s}{1 + e^{-(k-\mu_s)/s_s}}\right) \quad . \tag{13}$$

The factors m_h and m_s are the maximum number of households and second units, μ_h and μ_s are location parameters, s_h and s_s are scale parameters for the considered time frame. If no second units apply, m_s is set to zero.

D. Parameter Estimation

Three different estimation approaches for the parameters of the Bass diffusion model are discussed in [16]:

- Ordinary Least Squares (OLS)
- Maximum Likelihood Estimation (MLE)
- Non-linear Least Squares (NLS)

According to the results of extensive testing, the NLS outperforms the other approaches in terms of mean absolute deviation and mean squared error. Based on these results, the NLS is adopted to the estimation problem of the present paper. In [16], the market potential m is modelled by a single parameter. To cope with the more detailed market potential model presented in II-C4, more parameters are included in the estimation problem. Table I summarises which parameters are included in the estimation algorithm. The scale factor α only has to be estimated if the maximum number of appliances is lower than the number of households. The NLS algorithm minimises the equation

$$\min_x \sum_i \left(F(x, x_{\text{data},i}) - y_{\text{data},i}\right)^2 \tag{14}$$

and solves it for the arguments x of a given objective function $F(x)$, input data x_{data} and observed output data y_{data}.

III. Modelling Modified Appliance Introduction

A. Basic Market Penetration Model

The concept of modelling market penetration of load management (LM) compatible appliances is based on the projection of sales of conventional appliances into the future. In order

TABLE I
PARAMETERS

Appliance	α	m_h	μ_h	s_h	m_s	μ_s	s_s	p	q
Refrigerator	1.0	E	E	E	E	E	E	E	E
Freezer	E	E	E	E	X	X	X	E	E
Heat Pump	E	E	E	E	X	X	X	E	E

E: Parameter has to be estimated X: not used

to participate in a sophisticated load management scheme, conventional products have to be retrofitted, or replaced by an LM compatible appliance. These upgraded products begin to penetrate the market in year k_0 and cover a time-dependent share of the annual, projected sales. The relative share of new appliances in the sales of one year, called relative market share, is described by a function that has to be defined matching the market penetration behaviour. The multiplication of the relative market share functions with projected sales data gives the annual sales numbers for both new and old appliances:

$$S_{\text{new}}(k) = \textit{market share new}(k) \cdot S_{\text{projected}}(k) \quad , \quad (15)$$

$$S_{\text{old}}(k) = \textit{market share old}(k) \cdot S_{\text{projected}}(k) \quad . \quad (16)$$

B. Market Penetration Considering Incentives

If financial incentives for replacing a conventional with an LM compatible appliance are applied, the stock of LM compatible appliances is expected to grow faster. The model of incentive-based sales assumes that a certain share of conventional appliances of ages between $\textit{age}_{\text{min}}$ and $\textit{age}_{\text{max}}$ during the incentives duration $[k_0, k_{\text{end}}]$ are replaced prematurely. Therefore, the number of appliances with age between $\textit{age}_{\text{min}}$ and $\textit{age}_{\text{max}}$ still remaining in the stock in year k has to be determined and multiplied with the incentives share applied in the year k, resulting in the number of incentive-based sales $S_{\text{incentives}}$ for $k \in [k_0, k_{\text{end}}], i \in [k - \textit{age}_{\text{max}}, k - \textit{age}_{\text{min}}]$:

$$S_{\text{incentives}}(k, i) = \textit{incentives}(k) \cdot S_{\text{old}}(k, i) \cdot L(k - i) \quad . \quad (17)$$

In a second step, the numbers of sales of conventional appliances in year i have to be updated, as follows:

$$S_{\text{old}}(k, i) := S_{\text{old}}(k, i) - 1/L(k - i) \cdot S_{\text{incentives}}(k, i) \quad . \quad (18)$$

The third step consists of updating the replacement sales for conventional appliances R_{old}, LM compatible appliances from incentive-based sales $R_{\text{incentives}}$ and from replacements due to the natural aging process R_{new}. Equation (11) is applied in this calculations for $k \geq k_0$ and $i \leq k$.

In the next step, the total sales numbers are updated using the new replacement sales numbers. This step is performed for conventional and LM compatible appliances for $k \geq k_0$, as seen in

$$\begin{aligned} S_{\text{old}}(k) = \textit{market share old}(k) \cdot [X(k) + R_{\text{old}}(k) + \\ R_{\text{new}}(k) + R_{\text{incentives}}(k)] \quad (19) \end{aligned}$$

$$\begin{aligned} S_{\text{new}}(k) = \textit{market share new}(k) \cdot [X(k) + R_{\text{old}}(k) + \\ R_{\text{new}}(k) + R_{\text{incentives}}(k)] \quad . \quad (20) \end{aligned}$$

The stocks of "old", "new" and "incentives" appliances are computed using (1).

