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Effect of Demand Response on Transformer Lifetime Expectation

Johannes Jargstorf, Koen Vanthournout, Tom De Rybel, Dirk Van Hertem

***Abstract*—Demand Response is seen as important to support the integration of renewable energies into the grid. In Flanders, a residential Demand Response setup is realized in the Linear pilot. The aim is to assess the potential benefits and ways of technical realization of residential Demand Response. In this paper, household devices, like washing machines, are used to offer a flexible load. These are also devices which are used in the pilot. The effect of using flexible loads on the lifetime of a low-voltage transformer is assessed. An IEEE transformer model is used to calculate the lifetime. To calculate the effect of Demand Response, aging is first calculated based on the load of a group of customers and then based on their load being optimized by Demand Response. In this paper, devices are scheduled based on the transformer temperature. The temperature is optimized by using a simulation model based on a mixed integer quadratic programming (MIQP) scheduler. To assess the effect of Demand Response on the transformer lifetime, aging for the improved load curve is compared with aging for the initial load curve. To demonstrate the impact, realistic data for household load curves and the usage of household devices are employed. Results for this input data show reductions in aging of up to 75 % for transformers operating at rated load. The setup will be used to calculate a benchmark for the setup in the Linear pilot, which will use an on-line scheduler. It will be also used to determine potential outcome of a business case.**

***Index Terms*—Demand Response, Transformer Lifetime, Asset Management.**

I. Introduction

Europe has set a number of targets for the future growth of renewable energy [1]. This includes photovoltaics (PV), which inject to a large portion into the distribution grid. Electrical vehicles, on the other hand, may add excessive loads to the grid. Yet, the existing grids were not designed for such a use [2]. As a result, several issues of power quality and strain on the grid equipment arise. The classical approach used today is to reinforce the electricity grid. Yet, such reinforcement, for example by deploying transformers with a higher rated power, is costly, especially as average load factors are often rather low [3]. Demand Response or Demand Side Management, i.e. matching consumption to generation or requirements of the grid, is seen as a way to overcome these problems [3], [4]. Demand Response has various applications, all of which should be evaluated to see if they justify a larger scale roll-out of this type of technology. One potential benefit is to extend the lifetime of grid equipment by using Demand Response [5]. In this paper, the focus is on transformers since transformers are the single most valuable asset.

Peak shaving on a load curve is commonly used in Demand Response schemes [6], [7], [8]. Yet, for the transformer, the actual problem is the aging that is induced by this load profile. Ref. [9], [10], [11] name load related temperature increase the main mechanism of transformer aging and the main limit for loading.

In this paper, this type of aging is correlated to demand response.

Aging models express a relation between the loading of a transformer and its lifetime [12], [13], [14], expressed by the aging of the insulation. The use of flexible devices is optimized based on the aging calculated in [12]. A quadratic programming (QP) optimizer is used to schedule the use of devices. As a new approach, this includes the individual household devices that are used in the Linear pilot [15]:

- Washing machines
- Tumble dryers
- Dishwashers
- Electric domestic hot water buffers

Due to the on-off nature of scheduling household devices, this includes mixed integer programming, which makes the problem computationally more complex and time consuming. The result of this study is used as a benchmark for the Linear pilot. In the following sections the different parts of the model will be described.

II. Simulation Setup

A. Transformer Model

To predict the lifetime of a transformer based on the load, the IEEE standard C57.91 can be used [13]. Concerning temperature, transformers have absolute limits which may not be exceeded at any time. Below these absolute limits, lifetime is related to temperature, which is related to active loading and ambient temperature. Therefore, it makes sense to reduce the highest peaks. One relation for this can be found in the mentioned standard. It is a general guideline valid for oil immersed, distribution as well as power transformers. Here, an aging factor is defined as follows:

$$F_{AA} = e^{\left[\frac{15000}{383} - \frac{15000}{\Theta_H + 273}\right]} \tag{1}$$

where F_{AA} is the aging acceleration factor, and Θ_H is the so-called hottest spot temperature in °C. This relation calculates

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an aging relative to the normal aging, which gives a lifetime of 180,000 hours or 20.55 years. Normal aging occurs at 110°C hottest spot temperature, or 80°C rise of the transformers hottest spot above an ambient temperature of 30°C. The equivalent life can then be calculated as:

$$F_{EQA} = \frac{\sum_{n=1}^{N}(F_{AA,n}\Delta t_n)}{\sum_{n=1}^{N}(\Delta t_n)} \tag{2}$$

where F_{EQA} is the factor of equivalent aging, n is the index of the respective time interval and Δt is the time interval at which the respective aging occurs. This gives a life consumption for the respective time period relative to the life consumption at 110°C. If, for example, one year is considered and the equivalent life consumption is two, then two years of life time at 110°C were spent during this time. So, if the factor remains two for 10.275 years, then the transformer is assumed to be at end-of-life after this period. In the model, Θ_H is calculated as:

$$\Theta_H = \Theta_A + \Delta\Theta_{TO} + \Delta\Theta_H \tag{3}$$

where Θ_A is the ambient temperature, $\Delta\Theta_{TO}$ is the rise of the top oil temperature over ambient temperature and $\Delta\Theta_H$ is the hottest spot rise over top oil temperature, all in °C. Now, $\Delta\Theta_H$ is calculated as:

$$\Delta\Theta_H = (\Delta\Theta_{H,U} - \Delta\Theta_{H,i})(1 - e^{-\frac{t}{\tau_w}}) + \Delta\Theta_{H,i} \tag{4}$$

