Using Demand-side Management to Decrease Transformer Ageing

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***Abstract*—The introduction of local, often uncontrollable, generation units as well as larger loads such as electric vehicles (EVs) causes an increasing amount of stress on our energy supply chain, specifically on the distribution grids. Demand-side management (DSM) is often seen as a potential technology to counter-act this increasing stress on the (distribution) grid. An important and expensive asset within these grids are the power transformers. Thus, economic incentives for DSM can be obtained by decreasing transformer ageing. To study the potential of using DSM to decrease transformer ageing, we consider an ageing model of distribution transformers based on the load profile being supplied by the transformer. We combine this with an optimization problem to find optimal charging profiles of EVs w.r.t. transformer ageing. Furthermore, we compare the results of the optimization problem to three other charging strategies. We conclude that smart charging strategies can give improvements of up to two orders of magnitude in reducing the ageing incurred by EV charging over the base load. Furthermore, we show that for the considered scenarios, a DSM strategy that steers towards the flattening of a neighbourhood's load profile gives similar results to our approach, which directly optimizes transformer lifetime.**

I. INTRODUCTION

Motivated by climate change and a drive towards renewable energy sources, our energy supply chain has been changing rapidly in the past decade and is expected to continue doing so. Within the supply chain, the production is shifting from a small number of large generators towards a much larger number of small, local generation units. Furthermore, these small units are increasingly exploiting renewable, uncontrollable sources such as wind and sun. However, the infrastructure of our energy supply chain was designed decades ago, without these changes in mind. Hence, the stress put onto these infrastructures is increasing rapidly [1].

Next to the increasing use of small-scale generation residential consumption of energy is also increasing. This increasing use of electricity is motivated by the abundant clean, renewable ways to generate electricity, such as the aforementioned wind and sun. Several examples of this electrification include the adoption of electric vehicles (EVs), electric cooking and electric heating (using, e.g., heat pumps). These changes also contribute to an increasing amount of stress put on the infrastructure of our energy supply chain [2].

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Demand-side management (DSM) is seen as a promising technology to support the integration of local, renewable generation while simultaneously reducing stress on the electricity grid [3], [4]. In particular, DSM can be used to prevent local congestion problems by shaving peaks in load profiles. One of the more expensive assets in electricity distribution grids are transformers [5]. Hence, significant economic benefits can be obtained if the lifetime of these transformers can be extended. The ageing of a transformer depends on the wearing of the insulation which is largely dependent on the temperature of the windings. This temperature is in term related to the load profile of the transformer, which can be significantly changed using DSM. Hence, it is of interest to study the potential for DSM to decrease transformer ageing.

To assess this potential we require a model of transformer ageing. For this we use the IEEE C57.91-2011 standard [6]. The standard derives information about the ageing of the transformer from a load profile, it can also be used for our purpose. Jargstorf et al [7] use the same model and simplify it into a quadratic program to allow them to calculate the optimal use of DSM to decrease transformer ageing. Note that the simplification we make on the model are less restrictive. Humayun et al. [8] use a similarly simplified version of the model on a Finnish residential area with various forms of demand response. To specifically calculate the effect of (plug-in hybrid) EV introduction on transformer lifetime, Moghe et al. [9] used a Monte Carlo simulation type approach.

The main contributions of this work are as follows:

- Using mild assumptiosn we prove convexity of the problem of finding optimal EV charging profiles w.r.t. transformer ageing.
- Simulations that show significant improvements can be made w.r.t. transformer ageing in several scenarios with different EV penetration levels in a residential neighbourhood by adopting smart charging strategies.
- The results indicate that DSM methodologies that steer towards a flat neighbourhood profile also achieve very good performance w.r.t. transformer ageing.

The rest of the paper is outlined as follows. In the next section, we introduce and study the used ageing model and our optimization approach to obtain charging profiles for EVs. Then, in Section III we introduce the model used to simulate the ageing of the transformer in the Dutch town of Lochem under various levels of EV penetration. We also introduce the various charging strategies we implemented and compare their results. Finally, in Section IV, some conclusions are drawn.

II. Ageing model transformer

In this section we study the ageing of distribution transformers. We use the model given in the IEEE standard C57.91-2011 [6]. First, we introduce the model in detail. Then we make a simplifying assumption on the model. Using this assumption we show that the resulting optimization problem when using demand-side management to reduce the ageing of transformers is convex. This allows us to use a convex solver to calculate the optimal DSM strategy when minimizing transformer ageing.

