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Consideration of the Impacts of a Smart Neighborhood Load on Transformer Aging

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***Abstract*—Smart grid solutions with enabling technologies such as energy management systems (EMSs) and smart meters promote the vision of smart households, which also allows for active demand side in the residential sector. These technologies enable the control of residential consumption, local small-scale generation, and energy storage systems to respond to time-varying prices. However, shifting loads simultaneously to lower price periods is likely to put extra stress on distribution system assets such as distribution transformers. Especially, additional new types of loads/appliances such as electric vehicles (EVs) can introduce even more burden on the operation of these assets, which is an issue that needs special attention. Such extra stress can cause accelerated aging of distribution system assets and significantly affect the reliability of the system. In this paper, the impact of a smart neighborhood load on distribution transformer aging is investigated. The EMS of each household is designed to respond to prices and other signals emitted by the responsive load serving entity within the relevant demand response strategy. An optimization framework based on mixed-integer linear programming is presented in order to define the EMS structure. Then, the equivalent aging of the distribution transformer is examined with a thermal model under different scenarios. The case studies that are presented indicate that the integration of EVs in residential premises may indeed cause accelerated aging of the distribution transformers, while the need to investigate the efficiency of dynamic pricing mechanisms is rendered evident.**

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***Index Terms*—Distributed generation, energy management system, electric vehicle, smart neighborhood, transformer aging.**

NOMENCLATURE

Abbreviations

DR	demand response.
DS	distribution system.
EMS	energy management system.
ESS	energy storage system.
ESS2H	energy storage system-to-home.
EV	electric vehicle.
MILP	mixed-integer linear programming.
PV	photovoltaic.
PV2H	photovoltaic-to-home.
V2H	vehicle-to-home.
V2G	vehicle-to-grid.

Indices

h	smart household index.
t	period of the day index in time units [h].

Variables

$Cost_h$	total electrical consumption cost for each smart household of the neighborhood.
K	load factor (load current/rated current).
$P_{h,t}^{grid}$	power drawn from the grid by each household [kW].
$P_{h,t}^{PV,used}$	PV power used by the household [kW].
$P_{h,t}^{EV,used}$	power of EV battery used by the household [kW].
$P_{h,t}^{ESS,used}$	power of ESS used by the household [kW].
$P_{h,t}^{EV,ch}$	charging power of EV [kW].
$P_{h,t}^{ESS,ch}$	charging power of ESS [kW].
V	relative aging rate.
V_n	relative aging rate during interval n.
θ_h	winding hottest-spot temperature [°C].
θ_o	top-oil temperature [°C].
$\triangle\theta_{o,i}$	top-oil (in tank) temperature rise at start [°K].

Parameters

g_r	average winding to average oil (in tank) temperature gradient at rated current [°K].
H	hot-spot factor.
k_{11}	thermal model constant.
k_{21}	thermal model constant.
k_{22}	thermal model constant.
N	total number of time intervals.
$P_{h,t}^{in}$	inelastic electrical load for each household [kW].
P_r	distribution transformer rated power [kW].
R	ratio of load loss to no-load loss at rated current.
θ_a	the ambient temperature [°C].
x	exponential power of total losses versus top-oil (in tank) temperature rise (oil exponent).
y	exponential power of current versus winding temperature rise (winding exponent).
$\triangle\theta_{o,r}$	top-oil temperature rise at rated current [°K].
$\triangle\theta_{h,i}$	hot-spot-to-top-oil (in tank) gradient at start [°K].
$\triangle\theta_{h,r}$	hot–spot temperature rise at rated current [°K].
λ_t^{buy}	buying price of electrical energy from grid [cents/kWh].
τ_o	average oil time constant.
τ_w	winding time constant.

I. Introduction

Distribution system (DS), that serves as the bridge between transmission system and end-user premises for electric energy transfer, is considered as one of the most important points of a power system for the effective and efficient utilization of electricity. With the introduction of different kinds of electric loads on the market, the load shapes of end-user premises have started to change significantly, a fact that may lead to compelling circumstances for DS assets such as transformers, lines, etc.

As a new type of end-user appliance/load, electric vehicles (EVs) have recently gained more importance as the electrification of the transport sector, which traditionally is a major fossil fuel consumer, is promoted [1]. EVs differ from the traditional loads, in the sense that they may both consume and provide energy, posing challenges and offering opportunities that should be examined in detail [2], [3]. On the one hand, from the perspective of a load, the energy needs of EVs can reach the levels of new power plant installation requirements. For example, the recommended charging level of a Chevy Volt, a small sized EV, is 3.3 kW, which can even exceed the total installed power of many individual homes in an insular area [4]. On the other hand, EVs can also be employed as a system resource, especially during peak periods through the vehicle-to-home (V2H) and vehicle-to-grid (V2G) options [5], [6].