$\Delta\Theta_{H,i}$ is the initial temperature rise at the beginning of an interval, t is the duration of an interval in minutes and τ_w is the winding time-constant in minutes. For $\Delta\Theta_{TO}$ a similar equation is applied. This describes the heat-up process based on the ultimate temperature rises $\Delta\Theta_{H,U}$ and $\Delta\Theta_{TO,U}$ that are calculated based on the load in the time interval as:

$$\Delta\Theta_{H,U} = \Delta\Theta_{H,R} K_U^{2m} \tag{5}$$

$$\Delta\Theta_{TO,U} = \Delta\Theta_{TO,R}\left(\frac{K_U^2 R + 1}{R + 1}\right)^n \tag{6}$$

with K_U being the ratio of ultimate load to rated load and $\Delta\Theta_{H,R}$ and $\Delta\Theta_{TO,R}$ being the winding hottest spot temperature rise over oil and the top oil temperature rise over ambient at rated load. R is the ratio between no load loss and loss at rated. The factors m and n are between 0.8 and 1.0, depending on the transformer type.

B. Optimizer

The objective used in this paper is to increase the transformer life as much as possible. This shall be reached by influencing the transformer load curve through scheduling of flexible household devices. This scheduling is performed by an optimal scheduler. To calculate an optimal solution, the scheduler is assumed to have information about the future load curve and about the future use of the flexible devices.

The scheduling then is done based on the original load curve, the available flexibility, and the impact of load on the aging of the transformer. It is assumed that all load profiles of the individual households within the feeder can be summed-up. Grid losses are not taken into account.

Now, to optimize the lifetime of the transformer, the equivalent aging F_{EQA} for the respective time period has to be minimized. Given T identical time intervals Δt, this means to minimize the sum of the aging factors $\sum_{t=1}^{T}(F_{AA,t})$. According to Equation 1, the aging factor is an exponential function of the temperature Θ_H. The minimization of such a function cannot be solved by a usual solver like CPLEX [16] that can handle linear or quadratic input. To make it a solvable problem, it has to be linearized. This linearized function will be used for the optimization of the load curve. Based on this, aging is calculated with the original function. Linearization is done by approximating the initial function by a Fourier series until the first element as expressed in Equation 7.

$$F_{AA,\text{linear}} = e^{\left[\frac{15000}{383} - \frac{15000}{\Theta_{\text{lin}}+273}\right]} + \frac{15000}{(\Theta_{\text{lin}} + 273)^2} \times e^{\left[\frac{15000}{383} - \frac{15000}{\Theta_{\text{lin}}+273}\right]} \times (\Theta_H - \Theta_{\text{lin}}) \tag{7}$$

In this equation, Θ_{lin} is the temperature for which the equation is linearized. To compare the result of both equations, this temperature is chosen as the average $\Theta_{H,\text{avg.}}$ of the respective time period. Now, the sum of aging factors for a time period calculated by this function can be minimized if the sum of the temperatures for the same time period is minimized.

Because the original function is monotonic, such a linearization is possible. Yet, it has to be analyzed, if the aging calculated with the linear function is sufficiently similar to the aging calculated with the original function. Only then are the problems that are solved sufficiently similar.

A further adaption is made for the calculation of the temperatures $\Delta\Theta_{H,U}$ and $\Delta\Theta_{TO,U}$ calculated according to Equation 5 and Equation 6. In these equations the parameters m and n express a relation between loss and temperature rise. According to [13], these parameters should be 0.8 for transformers without forced cooling. Again, to make it a problem that can be solved with solvers as CPLEX, the input has to be quadratic. For this reason, both parameters are chosen to be 1.0. This value is only suitable for transformers with a directed, forced cooling.

A second linear objective is introduced to penalize shifting. Shifting consumption is related to certain costs. It creates for instance a deviation from an original load forecast. Thus, a penalty on shifting is needed to make sure that an efficient solution is found. Efficient means a solution with as few shifting as possible for a certain improvement in aging. This second objective is realized as a constraint for the optimization. In this context, this will be a limit on the amount of energy that can be shifted per time period. This limit is based on the total amount of energy that is shiftable.

The input for the calculation of the temperature according to paragraph II-A is a load curve for which the element for time step t is calculated as:

$$P_t = P_{\text{initial},t} + \sum_{n=0}^{N}(P_{\text{AD},n,t}) \tag{8}$$

where $P_{\text{initial},t}$ is the initial load curve, N is the number of households and $P_{\text{AD},n,t}$ the flexible load that is re-scheduled for household n.