C. Market Penetration Considering Retrofit

If the conventional appliances can be retrofitted with a communication interface for LM compatibility, they are not replaced. The model assumes that the appliances within a certain range of age are retrofitted according to the incentives share during a certain incentives duration as explained in III-B. These appliances pass simply from the stock of conventional appliances to the stock of LM compatible appliances. Due to this modelling, a joint "retrofit and replacement incentive" strategy cannot be evaluated since both instruments would interact in a non-trivial manner. It is assumed that the retrofit does not prolongate an appliance's lifetime. For the number of retrofitted appliances in the year $i \in [k_0, k_{\text{end}}]$ considering $l \in [i - \textit{age}_{\text{max}}, i - \textit{age}_{\text{min}}]$, the incentive-based sales $S_{\text{incentives}}(i, l)$ from (17) can be used. If the retrofit option is applicable, no update of replacement sales or total sales has to be performed. The stock of retrofitted appliances in the years $k \geq i_0$ is computed by

$$\textit{stock retrofit}(k) = \sum_{i=i_0}^{\min\{i_{\text{end}}, k\}} \sum_{j=i_0}^{k} \sum_{l=1}^{j} S_{\text{incentives}}(i, l) \cdot L(j - l). \quad (21)$$

The stock of conventional appliances is computed by (1), and the stock of retrofitted appliances is subtracted from this.

IV. CASE STUDY

The presented methodology is applied to the markets of refrigerators, freezers, and heat pumps in Switzerland. This serves to illustrate the model parameterisation with real input data and a set of assumptions. A further goal is to gain quantitative insights into the possible installed quantity of device-integrated communication interfaces at a certain point in the future. In order to capture long-term developments, 2080 is chosen as the simulation horizon.

A. Simulation scenarios

With the three appliance types under consideration and the option to simulate a base case without incentives or retrofit, a scenario with replacement incentive option and a scenario with retrofit, nine qualitatively different simulation scenarios can be defined. From these, the following five are selected due to their illustrative character:

1) Refrigerators, base case: This case assumes the penetration of modified refrigerators starting from a certain "introduction year". These appliances replace conventional refrigerators, which are withdrawn due to the natural aging process. The number of sales of LM compatible appliances covers a growing share described by the penetration model. No acceleration due to incentives is applied.

2) Freezers, base case: Same as 1), with freezers.

3) Heat pumps, base case: Same as 1), with heat pumps.

4) Refrigerators, replacement incentives: Replacement rate increased by a certain percentage during a time span, supposed to be caused by an incentive (e.g. financial) to replace an installed conventional refrigerator prematurely by an augmented new one. Incentives act on appliances within a certain range of age, supposed to be older ones.