Apart from EVs, non-dispatchable distributed generation technologies such as photovoltaic systems (PV) and wind energy conversion systems increase the uncertainty in the daily operation of the DS.

Herein, transformers, considered as core elements of DS, are given specific importance in industrial applications in order to increase the reliability of DS operation under high penetration levels of the aforementioned technologies in the DS. Transformers are significantly affected by operating conditions such as heavy loading and therefore it is important to evaluate the effects of possible extra loads that can have such impacts on transformer units. The transformer operating lifetime is normally declared by manufacturers under normal operating conditions. However, operating conditions beyond the nominal are likely to cause a decrement in the effective operating lifetime of a transformer unit, especially due to increased thermal load causing insulation aging (which depends on winding temperature). Thus, it is important to maintain the transformer's operating conditions within certain limits to ensure longer operation of this pivotal asset of DS. With this aim, "smart grid" solutions that are recently gaining increasing importance are likely to be applied in order to prolong the effective utilization period of such assets.

The "smart" grid has been considered to have a prominent position within the new concepts for operating the mature electric power grid in a more efficient and reliable way, that is also supported by high levels of investments from governments of both developed and developing countries. Within the smart grid concept, smart home structures together with smart home energy management systems (EMS) capable of controlling home size distributed energy production facilities, EV based storage/production options, and controllable new generation smart appliances have also been the specific topic of some research activities in the area of residential demand-side management [7]–[13].

Specifically considering smart solutions in the DS areas for the effective utilization of transformers, the impact of EV charging on the distribution transformers was studied in [14]. Randomized plug-in time, random departure time, and battery charging characteristics as well as the control and optimization of the EV charging were neglected and presented as the aim of future studies in [14]. Besides, [14] solely considered the impacts of EVs under several scenarios without taking into account any other end-user characteristics. Moreover, [14] neglected the V2G possibility that can raise issues in terms of the magnitude and the duration of transformer overloading. As an extension of the study presented in [14], Vicini *et al.* [15] also considered the coordination of EV charging activities within a neighborhood via home EMS, considering incentive based demand response (DR). However, in [15] no issue related to the minimization of individual home owner daily electric energy costs was taken into account. Besides, in [15] the V2G possibility is neglected. A method for describing the EV charging effects on overhead distribution transformers and a method for mitigating this impact through a transformer temperature-based smart charging algorithm provided to reduce transformer overloading was proposed in [16]. However, this study neglected the individual home owner cost minimization. There are also other studies, not mentioned here, that have provided important insights on the area. However, none of them considered the impact of a time-varying DR scheme on the aging of a distribution transformer serving a residential neighborhood. Such considerations are important in order to investigate potential tradeoffs between the

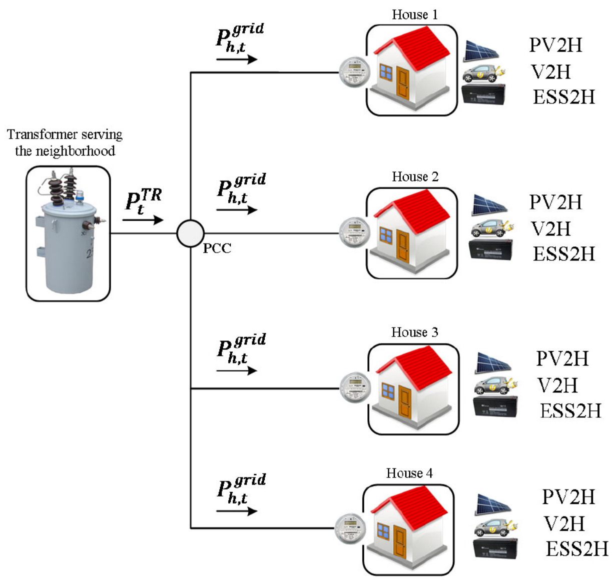

Fig. 1. Schematic diagram of a transformer serving a neighborhood composed of 4 smart households.

benefits that emerge from rendering available dynamic tariffs to residential end-users and the inefficient utilization of the DS infrastructure.

In this study, the impact of the operation of a neighborhood of smart households contracted under a time-varying pricing scheme on the local distribution transformer aging is studied, which has not yet been considered in the relevant literature. The investigation of this issue constitutes the major contribution of the paper.