A. Thermal ageing model

The model from the IEEE standard is based on the relation between the temperature of the transformer and its degradation. The temperature is related to the ambient temperature and the load on the transformer. For a given time interval t, an ageing factor F_{AA}^t can be calculated using:

$$F_{AA}^t = e^{\frac{15000}{383}} e^{-\frac{15000}{\Theta_H^t + 273}}, \tag{1}$$

where Θ_H^t is the so called hottest spot temperature in °C. This is the temperature of the hottest spot on the transformer windings, i.e., the point where the transformer is assumed to degrade the quickest. The ageing factor F_{AA}^t indicates how much the transformer is assumed to have degraded relative to normal ageing, which occurs at 110°C. For multiple time intervals, indexed by t, the total equivalent ageing factor F_{EQA} is given by:

$$F_{EQA} = \frac{\sum_t F_{AA}^t \delta^t}{\sum_t \delta^t}, \tag{2}$$

where δ^t is the length of time interval t. Note that, in case all time intervals are of equal length, F_{EQA} is simply the average of the ageing factors of the considered time intervals.

The hottest spot temperature Θ_H^t is calculated as:

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

where Θ_A^t is the ambient temperature, $\Delta\Theta_{TO}^t$ is the temperature *rise* of the oil, used as coolant, over the ambient temperature and $\Delta\Theta_H^t$ is the temperature *rise* of the hottest spot on the winding over the temperature of the oil both for time interval t. $\Delta\Theta_{TO}^t$ is calculated using:

$$\Delta\Theta_{TO}^t = (\Delta\Theta_{TO,U}^t - \Delta\Theta_{TO,i}^t)\left(1 - e^{\frac{-\delta^t}{\tau_{TO}}}\right) + \Delta\Theta_{TO,i}^t, \tag{4}$$

where $\Delta\Theta_{TO,i}^t$ is the initial temperature rise at the start of the interval, τ_{TO} is a parameter given in minutes and $\Delta\Theta_{TO,U}^t$ is the ultimate temperature rise at the given load for the time interval, i.e., the temperature the oil will reach if the transformer is loaded indefinitely at the load value given for t. If several consecutive time intervals are considered, $\Delta\Theta_{TO,i}^T$ is assumed to be equal to $\Delta\Theta_{TO}^t$, the temperature rise of the previous time interval. Similarly $\Delta\Theta_H^t$ is calculated as:

$$\Delta\Theta_H^t = (\Delta\Theta_{H,U}^t - \Delta\Theta_{H,i}^t)\left(1 - e^{\frac{-\delta^t}{\tau_w}}\right) + \Delta\Theta_{H,i}^t, \tag{5}$$

with the various parameters similarly defined as in (4). While the parameter τ_w can be assumed to be independent of the temperature of the winding, the parameter τ_{TO} does depend on the initial and ultimate temperature rises $\Delta\Theta_{TO,i}^t$ and $\Delta\Theta_{TO,U}^t$ as:

$$\tau_{TO} = \tau_{TO,R} \frac{\left(\frac{\Delta\Theta_{TO,U}^t}{\Delta\Theta_{TO,R}^t}\right) - \left(\frac{\Delta\Theta_{TO,i}^t}{\Delta\Theta_{TO,R}^t}\right)}{\left(\frac{\Delta\Theta_{TO,U}^t}{\Delta\Theta_{TO,R}^t}\right)^{\frac{1}{n}} - \left(\frac{\Delta\Theta_{TO,i}^t}{\Delta\Theta_{TO,R}^t}\right)^{\frac{1}{n}}}, \tag{6}$$

where $\tau_{TO,R}$ is the value of parameter τ_{TO} for rated load, $\Delta\Theta_{TO,R}^t$ is the ultimate temperature rise of the oil at rated load, and n is an exponent based on the type of cooling used. Note that n typically takes values between 0.8 and 1, where in the case that $n = 1$, τ_{TO} is assumed to be equal to $\tau_{TO,R}$ for any initial and ultimate temperature rises.

Finally, $\Delta\Theta_{TO,U}^t$ and $\Delta\Theta_{H,U}^t$ can be calculated as:

$$\Delta\Theta_{TO,U}^t = \Delta\Theta_{TO,R}\left(\frac{(K^t)^2 R + 1}{R+1}\right)^n, \tag{7}$$

$$\Delta\Theta_{H,U}^t = \Delta\Theta_{H,R}(K^t)^{2m}, \tag{8}$$

where K^t is the ratio of load for interval t to rated load, $\Delta\Theta_{H,R}^t$ is the hottest spot temperature rise over the oil at rated load, and m is an exponent similar to n, also typically taking values between 0.8 and 1.