Yet, this setup is used to define a benchmark. For the field test and further models, an on-line scheduler is used. Such a setup has to find a solution that is "sufficiently" optimal.

C. Input

1) Load profiles: To determine the transformer load curve, individual residential load curves are summed. These are generated based on information taken from [17]. In this reference, a method to specify household characteristics, such as household size, based on quota is presented. In this way, more representative profiles can be generated.

For PV profiles, data from a single PV generator in Belgium is used and rescaled to be representative for residential injection. Every fifth household is assumed to be equipped with a PV generator. From these profiles, a load curve is build for a hypothetical network with 20 households. For the year 2007 those profiles have a cumulated peak load of 30 kW.

A share of 50 % (10) households with flexible devices is assumed. This small size is chosen, as this problem gets computationally very extensive with an increasing number of households. Yet, to have similar scales with bigger scenarios, the rated power of the transformer is scaled-down. A 80 kVA transformer is assumed which is further scaled-down to 20 kVA, although such transformers are not common in Belgium. Results in this paper are also validated with a scenario with 63 households of which 31 are equipped with flexible devices.

For the ambient temperature, an hourly-based curve for Saarbruecken was taken, derived from [18]. Concerning the ambient temperature in Equation 3, the IEEE guide recommends to use a daily average of the ambient temperature if such data is available. Yet, other references also use the ambient temperature in an hourly resolution [19]. This is also used here.

For the transformer the parameters depicted in Table I are used.

TABLE I
TRANSFORMER PARAMETERS.

	initial	alternative
hottest-spot rise over ambient at rated $\Delta\Theta_{HA,R}$	80°C	75°C
top-oil rise over ambient at rated $\Delta\Theta_{TO,R}$	36°C	55°C
load loss at rated load to no-load loss R	3	2.7
time constant winding τ_W	5 min	5 min
time constant oil τ_{TO}	210 min	210 min
parameters n, m	1.0	1.0

These values are taken from [13]. Though, in the reference, these values are taken from bigger transformers, for instance in [10] similar values for time constants and oil temperature rise over ambient are applied. The alternative parameters are taken from [20]. Here, the winding temperature has much less impact on the overall temperature. The parameters n and m are chosen to be one to have a quadratic input for the optimization as explained in Chapter II-B.

2) Demand Response: In the Linear field test, washing machines, tumble dryers, dishwashers and domestic hot water (DHW) buffers are used as flexible devices. The consumption of these devices is considered to be included in the household load curves. Thus, downward reserve has to be removed while upward reserve is added. Due to the aggregation of the load curves, this is seen as a suitable approach, even if there is no information about the use of a device in an individual profile.

TABLE II
PARAMETERS OF DEVICES.

Device	Load in kW	Setup
Washing Machine	heating: 2.0, spinning: 0.5	avg. 3.3 delayed cycles per week and household, avg. 450 Wh per cycle
Tumble Dryer	heating: 2.0	avg. 1.5 kWh per cycle, used for 70% of wash cycles
Dishwasher	heating: 2.0 - 2.5	avg. 3.1 delayed cycles per week and household, avg. 1.01 kWh per cycle
DHW Buffer	2.4	200 l storage, daily outtake per person: 35.4 - 38.7 l, avg. 5.5 kWh daily consumption per buffer

For the optimization model, two different basic models for the devices are assumed: Fixed Program Schedule (FPS) devices and State of Charge (SOC) devices. FPS devices include all devices that have a fixed schedule that can be delayed, but not interrupted, i.e., washing machines, tumble dryers and dishwashers. These devices are started by the user at a certain point in time. If the device is a flexible device, the user can define a certain time period in which the device is waiting and can be started on demand, for example, via an interface by a price signal or by direct load control. In this model, given that flexible devices are included in the household load curves, they offer downward flexibility only at the time they were initially running and upward flexibility during the delayed start waiting period.

SOC devices include buffered devices that produce heat from electricity, e.g. an electric domestic hot water (DHW) buffer. In the DHW buffer, the temperature of the tapped water has to stay between predefined comfort limits. The energy in the buffer is reduced by outtake and by losses, while the thermal energy can be increased by an electric heater. Flexibility can be created by storing thermal energy in the buffer before the energy consumption occurs, thus temporally disconnecting production and consumption, while respecting the user's comfort settings, which means minimum and maximum outlet temperature and minimum energy content of the buffer (minimum SOC).

For the model, usage patterns and consumption models from [21] and [22] are used to calculate the load curves. This is done in a model that is implemented in JAVA which calculated load curves for the individual devices, based on the input data from the mentioned references. Most important parameters of the devices are depicted in Table II For the delay function, it is assumed that in 56 % of cycles the delay is $\leq$ 3 h, in 28 % of cycles the delay is $\leq$ 6 h and for the remainder the delay is $\leq$ 12 h. Additionally, it is also assumed that washing machines are delayed in 85 % of the wash cycles and dishwashers in 75 % of the cycles.