Furthermore, the effect of the possibility of EVs to cover a portion of the household load through V2H mode is analyzed as well. The aim of the numerical simulations is to demonstrate that the integration of EVs may indeed accelerate the aging of the distribution transformers and to investigate the efficiency of the dynamic pricing scheme.

The remainder of the paper is organized as follows: in Section II the proposed methodology is developed. Then, in Section III a realistic test case is presented and the obtained results are thoroughly discussed. Finally, conclusions are drawn in Section IV.

II. Methodology

The schematic diagram of a transformer serving a neighborhood composed of multiple smart households is depicted in Fig. 1.

A. Minimization of the Cost of Each Individual Household

The equations concerning the smart-household appliances are given below as part of the model of optimizing the cost for electricity usage for each smart household.

The objective of each household h is to minimize the cost of buying energy from the grid. This is expressed by (1).

$$h \in H: \mathit{Minimize}\ \mathit{Cost}_h = \sum_t \left(P_{h,t}^{grid} \cdot \Delta T \cdot \lambda_t^{buy} \right) \tag{1}$$

Algorithm 1 Cost Minimization for All the Households of the Neighborhood

1: $h \leftarrow 1$
2: $P_t^{TR} \leftarrow 0$
3: *for* $h = 1{:}card(H)$
  Minimize (1)
  subject to (2)-(3)
  $P_t^{TR} \leftarrow P_t^{TR} + P_{h,t}^{grid}$
end
4: The power that the transformer has to serve is known ($P_t^{TR,pro}$) together with the individual cost and appliance scheduling of each household.

In (1), $P_{h,t}^{grid}$ is the power drawn from the grid (kW) from household h in period t, ΔT is the duration of the optimization interval (h) and λ_t^{buy}(€/kWh) is the hourly varying price signal. The electricity price is assumed to be the same for all the houses fed by the transformer.

The power balance for each household is:

$$h \in H: P_{h,t}^{grid} + P_{h,t}^{PV,used} + P_{h,t}^{EV,used} + P_{h,t}^{ESS,used} = P_{h,t}^{in} + P_{h,t}^{EV,ch} + P_{h,t}^{ESS,ch}, \ \forall t \tag{2}$$

The amount of energy consumed to cover the needs of each smart household includes the inelastic load used by all the appliances of the house ($P_{h,t}^{in}$), the charging needs of the ESS of the household ($P_{h,t}^{ESS,ch}$) and also the charging needs of the EV battery ($P_{h,t}^{EV,ch}$). This total amount of electricity consumption is covered, for each household, either by power drawn from the grid through the distribution transformer ($P_{h,t}^{grid}$), or by the power produced by the PV installation ($P_{h,t}^{PV,used}$), or the power stored in the ESS ($P_{h,t}^{ESS,used}$) and the EV ($P_{h,t}^{EV,used}$).

The EV and ESS modeling includes the equations and constraints which have been presented and explained in detail in [4] and [17]. These constraints are represented by the general expression (3) in which $\bar{\boldsymbol{x}}_h$ is the vector of the decision variables pertaining the constraints of each household h, while S_h is the set of feasible solutions.

$$h \in H: \bar{\boldsymbol{x}}_h \in S_h \ \forall t \tag{3}$$

The optimization of the smart household is performed through Algorithm 1.

The EMS of each smart household solves its own appliance scheduling problem in a decentralized fashion. Then, the transformer monitoring unit receives the information regarding the request of power by the neighborhood and calculates the equivalent aging.

B. Transformer Aging Effect Modeling

1) Loss of Life Calculations: A proper preservation of mineral-oil-tilled distribution transformers is of a key importance in power systems, and therefore, there is the need to adopt a caring approach concerning transformer loading, in order to benefit as much as possible from their availability and life service.

The insulation of a power transformer is essentially made of paper and oil which suffers from aging. Unexpected rise of the load results in a rise in the hot-spot temperature and subsequently affects the thermal decomposition of [18]–[20].

Since the temperature distribution is not uniform, the hottest section of the transformer will consequently be the most damaged. Thus, the hot-spot temperature directly affects the life duration of transformers [21], [22].

The rate at which the aging of paper insulation for a hot-spot temperature is increased or decreased compared to the aging rate at a reference hotspot temperature [18] is the relative aging rate V, which is the rate at 110 °C according to [19].