B. Simplifying assumption

The parameter τ_{TO} for the top oil temperature rise, calculated by (6) depends, through a complex relation, on the initial and ultimate temperature rise. Furthermore, the guide states that the relation given in (6) is chosen such that both the initial rate of change and the final temperature rise of the oil are correctly approximated by the model. However, intermediate values of the oil temperature rise might deviate. As we are exactly interested in these intermediate temperatures we make the following assumption for our optimization strategy.

Assumption 1. The effect on the ageing factors of different values of the parameter τ_{TO} for different initial and ultimate temperature rises of the oil over the ambient temperature can be neglected. Thus, we take $\tau_{TO} = \tau_{TO,R}$.

With the above assumption in mind, we consider (4). As noted, for consecutive time intervals we have $\Delta\Theta_{TO,i}^t = \Delta\Theta_{TO}^{t-1}$. Furthermore, we assume that each time interval is of equal length, i.e., we take $\delta^t = \delta$ for all t. Now, backwards substitution allows us to rewrite (4) into:

$$\Delta\Theta_{TO}^t = \sum_{s=1}^{t}\left[(1 - e^{\frac{-\delta}{\tau_{TO}}})e^{\frac{(s-t)\delta}{\tau_{TO}}}\Delta\Theta_{TO,U}^s\right] + e^{\frac{-t\delta}{\tau_{TO}}}\Delta\Theta_{TO,i}^1, \tag{9}$$

where $\Delta\Theta_{TO,i}^{1}$ is the temperature rise of the oil over ambient at the start of the considered time horizon. Similarly we can rewrite (5) into:

$$\Delta\Theta_{H}^{t} = \sum_{s=1}^{t} \left[(1 - e^{\frac{-\delta}{\tau_H}}) e^{\frac{(s-t)\delta}{\tau_H}} \Delta\Theta_{H,U}^{s} \right] + e^{\frac{-t\delta}{\tau_H}} \Delta\Theta_{H,i}^{1}, \quad (10)$$

where $\Delta\Theta_{H,i}^{1}$ is the temperature rise of the hottest spot over the oil at the start of the considered time interval.

C. Reducing ageing with DSM

As mentioned, the ageing of a transformer depends on the load profile it supplies and thus can be influenced by DSM. In this work we focus on residential charging of EVs, as these are novel, large loads that are expected to have a large impact on the distribution grid [2]. We aim to optimize the charging of the EVs such that the ageing of the transformer is minimized. We consider a set $\mathcal{E}$ of EVs and produce a schedule $x_e = (x_e^1, x_e^2, \dots, x_e^T)$ for each $e \in \mathcal{E}$ over a time horizon of T time intervals, such that it is charged completely before its next departure. More precisely, for EV e and some charging interval given by an arrival time t_a and a departure time t_d we require that:

$$\sum_{t=t_a}^{t_d} x_e^t = C \quad (11)$$

where C is the energy requirement to fully charge the EV's battery between t_a and t_d, i.e., the depth of discharge of the battery upon arrival at t_a. Furthermore, we assume that the EV can be charged with any amount of energy between 0 and $E_{e,max}^{t}$, the total energy charged into the battery when the EV is charged at maximum power:

$$0 \leq x_e^t \leq E_{e,max}^{t} \forall t, e. \quad (12)$$

If the EV is not present for time interval t, we set $E_{e,max}^{t}$ to 0. In our model we neglect grid losses implying that the total load of the neighbourhood for time interval t can be calculated by adding the load of each of the given EVs to the base load of the neighbourhood, i.e., the load of the devices that cannot be controlled. The ratio of load at interval t to rated load of the transformer can then be calculated by:

$$K^t = \frac{B^t + \sum_e x_e^t}{M}, \quad (13)$$

where B^t is the load of the uncontrolled devices for time interval t and M is the rated load of the transformer. Since we consider equal length time intervals, minimizing transformer ageing is equal to minimizing the average ageing factor over the considered time horizon. This is in turn equivalent to minimizing the sum of the ageing factors. This leads to the following optimization problem:

$$\begin{aligned} \min \ & \sum_{t} F_{AA}^{t}, \\ \text{s.t.} \ & (1), (3), (9) - (13). \end{aligned} \quad (MA)$$

Optimization problem *MA* is a nonlinear problem. However, as we show below, it is convex. To obtain this convexity result, we first show that the ultimate temperature rise of both the oil and the hottest spot is convex in the ratio of the load of any time interval to the rated load of the transformer.