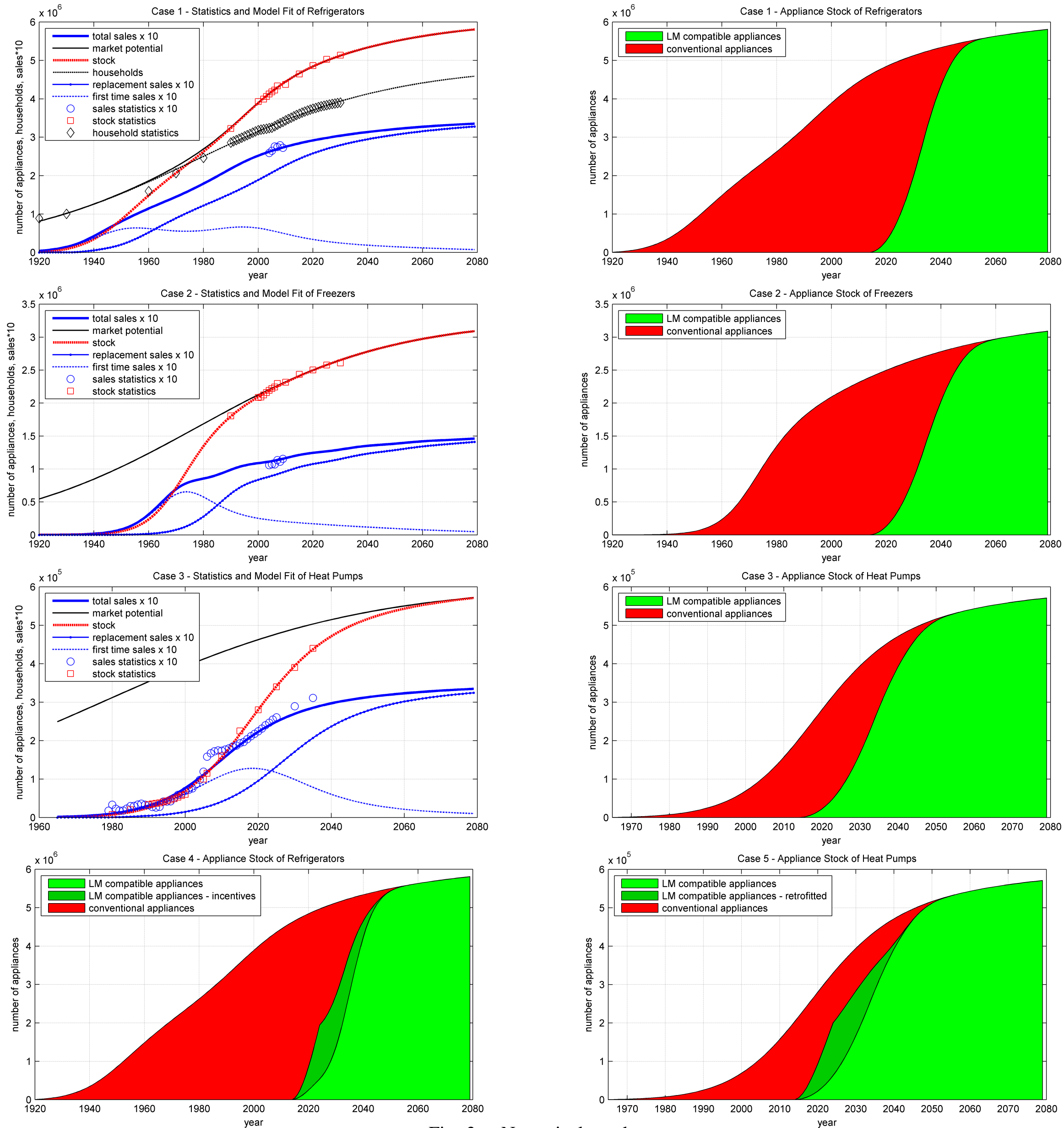

Fig. 3. Numerical results

5) Heat pumps, retrofit: Same as above, but with retrofit instead of replacement. It is assumed that incentives act on recently installed conventional appliances.

B. Model Parameterisation and Input Data

Statistical data for sales, stock, and average service lifetime of the appliance have to be supplied to run the model. This data can be retrieved from different sources: statistics departments of governments, market surveys, associations of appliance manufacturers, or associations of retailers. Given the available input data, the ownership approach is chosen for the simulations in this work as described in section II-A. 2015 is chosen as hypothetical "introduction year" in which the first LM compatible appliances enter the stock. The "base year" 1920 is the hypothetical year when the first conventional appliances enter the stock.

1) Household Statistics: Historical household statistics are taken from the census data published by [17], whereas forecasts of the future numbers of households could be found for 2010–2030 in [18]. Missing data was interpolated linearly.

2) Stock Statistics: Historical stock data for the Swiss market of refrigerators and freezers was found in [19] and for heat pumps in [20], [21]. Forecasts of future appliance stocks could be retrieved from [22], [23]. The predictions under consideration in [22] assume the same trend in the GDP, energy prices, and climate as up to now.

3) Sales Statistics: Sales data is synthesised by the sales model based on stock data. Sales statistics published by [24] are used to evaluate the model fit. Only historical data could be found for the Swiss market.

4) Input Data for Survival Model: The survival model has two input parameters: The average service lifetime and

TABLE II
PARAMETERISATION OF SIMULATION CASES

Parameter	Case 1	Case 2	Case 3	Case 4	Case 5
Survival Model					
Survival Distribution	normal	normal	normal	normal	normal
Average Lifetime	17y	21y	16.8y	17y	16.8y
Std Deviation	3.5y	4y	3y	3.5y	3y
Market Penetration					
Penetration Model	linear	linear	linear	linear	linear
Annual Growth	5%	5%	5%	5%	5%
Introduction Year	2015	2015	2015	2015	2015
Base Year	1920	1920	1965	1920	1965
Incentives					
Affected Age: from				14y	1y
Affected Age: to				17y	5y
Annual Growth				5%	5%
Duration				10y	10y
Retrofit	no	no	no	no	yes

the standard deviation. Both parameters are considered time-invariant. Average appliance lifetimes of refrigerators, freezers and heat pumps are mentioned in [5], [6], [7]. This paper assumes an average lifetime of refrigerators lower than values mentioned in the literature to provide a better model fit. Since no data for standard deviations could be found, the range of lifetimes given in [8] and a confidence interval of 97.73% was used to estimate the standard deviation. The outlined parameterisation is summarised in Table II.

C. Numerical results

Figure 3 shows the numerical results for the simulation scenarios outlined above. The raw data and the model fit are given for the base cases. The simulations have shown that a linear penetration model with higher annual growth than 5% does not substantially accelerate the penetration of modified appliances. With incentives and retrofit, however, higher stock numbers can be achieved in the first years after introduction. The impact of replacement incentives on the stock lasts longer than the retrofit option due to the fact that replaced appliances have full lifetime expectancy, whereas retrofitted appliances have shorter service lifetimes. Moreover, case 5 shows a higher impact of incentives on the relative share of LM compatible heat pumps, since this market is still growing substantially.

V. CONCLUSION

This paper presented a method for modelling the introduction of newly developed modified household appliances into a stock of existing appliances. Existing stock modelling techniques were extended to represent the effect of incentive-based additional sales and the option to retrofit the appliances.

The quantitative results suggest that the introduction of household appliances with a communication interface for "Smart Grid" applications should be backed up by additional measures such as purchase incentives. The mere presence of such appliances in the retail stores is unlikely to yield substantial load management potentials in the immediate future. Wherever possible, retrofit options (such as intelligent power plugs) should be investigated, and the development of load control strategies should be adapted to the probably limited device access that these options provide.

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