As the DHW buffer represents an important load, it is important at which time of the day the water is heated. According to [21], heating can be shifted to the night, or

TABLE III
SCHEDULING OF FPS DEVICES.

	t1	t2	t3	t4	t5	t6
downward	-load1	-load2	-load3			
upward1		load1	load2	load3		
upward2			load1	load2	load3	
upward3				load1	load2	load3

happens when it is needed, which means when temperature drops below a certain limit. The latter is assumed for most of this analysis. This means that that the DHW buffer can run anytime of the day. It is assumed that this load is part of a households' daily load curve. The impact of a DHW buffer that runs only at night is also analyzed. In the latter case, the buffer will run either just after midnight or if the temperature drops below a lower limit. In this model, this is the case for the four and five-person households. Here, the buffer usually turns on late in the evening.

3) Model FPS devices: In the model, devices are addressed individually. For the FPS devices, it is assumed that only a limited number of downward and upward combinations exists. As depicted in Table III, each downward flexibility can be shifted to certain later points in time. This time span is defined by the user. The model input for FPS devices is a time series for the downward power and a binary time series indicating whether the device offers flexibility or not. These time series are calculated by the JAVA model already mentioned. In a matrix of the possible combinations, the downward profile, as depicted in Table III, is added to possible upward profiles. In this paper, a Δt of 15 minutes is assumed. Then, a $((N \cdot T), T)$ matrix $\underline{LP}$ is filled with possible combinations where N is the number of households and T the number of time steps. For the optimization, CPLEX in combination with Yalmip [23] is used. In Yalmip, a binary $(1, (N \cdot T))$ decision vector $\underline{dcv}$ can be defined. This vector then chooses the best possible combinations. Thus, the contribution of FPS devices can be expressed as:

$$\underline{P_{\text{AD,FPS}}} = \underline{dcv} \times \underline{LP} \tag{9}$$

$\underline{P_{\text{AD,FPS}}}$ is a (1, T) vector that contains for every time step t the sum of all devices

$$P_{\text{AD,FPS},t} = \sum_{n=0}^{N} \sum_{k=0}^{T} (dcv_{(n-1)\cdot T+k} \cdot LP_{(n-1)\cdot T+k,t}) \tag{10}$$

As a constraint, every downward profile may be chosen only once. To guarantee this, the chosen downward profile may not exceed the initial load profile P_{initial}:

$$P_{\text{initial},n,t} \leq \sum_{k=0}^{T} (dcv_{(n-1)\cdot T+k} \cdot LP_{(n-1)\cdot T+k,t}) \tag{11}$$

For these devices, it will be assumed that they have to be balanced over a day, so no shifting from one day to another is allowed. This is done for computational reasons. It will be later analyzed whether there is an impact on the use of FPS devices, if such shifting is allowed.

4) Model SOC devices: For SOC devices, the amount of used flexible load is the difference between a calculated load curve based on an optimized use of the device and an original load curve. For the original load curve, it is assumed that, given a water consumption profile W_D, the heating element switches on if a certain temperature T_{min} is reached and switches off if a T_{max} is reached. For calculating the contribution to the transformer load curve, a $((N \cdot T), T)$ matrix $\underline{LP}$ is used, similar to the FPS devices. This matrix consist of N (T, T) diagonal matrices of the SOC device power for household n. Similar to the FPS devices, this can be expressed as:

$$\underline{P_{\text{AD,SOC}}} = \underline{dcv} \times \underline{LP} - \underline{P_{\text{initial}}} \tag{12}$$

This usage of the device for influencing the load curve is constrained by the SOC, which is the water temperature in case of a domestic hot water (DHW) buffer. As a constraint, the temperature has to stay within certain limits, which also constrains the usage of the buffer for shifting:

$$T_{min} \leq T_H(t) \leq T_{max} \tag{13}$$

These limits have to be lower, respectively higher, than the original limits to allow a delayed start or end of the heating process. The temperature in the buffer depends on the buffer usage, the out-take of hot water and possible losses. Based on the usage of the buffer and an out-take curve, the water temperature is calculated as given in [6]:

$$\begin{aligned} T_H(t) &= T_H(0)e^{-\left(\frac{1}{R'C}\right)(t)} \\ &+ \{GR'T_{out} + BR'T_{in} + QR'\} \\ &\times \left[1 - e^{-\left(\frac{1}{R'C}\right)(t)}\right] \end{aligned} \tag{14}$$

where $T_H(t)$ and $T_H(0)$ is the water temperature at time t and the initial water temperature, respectively. For 15 minutes time steps, t is 0.25 h. T_{out} is the temperature outside the tank in K, T_{in} is the temperature of the inflow, also in K. Q is the energy input in W, which is the power of the heating element. R is the tank thermal resistance, SA the surface area. $G = SA/R$, W_D is the water demand in l/h. C_p is the specific heat of water, D is the density of water which is 1 kg/l. Also:

$$B = W_D C_p D \tag{15}$$

$$C = (V_{\text{buffer}})C_p D \tag{16}$$

$$R' = 1/(B + G) \tag{17}$$

where V_{buffer} is the buffer volume. Also for the buffered devices, it is assumed that they have to be balanced over a day. The temperature will also be reset at the end of every day to the temperature that was originally calculated. In this way, every day can be calculated individually. To avoid continuously switching, it is also assumed that the heating element has to be switched on for at least an hour if it is switched on.