Lemma 1. *Both $\Delta\Theta_{H,U}^{t}$ and $\Delta\Theta_{TO,U}^{t}$ are convex in the ratio of the load for time interval t and the rated load of the transformer.*

Proof. We first consider $\Delta\Theta_{H,U}^{t}$, which is given by (8). The second derivative of (8) w.r.t. K^t is given by:

$$2m(2m-1)\Delta\Theta_{H,R}^{t}(K^t)^{2m-2},$$

which is positive since $m \in [0.8, 1]$ and x^{2m-2} is positive for $x \geq 0$.

Next we consider $\Delta\Theta_{TO,U}^{t}$, which is given by (4). The second derivative of (4) w.r.t. K^t is given by:

$$\frac{2nR((K^t)^2R+1)^{n-2}((2n-1)(K^t)^2+1)}{(R+1)^n}$$

which is positive because $n \in [0.8, 1]$. □

Lemma 1 allows us to show that *MA* is a convex problem.

Theorem 1. *Optimization problem MA is convex for realistic load values.*

Proof. For each $e \in \mathcal{E}$, the feasible set is convex since (11) is linear for every charging interval and (12) is a bounding box. Thus, it remains to show that the ageing factor is a convex function of x_e^t. For any given t, K^t is given by an affine map of the x_e^t's for all $e \in \mathcal{E}$. Hence, $\Delta\Theta_{H,U}^{t}$ and $\Delta\Theta_{TO,U}^{t}$ are convex in each x_e^t by Lemma 1. Furthermore, $\Delta\Theta_{H}^{t}$ and $\Delta\Theta_{TO}^{t}$ are given by increasing affine maps of the $\Delta\Theta_{H,U}^{s}$'s and $\Delta\Theta_{TO,U}^{s}$'s respectively. Hence these are convex in each of the x_e^t's. Finally, note that Θ_{H}^{t} is an increasing affine map of $\Delta\Theta_{H}^{t}$ and $\Delta\Theta_{TO}^{t}$, hence it is convex in each of the x_e^t's.

Next we consider F_{AA}^{t} which is given by (1). The first derivative with respect to Θ_{H}^{t} is given by:

$$e^{\frac{15000}{383}} e^{\frac{15000}{\Theta_H^t + 273}} \frac{15000}{(\Theta_H^t + 273)^2}.$$

The second derivative is given by:

$$15000 e^{\frac{15000}{383}} e^{\frac{15000}{\Theta_H^t + 273}} \left(\frac{15000}{(\Theta_H^t + 273)^4} - \frac{2}{(\Theta_H^t + 273)^3} \right).$$

Note that the first derivative is strictly positive for any value of Θ_{H}^{t} and the second derivative is strictly positive for

$$\frac{15000}{(\Theta_H^t + 273)^4} > \frac{2}{(\Theta_H^t + 273)^3}$$

which is true for $\Theta_{H}^{t} < 7227$, i.e., for all realistic temperatures. Thus, the ageing factors F_{AA}^{t} are indeed convex in Θ_{H}^{t} for any realistic loading pattern. The theorem now follows from the fact that Θ_{H}^{t} is a convex function of each of the x_e^t's and F_{AA}^{t} is a convex and increasing function of Θ_{H}^{t}. □

TABLE I
USED PARAMETER VALUES WITHIN PROBLEM *MA*.

Parameter	Value	Parameter	Value
$\Delta\Theta_{TO,R}$	55° C	$\Delta\Theta_{H,R}$	20° C
τ_{TO}	210 min	τ_w	5 min
B	97897 W	R	2.7
$\Delta\Theta^1_{TO,i}$	21.0° C	$\Delta\Theta^1_{H,i}$	1.53° C
n	0.8	m	0.8

TABLE II
DIFFERENCES BETWEEN OUTCOMES OF THE AGEING MODEL WITH AND WITHOUT ASSUMPTION 1 FOR OPTIMIZED EV CHARGING FOR THE SCENARIOS

Scenario	Maximum absolute temperature difference (° C)	Ageing difference (%)
light penetration	0.02	0.04
medium penetration	0.03	0.17
heavy penetration	0.09	0.65

Theorem 1 allows us to solve the optimization problem *MA* using a convex solver. We can then compare the obtained load profile to the load profile obtained using other charging strategies for the EVs.