The relative aging rate for the thermally upgraded paper, that is chemically modified to improve the stability of the cellulose structure, is above one for hot-spot temperatures greater than 110 °C and means that the insulation ages many times faster compared to the aging rate at a reference hotspot temperature, while it is lower than one for hot-spot temperatures less than 110 °C [16]. For thermally upgraded paper the relative aging rate V is given by (4) [19].

$$V = e^{\left(\frac{15000}{110+273} - \frac{15000}{\theta_h+273}\right)} \tag{4}$$

Over a certain period of time, the loss of life L is calculated using (5).

$$L = \int_{t_1}^{t_2} V dt \text{ or } L \approx \sum_{n=1}^{N} V_n \times t_n \tag{5}$$

2) Hot-Spot Temperature in Transient Conditions: The key idea behind the top-oil temperature rise model is that an increase in the losses is a result of an increase in the loading of the transformer and subsequently the global temperature of the transformer.

The temperature fluctuations are dependent on the overall thermal time constant of the transformer, which in turn depends on the rate of heat transfer to the environment and the thermal capacity of the transformer.

In steady state, the total transformer losses are proportional to the top-oil temperature rise. In transient conditions, the hot-spot temperature is described as a function of time, for varying load current and ambient temperature [18].

The temperature rise of the oil may be modeled as a capacitance in the RC circuit, so that the heat transfer equations are expressed as exponential functions, taking into account the charge and discharge of an equivalent RC circuit.

For an increasing step of loads, the top-oil and winding hot-spot temperatures rise to a level corresponding to a load factor of K. In this case, the top-oil temperature is defined by (6) and (7).

$$\theta_o(t) = \triangle\theta_{o,i} + \left\{\triangle\theta_{o,r} \times \left[\frac{1+R\times K^2}{1+R}\right]^x - \triangle\theta_{o,i}\right\} \times \left(1 - e^{-t/(k_{11}\times\tau_o)}\right) \tag{6}$$

TABLE I
TRANSFORMER PARAMETERS

Symbol	Value	Units
g_r	14.5	Ws/K
H	1.4	-
k_{11}	1	-
k_{21}	1	-
k_{22}	2	-
P_r	25	kW
R	8	-
x	0.8	-
y	1.6	-
$\Delta\theta_{o,r}$	20.3	ºK
τ_o	180	min
τ_w	10	min

$$\triangle\theta_h(t) = \triangle\theta_{h,i} + \left\{H \times g_r \times K^y - \triangle\theta_{h,i}\right\} \times\left[k_{21} \times \left(1 - e^{-t/(k_{22}\times\tau_w)}\right) - (k_{21}-1) \times\left(1 - e^{-(t\times k_{22})}/\tau_o\right)\right] \tag{7}$$

For a decreasing step of loads, the top-oil and winding hot-spot temperatures decrease to a level corresponding to a load factor of K [18]. In this case, the top-oil temperature is calculated by (8) and (9).

$$\theta_o(t) = \triangle\theta_{o,r} \times \left[\frac{1+R\times K^2}{1+R}\right]^x + \left\{\triangle\theta_{o,i} - \triangle\theta_{o,r} \times \left[\frac{1+R\times K^2}{1+R}\right]^x\right\} \times\left(e^{-t/(k_{11}\times\tau_o)}\right) \tag{8}$$

$$\triangle\theta_h(t) = H \times g_r \times K^y \tag{9}$$

In conclusion, with $\theta_o(t)$ and $\triangle\theta_h(t)$ obtained using (6) and (7) for increasing load steps, or (8) and (9) for decreasing load steps, the overall hot-spot temperature equation is (10).

$$\theta_h(t) = \theta_a + \theta_o(t) + \triangle\theta_h(t) \tag{10}$$

III. TESTS AND RESULTS

A. Input Data

The mathematical model of the smart households described above has been implemented in GAMS v.24.1.3. and was solved using the commercial solver CPLEX v.12. The utilized optimization interval is 4 minutes (0.066h) and as a result there are 360 periods. The transformer aging has been calculated following the procedure suggested in the IEC 60076-7 standard and the relevant code has been developed using MATLAB.