5) Objective function: Given the considerations so far, the objective function is:

$$minimize \sum_{t=0}^{T} (\Theta_{H,t}) \tag{18}$$

with T the number of time steps and $\Theta_{H,t}$ the temperature in time step t. This function is subject to the constraints (19)-(**??**). Every FPS profile may be chosen only once. To achieve this, the inversed used flexible load $P_{\text{AD,FPS},n,t}$ may not exceed the initial load curve without shifting $P_{\text{initial,FPS},n,t}$.

$$-P_{\text{AD,FPS},n,t} \leq P_{\text{initial,FPS},n,t} \tag{19}$$

The temperature has to stay within limits

$$T_{min} \leq T_H(t) \leq T_{max} \tag{20}$$

The sum of shifted energy may not exceed a defined limited of shifted energy W_{lim} for the respective time period. This is first translated into:

$$P_{\text{lim}} = 2 \cdot \frac{\text{60 min/h}}{\text{timestepsize in minutes}} \cdot W_{\text{lim}} \tag{21}$$

and then limited as:

$$\sum_{k=0}^{T} abs(P_{\text{AD},t}) \leq P_{\text{lim}} \tag{22}$$

All devices for all households also have to be balanced over a time period, in this case every day:

$$\sum_{n=0}^{N}\sum_{k=0}^{T}(P_{\text{AD},n,t}) = 0 \tag{23}$$

If shifting to the next day is allowed, T is adapted for the FPS devices. A relaxation is made to the search criteria for computational reasons. In CPLEX, it can be defined how close a solution has to be to the optimal solution before the solver stops looking for further solutions. This parameter is set to 5 %. This means that there might be solutions with a calculated average aging up to 5 % better than the one found.

D. Results

As a first scenario, the network with 20 households and an 80 kVA transformer is assumed. For these considerations, a unity power factor is assumed. With this setup, a maximum hottest spot temperature, Θ_H, of 41.6°C is calculated. Maximum values for the rise of oil temperature over ambient temperature, $\Delta\Theta_{TO}$, and the hottest spot temperature rise over oil temperature, $\Delta\Theta_H$, are 12.0°C and 6.1°C, respectively.

On average, based on the input data, every household provides 6.9 kWh flexible energy per day. This is all the energy used for water heating and the energy for those devices that were started as flexible. On this amount the second objective is based. The maximum of flexible energy that can be used to improve the transformer load curve is initially set to 5 % of the total available energy. For the scenario with 10 flexible households, this means a maximum of 3.5 kWh (0.35 kWh per household) per day that may be shifted.

This case is calculated for January and August. In January, the peak load is 25.3 kW while in August it is 19.5 kW. In January, an average 3.06 kWh are shifted per day. Of this, 2.8 kWh or around 93 % come from shifting the DHW buffers, 0.13 kWh or 4% come from washing machines and dryers combined. For August 3.08 kWh are shifted on average of which 96 % come from the DHW buffers. The result of this setup is depicted in Table IV[1].

TABLE IV
EFFECT OF LOAD SHIFTING.

Jan, P_{max} = 25.3 kW, $P_{max,\text{new}}$ = 22.9 kW	initial[a] $\Theta_{H,\text{Peak}}$ in °C	change avg. Aging in %	change avg.Θ_H in %	change avg.$\Delta\Theta_{TO}$ in %
rated 80 kVA	24.6	-0.36	-0.12	-0.07
rated 60 kVA	28.0	-0.77	-0.21	0.13
rated 40 kVA	37.7	-2.92	-0.42	-0.27
rated 20 kVA	94.2	-47.36	-1.01	-0.75
Aug, P_{max} = 19.5 kW, $P_{max,\text{new}}$ = 19.5 kW	**initial $\Theta_{H,\text{Peak}}$, in °C**	**change avg. Aging in %**	**change avg.Θ_H in %**	**change avg.$\Delta\Theta_{TO}$ in %**
rated 80 kVA	38.5	-0.46	-0.10	-0.11
rated 60 kVA	38.9	-0.84	-0.18	0.19
rated 40 kVA	39.9	-1.99	-0.39	-0.41
rated 20 kVA	69.6	-11.1	-1.29	-1.36

[a]starting with time step 30

The impact on the average load curve is depicted in Figure 1 and Figure 2.