III. COMPARISON STUDY

In this section we use load data from a real world neighbourhood transformer in the town of Lochem in the Netherlands to construct instances of *MA* that represent scenarios with significant penetration levels of EVs. We compare the optimization results, based on Assumption 1, with the temperature profile and ageing factors calculated using the model described in II-A. Furthermore, we implement the DSM methodology called profile steering [10] to manage the charging of the EVs. We calculate the ageing of the transformer when the profile steering methodology is applied and compare this to the results of our optimization approach. Finally, we calculate the ageing when the EVs are uncontrolled and consider the cases that the EVs are either charged as quickly as possible upon arrival or the charging is equally spread over the time period that the vehicle is available for charging.

A. Considered scenario

We consider a transformer in the town of Lochem for which we have detailed load measurements available. The transformer supplies a neighbourhood of residential customers in Lochem. The transformer is rated at 400 kVA with an average winding rise of 65° C. As a test case we use data from November 3rd until November 9th in 2014, for which the base load profile is given in Fig. 1a as Base. From this data we use the 15 minute averaged load values. The temperature profile of the transformer resulting from the base load is given in Fig. 1b.

The values of the required parameters to calculate the ageing are given in Table I. Cooling of the transformer is done through natural convection, known as ONAN cooling. For this type of cooling [6] suggests that the values of the exponents n and m are set to 0.8. For the initial temperature of the top oil and hottest spot we use an equivalent load B to the load profile of the previous day (for details see [6]).

For the other parameters of the transformer we used values from [11] for a 65 degrees average winding rise transformer. Finally, for the ambient temperature we used measurement data from a weather station in Eefde, close-by Lochem.

Next we specify the data used for the EVs in the considered scenarios. We assume there are 50 EVs in the neighbourhood. We assume that each of the EVs arrives randomly between 17:00 and 19:00. Furthermore we assume that they have to be fully charged by a time randomly selected between 6:00 and 8:00 the next day. The total required charge and maximal charging power of the EV is varied over the scenarios. This is done to simulate the effect of a higher penetration of EVs, as doubling the required charging and maximal charging power of each EV is essentially the same as modelling twice as many vehicles. As a basis, we use the scenario where each EV can charge with a maximal power of 3.8 kW and has to charge a random amount between 10 and 15 kWh every night. We call this scenario *low penetration*. Also, we performed simulations for the case that the required charging and maximal charging power are either doubled or tripled. These scenarios are called *medium penetration* and *high penetration* respectively.

B. Optimizing transformer lifetime

To optimize the transformer lifetime by controlling the charging of the EVs, we implemented optimization problem *MA* in the AIMMS modeling software [12]. Within AIMMS we used the CONOPT solver to produce a solution. While CONOPT only finds a local optimum, the convexity result from Section II-C ensures that this is in fact a global optimum.

As discussed in Section II-B, we made a simplifying assumption in order to be able to derive our results. To verify that our results do not deviate too far from the model presented in Section II-A we compared the temperatures and resulting ageing for the load profile found by our optimization strategy with and without Assumption 1, listed in Table II.

For the considered scenarios and found charging profiles of the EV using Assumption 1 gives slightly lower temperature values and hence gives slightly lower ageing. However, for the considered cases, the differences are small enough to assume that the found charging profiles give minimal transformer ageing. The resulting load profiles can be found in Fig. 1a-3a for the low, medium and high penetration scenarios respectively, where the curve is denoted by Opt. Furthermore, the temperature profiles of each of these scenarios can be found in Fig. 1b-3b. Finally, the increase of transformer ageing for each of the scenarios is listed in Table III. Our optimization strategy has a slight preference for charging during the time intervals later at night, as can be seen by a slightly increasing total load profile through the night for each day.