To demonstrate the proposed methodology, a sample neighborhood consisting of 4 houses that are supplied by a 25kVA single phase pole mounted transformer as a local part of the distribution system is considered the parameters of which are presented in Table I [23]. It should be noted that the distribution system can use medium or low voltage regarding the consumer type and system configuration. There are

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TABLE II
HOUSEHOLD APPLIANCES DATA

Appliance	Rated Power [kW]
Refrigerator	1.67
Iron	2.4
Toaster	0.8
Kettle	2
Hairdryer	1.8
Telephone	0.005
TV	0.083
Desktop Computer	0.15
Air Conditioner	1.14
Hair Straightener	0.055
Oven	2.4
Microwave	1.2
Printer	0.011
Cooker hood	0.225
Lighting	0.1
Other (fixed)	0.1

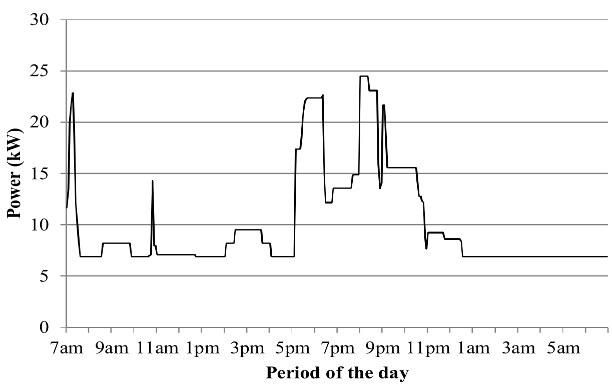

Fig. 2. Inelastic load of the neighborhood.

also international and regional differences as regards system configurations used for power distribution. The structure in Fig. 1 considers a split phase low voltage distribution system which is typical in the U.S., Japan, Canada, etc. [24], [25].

The houses are assumed to host different kinds of consumers with different load profiles. These load profiles are created considering several typical domestic appliances the nominal power of which is presented in Table II [26].

The total inelastic load profile of the neighborhood is portrayed in Fig. 2. Furthermore, each household has a battery based ESS and a rooftop PV installation. Since the households are considered to be close to each other, a PV power curve normalized per 1kW of installed capacity, is used for all the houses, measured in the smart household prototype in Yildiz Technical University, during the summer of 2013, assuming random small deviations that could be possibly caused by differences in the efficiency of the PV systems, for example, due to dirty PV panel surfaces etc.

The PV production for the 4 households is presented in Fig. 3. Also, the recorded temperature for this day is portrayed in Fig. 4.

There are already different types of EVs available on the market. Eight different EVs are considered in this study and the relevant EV data are provided in Table III. Besides, three different cases are evaluated with respect to different EV type ownership for each household as presented in Table IV.

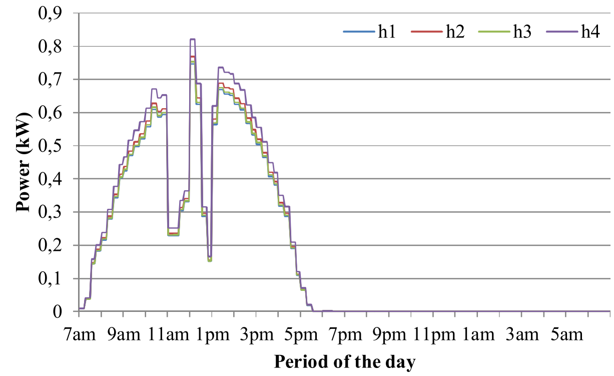

Fig. 3. PV power production of the households.

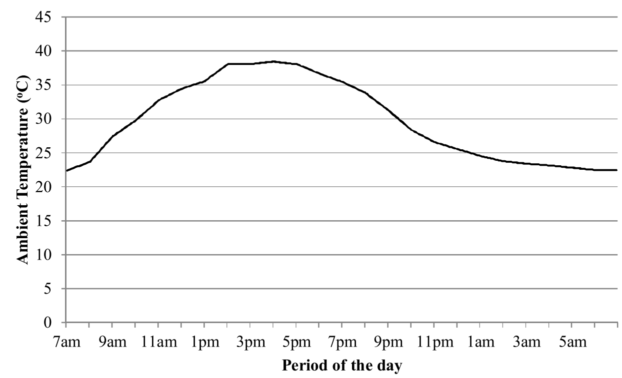

Fig. 4. Ambient Temperature.