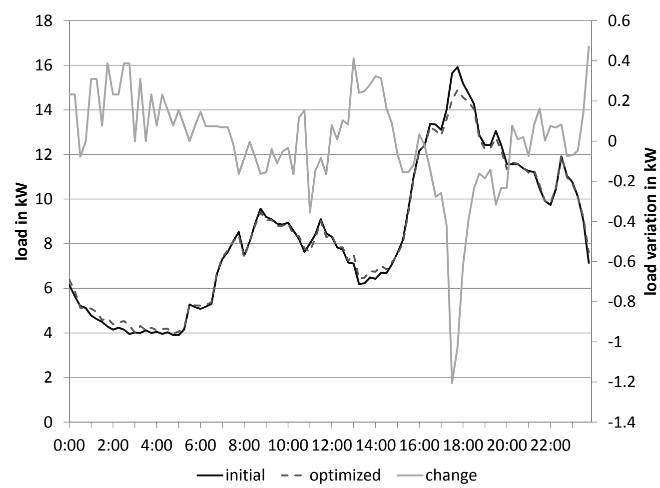

Fig. 1. Average daily load curve January, 10 households, max. 3.5 kWh shifted Energy.

With this limited amount of shifted energy, results indicate a rather limited improvement by load shifting, unless the transformer is loaded in peaks almost to or even beyond its rated load. Yet, in this case, the improvement increases fast, as depicted in Figure 3. Another outcome is that the peak load is not necessarily reduced. As can be seen for August, the absolute peak load remains unchanged. In in Table IV, it can also be seen that the effect on aging is much bigger than the effect on the temperature.

Concerning the temperatures, the main impact on aging comes from a reduction in the winding-hot-spot temperature. This is due to the short time-constant. The oil temperature reacts much slower. On the other hand, the oil temperature is

[1]assuming a reduced rated load for the age calculation but based on the load curve calculated for 80 kVA

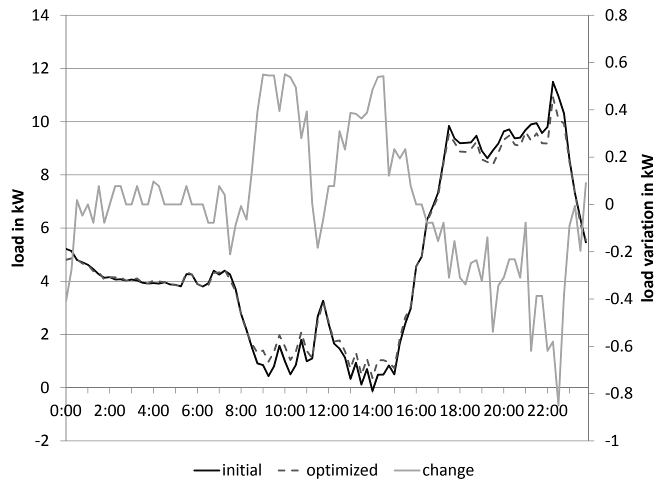

Fig. 2. Average daily load curve August, 10 households, max. 3.5 kWh shifted Energy.

more affected than the winding temperature by a reduction of the rated load of the transformer. As can be seen in Table IV, the average improvement raises with a reduction in rated load. This value remains constant for the winding temperature.

The impact on the load curve shows, how in January load is mainly shifted from the afternoon peak load, while in August it is shifted towards times with high PV injection during midday.

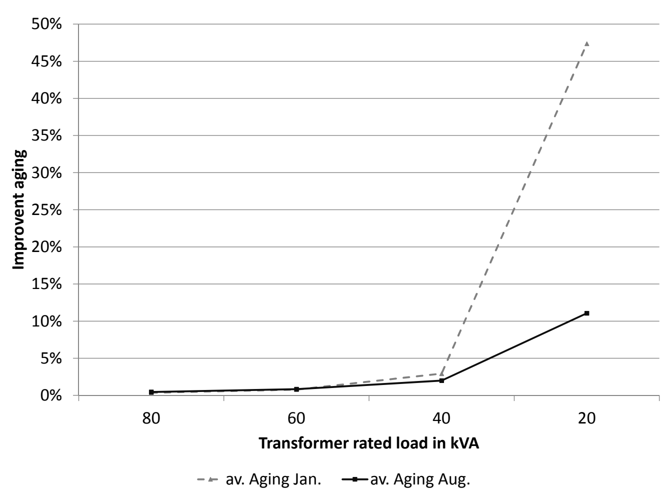

Fig. 3. Improvement average aging, 10 households.

These results indicate a limited impact of load shifting on the transformer lifetime, unless peak load is close to, or beyond, the rated load. The main device to be shifted are the DHW buffers.

If the limit on the shifted energy is relaxed, more energy is shifted and the aging can be further reduced. The limitation can be seen as a cap on the costs of shifting. In Figure 4 and Figure 5, a relation between the shifted energy and the improvement in aging is depicted. Here, the combined use of Demand Response for all households together was limited to 3.5 kWh per day, to 17.5 kWh per day and unlimited. It can be seen that the aging decreases with an increased amount of