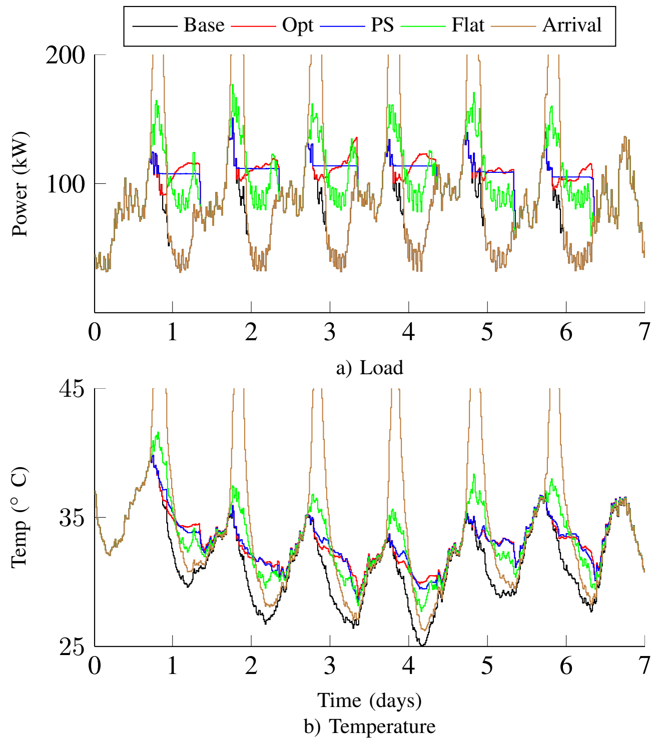

Fig. 1. The load (a) and temperature (b) profile for the low penetration scenario.

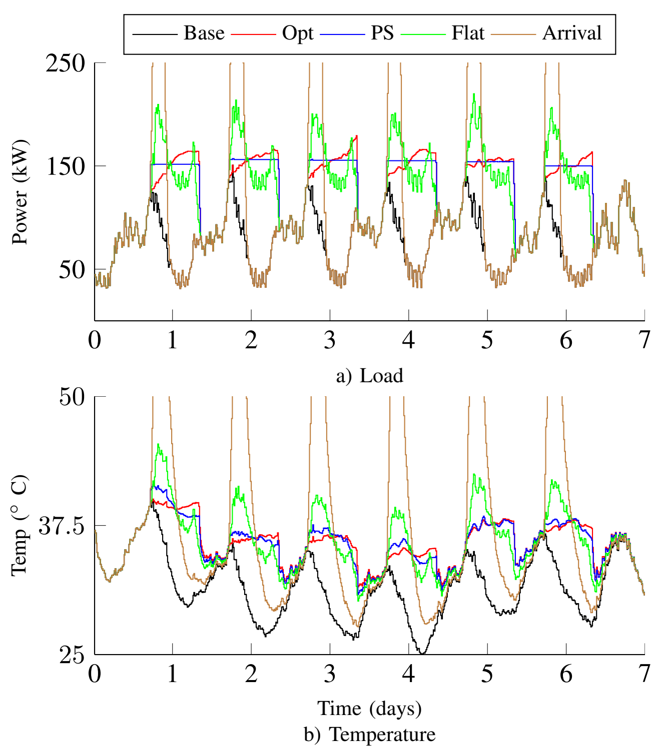

Fig. 2. The load (a) and temperature (b) profile for the medium penetration scenario.

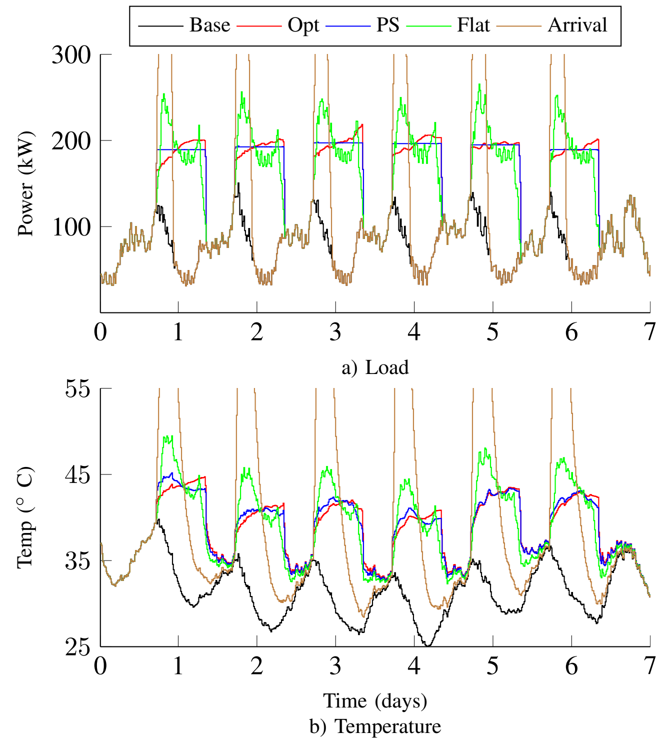

Fig. 3. The load (a) and temperature (b) profile for the high penetration scenario.