TABLE III
EV PARAMETERS

	Battery capacity [kWh]	Charging/discharging rate [kW]
BMW i3	22	6.6
Chevy Volt	17	3.3
Ford Focus Electric	23	6.6
Mercedes B-Class	28	10
Kia Soul EV	27	6.6
Mitsubishi i-MIEV	16	3.3
Tesla Model-S	85	10
Volkswagen E-Golf	24	7.2

TABLE IV
CASE STUDIES

	Case-1	Case-2	Case-3
House 1	No EV	Chevy Volt	Mercedes B-Class
House 2	No EV	BMW i3	Kia Soul EV
House 3	No EV	Mitsubishi I-MİEV	Volkswagen E-Golf
House 4	No EV	Ford Focus Electric	Tesla Model-S

Data concerning the EV, the PV and the ESS of each household are presented in Table V. These assets may be also used to partly or fully cover household energy needs through V2H, energy storage system to home (ESS2H) and

TABLE V
ASSET DATA OF EACH HOUSEHOLD

	House 1	House 2	House 3	House 4
	Electric Vehicle			
Charging/discharging efficiency [%]	95			
Arrival time	5:08 pm			
	PV Installation			
Installed capacity [kW]	1			
	Energy Storage System			
Battery capacity [kWh]	3	3	2.4	2.4
Maximum Charging/Discharging rate [kW]	0.6			
Initial SOE [%]	50	50	62.5	62.5
Minimum SOE [%]	25	25	41.6	41.6
Charging/discharging efficiency [%]	95			

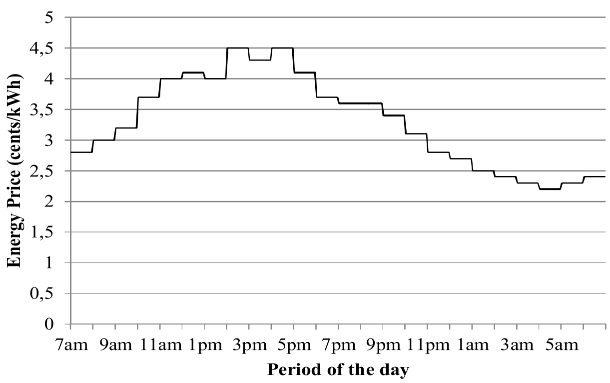

Fig. 5. Hourly energy price signal.

PV to home (PV2H) options. The retailer announces a price signal for the 24h of the optimization horizon as displayed in Fig. 5.

B. Simulation and Results

As mentioned before, in order to evaluate the impacts of incentive-based DR activities on transformer loading, three test cases considering different EV types are presented.

It is to be noted that another issue related to EVs that can be considered in the mentioned case studies, is the time and location based uncertainty of EV integration to DS, which is likely to pose a considerable challenge to the distribution system operator in the future together with the expected increase in EV penetration [27]. However, this study follows a deterministic framework in which the impacts of EV based uncertainty are not considered.

Case 1 does not consider EV availability and the relevant results are depicted in Fig. 6. As it can be observed, no overloading occurs as no extra EV charging load exists. The PV and ESS partly cover the inelastic load of each household. As a result, a reduction in the transformer loading is noticed especially from 9 am to 5 pm during which the electricity prices are relatively high. Furthermore, before 9 am, the ESSs of the

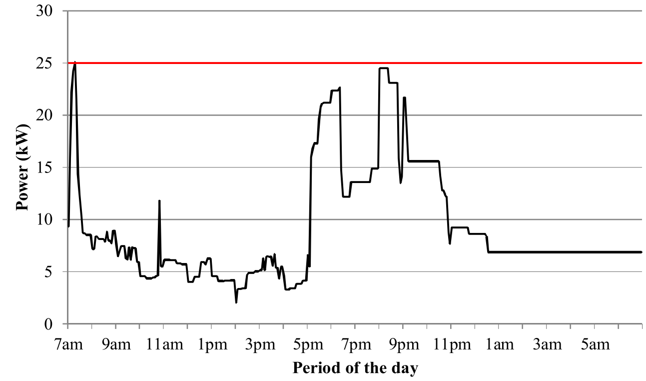

Fig. 6. Total transformer load for Case 1.

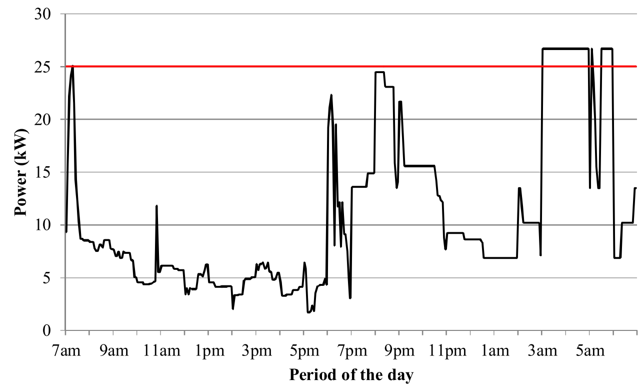

Fig. 7. Total transformer load for Case 2.

households are charging in order to be able to provide this power later, causing a peak to the transformer loading.