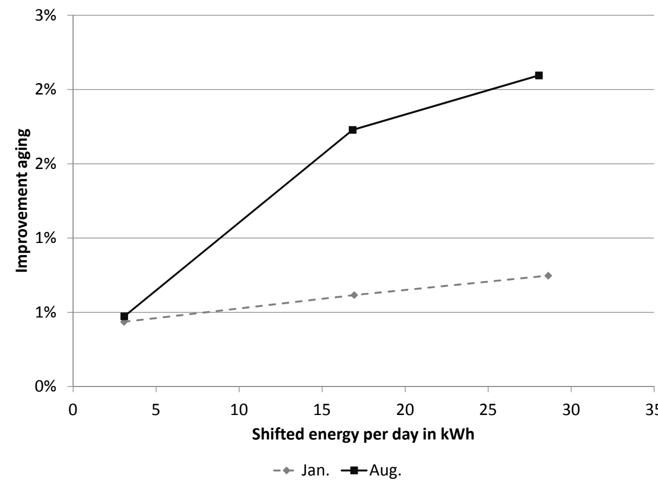

Fig. 4. Relation between shifted energy and improvement Aging, 80 kVA

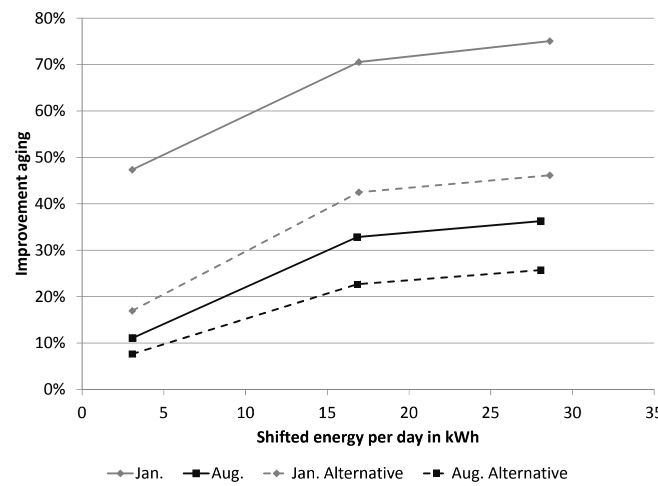

Fig. 5. Relation between shifted energy and improvement Aging, 20 kVA.

shifted energy, but with a declining rate. It can be also seen that for the alternative parameters according to Table I, with less impact of the winding temperature, the improvement in aging is reduced. Yet, for all scenarios, a significant improvement in average aging can be achieved.

DHW buffers remain the most important flexible device if no limit is applied. In this case, around 2.9 kWh per household and day are shifted, for example in January, compared with around 0.31 kWh given a limit of 0.35 kWh. As depicted in Figure 6, around 80 % come from DHW buffers compared to 93 % in the case with a limit.

Yet, it is also important to note that the amount of flexibility provided by the FPS devices is assumed to be smaller than the amount provided by the buffers. Therefore, it is also important to analyze how much of the available flexibility is used. This is depicted in Figure 7.

The share of used flexibility rises with the relaxation of the limit on used flexibility. Without a limit, around 50 % is used. This share drops by around 10 percentage points, if a limit of 17.5 kWh is applied, and only FPS devices are used. If shifting to the next day is allowed, this share raises again by around

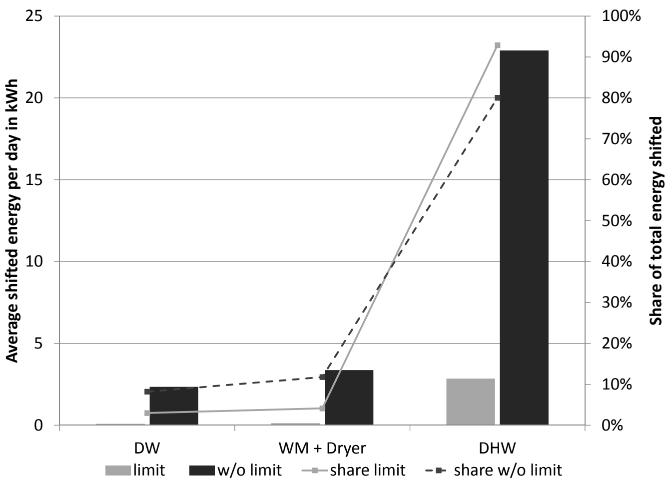

Fig. 6. Share of devices on shifted load without limit.

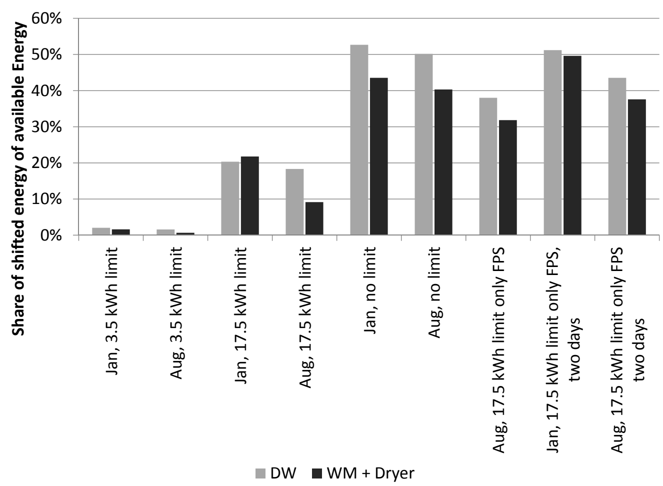

Fig. 7. Share shifted energy of total energy for FPS devices.