C. *Profile Steering*

For the used model of transformer ageing, the temperature rise of both the oil and hottest spot is an increasing convex function of the load on the transformer and the ageing of the transformer is an increasing convex function of the hottest spot temperature. Therefore, flattening the load profile should intuitively reduce the ageing of the transformer significantly. As a comparison to our optimization strategy introduced in Section III-B, we implemented the profile steering DSM methodology [10] with the goal of obtaining a flat profile for the neighbourhood. This methodology attempts to coordinate the steerable loads in a neighbourhood, in our case the EVs, such that the total load profile follows a desired profile as good as possible, while keeping the local profile within bounds [13]. The resulting temperature and load profiles can be found in Figures 1-3 and Table III where they are listed as PS. The profile steering methodology spreads the charging of the EVs such that the resulting profile is as flat as possible.

D. *Uncontrolled charging*

For comparison, we simulated the scenarios without a coordination mechanism for the EV charging. While currently most EVs maximally charge when plugged-in until they are fully charged, several studies have shown that this can cause a tremendous amount of stress on the grid [14]. Hence, in the future EV owners might be incentivized to spread the charging of their own vehicle equally over the time interval for which the EV is available. To be able to assess the potential

TABLE III
THE INCREASE IN PERCENTAGES OF THE AGEING OF THE DIFFERENT EV LOADING STRATEGIES FOR THE DIFFERENT SCENARIOS OVER THE BASELOAD.

	light penetration	medium penetration	heavy penetration
Opt	20.6	76.5	200.9
PS	20.9	77.6	202.1
Flat	27.6	92.2	243.9
Arrival	161.0	4763.5	22306.9

of our optimization approach we implemented both cases. The resulting temperature and load profiles for both cases in each of the scenarios can be found in Figures 1-3 respectively, where Arrival denotes the case of maximal charging upon arrival and Flat denotes the case of equal loading over the entire charging interval. The increase in ageing over the base load can be found in Table III in the rows Arrival and Flat. The figures are scaled to not fully show the results for the Arrival case, to better show the results of the other cases.

E. Comparison of the cases

The results of the simulation study show a very large reduction in transformer ageing when smart charging is adopted. Specifically in the high penetration case, the transformer ages rapidly when the vehicles are fully charged upon arrival. This is mainly caused by the high peaks in this case that overload the transformer, causing high temperatures and extreme wearing. While flat charging already significantly decreases transformer ageing, this can be further improved by applying a DSM methodology steering the EV charging.

When comparing our optimization approach, which directly optimizes towards transformer lifetime, with the profile steering approach, it can be seen that the differences in temperature and ageing are minimal. For all considered scenarios, our approach slightly favours time intervals later during the night for charging. This can be explained by a lower ambient temperature for these time intervals, which allows a slightly higher load on the transformer with the same resulting temperature and thus ageing. For the considered scenarios however, a DSM approach that steers towards flattening the load profile of the neighbourhood seems to provide adequate results w.r.t. minimizing transformer ageing.

IV. CONCLUSION

In this work we considered an ageing model of distribution system transformers relating load profiles to ageing. To investigate the potential of DSM for minimizing transformer ageing, we considered several scenarios with different levels of EV penetration. In these scenarios we investigated the increase in transformer ageing under several smart charging approaches compared to the ageing under the base load. Specifically we considered an optimization approach for finding optimal charging profile with respect to transformer ageing and compared this with charging profiles of the profile steering approach and uncontrolled charging either through maximal charging upon arrival or charging equally over the charging interval. Under mild assumptions we showed that the considered optimization problem is convex and can thus be solved by convex solvers.

The results show that significant improvements in transformer lifetime can be obtained when the EVs are charged in a smart way. While equally charging over the entire charging interval already gives a large improvement, further improvements are obtained by further flattening the load profile of the entire neighbourhood. We also showed that, for the considered cases, profile steering gives results very similar to the formulated optimization approach in this work. This indicates that DSM approaches that flatten the neighbourhood load profile could be good candidates for increasing transformer lifetime. The resulting economic gains from the increased lifetime can then be used to incentivize customers to participate in such a DSM approach.

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