In Case 2 each household is considered to possess a relatively small-sized EV. The relevant results are depicted in Fig. 7. Evidently, an excessive transformer loading occurs, reaching nearly 110% for several late-night periods, especially during the lowest price hours, even if the EV capacities are relatively low in this test case. Another point to be observed is that the inelastic load is partially covered by the V2H option of EVs during the periods after the arrival time of the EVs because of the higher prices the hold during these periods in comparison with the prices in later periods.

Case 3 results in the transformer loading shown in Fig. 8. This test case is relatively worse in terms of EV capacities that have the capability of being charged with greater power levels than the EVs considered in Case 2.

However, the greater the EV capacity is, the greater the opportunity of covering a more significant portion of the household power requirements by V2H option. This results in lower total transformer loading, especially in higher price periods during which using available EV energy to partly cover the household load and charge later is more profitable than procuring power from the grid. As expected, the capability of greater charging power levels leads to transformer overloading with longer duration and significantly higher levels (exceeding 160%) in comparison with Case 2. This is likely to accelerate the transformer unit aging, a fact that should be examined further with the analysis of the transformer hot-spot temperature.

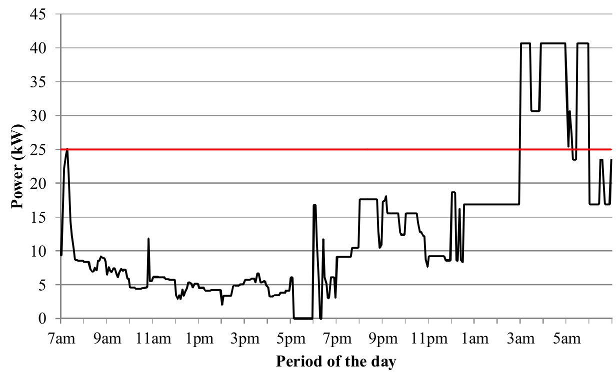

Fig. 8. Total transformer load for Case 3.

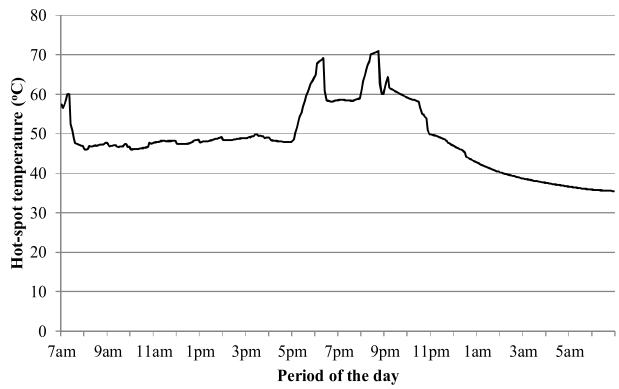

Fig. 9. Transformer hot-spot temperature for Case 1.

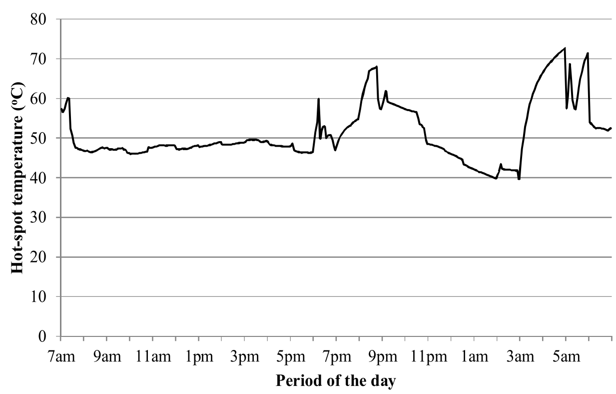

Fig. 10. Transformer hot-spot temperature for Case 2.

In this regard, the hot-spot temperature of the transformer for the three test cases is presented in Figs. 9–11, respectively. Case 1 results in acceptable levels of temperature increase in the transformer unit while Case 2 and Case 3 boost the temperature variations due to the increasing requirement of charging power levels, especially due to the choice of EMS to charge the EV batteries after midnight due to the relatively lower prices during these periods. Even if each household owner benefits from such actions of their EMS in terms of total cost, the distribution transformer faces increasing stress that is very likely to cause more rapid aging of the insulation.