5 percentage points. As mentioned, it was assumed that the FPS devices can have a higher share of shifted energy if there are more households. For a scenario with 31 households, no improvement for these shares can be found. There was also no significant impact from the setup in which the buffers ran preferably at night, as they had to run in the evening for the 4 and 5 person households.

As mentioned so far, there were simplifications made to make this setup a solvable problem. Their impact has to be assessed. The first one is the linearization according to Equation 7. Comparing the aging factor calculated with the original model with the linearized one shows a constant difference of factor 3 between the two. However, for the optimization, the absolute value is not important but whether the two time series are sufficiently similar to base scheduling on the linearized one. To estimate this, the correlation between the original aging factor and the linearized aging factor is calculated based on the original load curve. For January for instance a value of 0.93 is calculated. For individual days, the value is much higher, between 0.98 and 1. Therefore, it can be assumed that the optimization based on the linearized equation is sufficiently close to an optimization based on the original equation, especially for an integer problem. It is also important that the optimization gives a lower average aging factor for every single day of a period. This is the case for all results. So all solutions are valid solutions.

The impact of the parameters m and n in Equation 5 and Equation 6, which were set to 1.0 for the optimization, can be only assessed for calculating the aging factor based on the optimized load curve. Using these values, has a negative impact when the age reduction is high. The January values, depicted in Figure 5, are for instance around 12 percentage points lower if a value of 0.8 is used. For the cases with a low improvement, there is no impact from using a value of 0.8. Again, it is controlled for every individual day, that the aging factor is reduced for m and n set to 0.8 and therefore the result of the optimization is valid.

The impact of relaxing the search criteria of the solver can be analyzed by letting the simulation run several times and compare results. Yet, given that there might be better solutions, this criterion rather underestimates the impact on the aging of the transformer. As a solution is still within 5 % of the best solution and as this is an integer problem with only a limited number of solutions, the impact is assumed rather small. Repeating the simulation confirms this as the results differ by less than 2 %.

Results show a high reduction in aging if the transformer is loaded close to its rated load. For loading much lower than that, the improvement in aging is very limited. From this, it can be derived that it can be reasonable to control load on an aged and highly loaded transformer to extend its lifetime, while it makes less sense to control the load curve right from the beginning. Yet, it could be seen that there is a relation with other objectives. In this case, load was shifted to times with high PV generation. Thus, there might be a positive effect on the transformer, if this kind of shifting is the original objective. Results also show the relative importance of DHW buffers for the outcome. It could not be shown, that the share of devices like washing machines rises with more households.

Concerning a business case, results indicate potential impact for transformers operating at rated load.

III. Conclusion

In this paper, the effect of Demand Response on the lifetime of a distribution transformer is analyzed. In a simulation, smart household devices like washing machines or DHW buffers are scheduled to enhance the expected lifetime of a distribution transformer. This is done by a MIP-solver based on the temperature of the transformer. Aging is calculated by an IEEE model for insulation aging. Results show significant reduction in aging for transformers loaded close to the rated load. Here, aging could be reduced by up to 75 % For transformers loaded much lower, reduction in aging was not significant. The main device to be scheduled for a small number of households are DHW buffers. They make up for 80 % to 92 % of the shifted energy. Results also show the decreasing efficiency of using additional flexibility. They also indicate potential business cases.

This setup is an initial benchmark for further work to estimate the effects of Demand Response on transformer aging. For the field test and further models, an on-line scheduler is used. Such a setup, then, has to find a solution that is "sufficiently" optimal, compared to the benchmark. Future work will include:

- Parameters of real transformers and real load measurements will be used to estimate the impact.
- Business cases will be calculated based on the impact of this scheme.
- Electric vehicles will be included as they can represent an important flexible load.
- The results will be compared with data collected in the field test.

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V. Biographies

Johannes Jargstorf works currently as a PhD researcher at the ELECTA group of KU Leuven, Belgium. His research interests include business cases for smart-grids. Johannes Jargstorf has a Diploma in Business Administration from Hamburg University, Germany and a Diploma in Electrical Engineering from Hagen University, Germany. He also worked at the Fraunhofer IWES in Kassel, Germany and in Marketing / Sales at carmakers Nissan and Daimler.

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Dirk Van Hertem (S'02, SM'09) was born in 1979, in Neerpelt, Belgium. He graduated as a M.Eng. in 2001 from the KHK, Geel, Belgium and as a M.Sc. in Electrical Engineering from the KU Leuven, Belgium in 2003. In 2009, he has obtained his PhD, also from the KU Leuven. In 2010, Dirk Van Hertem was a member of EPS group at the Royal Institute of Technology, in Stockholm, Sweden where he was the program manager for controllable power systems for the EKC^2 competence center at KTH. Since spring 2011 he is back at the University of Leuven where he is an assistant professor in the ELECTA group. His special fields of interest are power system operation and control in systems with FACTS and HVDC and building the transmission system of thefuture, including offshore grids and the supergrid concept. He is an active member of both IEEE (PES and IAS) and Cigré.