Table VI presents the relevant equivalent aging for each test case. As expected, excessive power drawn from the grid through the transformer unit results in a significant increase in

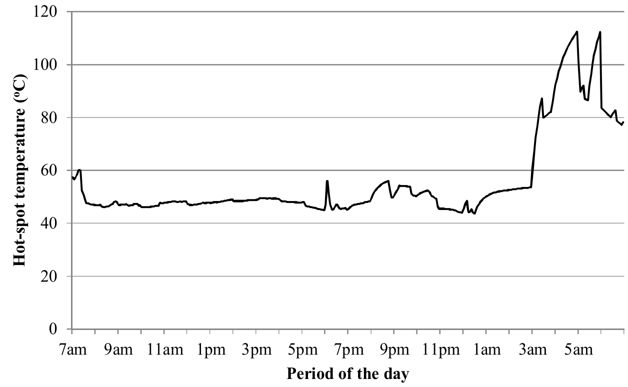

Fig. 11. Transformer hot-spot temperature for Case 3.

TABLE VI
AGING RESULTS

	Aging in equivalent hours [h]	
	With V2H option	Without V2H option
Case-1	1.68	1.68
Case-2	2.23	2.05
Case-3	67.84	16.77

transformer aging in Case 3 in comparison with Cases 1 and 2. It may be also observed that the increase in EV capacities results in an undesired decrease in transformer lifetime that is a main concern for the DS Operators, although it guarantees that EVs can cover longer travelling distances and as a result may promote the electrification of personal transport and the smart grid enabling technologies in general.

As a different analysis, the previous case studies are re-evaluated by considering that the V2H option of the EVs is not available. Normally, the availability of the V2H option allows for higher flexibility for the EMS of the end-user that may also decide to cover a part of the household load requirements from the EV, when the price of procuring power from the grid is high. However, this will in turn result in greater energy requirements to fully charge the EV battery in order to satisfy the comfort conditions of the EV owner, which means a greater peak in the total load of the transformer when the power procurement costs are lower, typically after midnight. Thus, the utilization of the V2H option is very likely to have a more adverse effect on the loading and the thermal stress of the distribution transformer.

The results regarding the total transformer load and the transformer hot-spot temperature considering that V2H option is not available are presented in Figs. 12 and 13 for Cases 2 and 3, respectively. As Case 1 does not consider EV availability, the results that were previously depicted in Figs. 6 and 9 do not change and thus are not repeated. It can be seen from the total transformer load for both cases that the observed power peaks are considerably lower and with shorter duration. This is caused by the fact that since no discharge is possible when the EV is at home, less amount of energy is required to charge the EV batteries.

The impact on reduction of power peaks also results in less increase in transformer hot-spot temperature as it can be observed in Fig. 13. Thus, a significant reduction in the aging

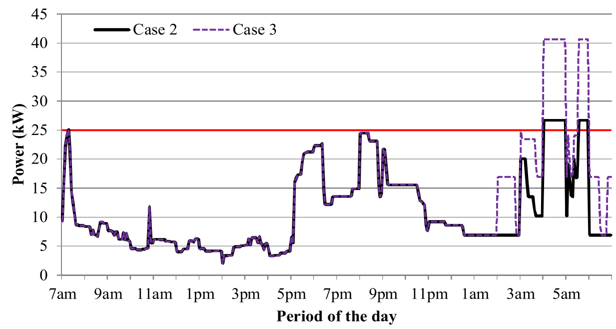

Fig. 12. Total transformer load for Cases 2 and 3 without V2H option.

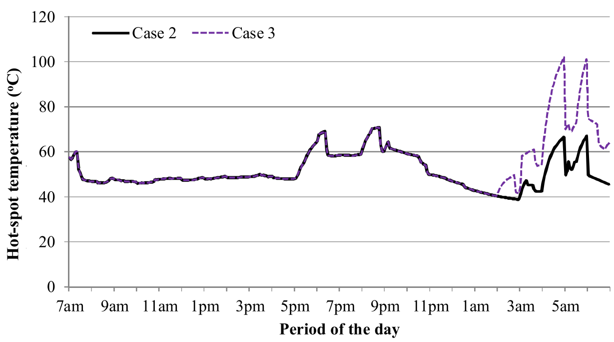

Fig. 13. Transformer hot-spot temperature for Cases 2 and 3 without V2H option.

TABLE VII
ENERGY PROCUREMENT COST OF DIFFERENT HOUSEHOLDS

	With V2H option				Without V2H option			
	H1	**H2**	**H3**	**H4**	**H1**	**H2**	**H3**	**H4**
Case 1	1.83	1.83	1.83	1.80	1.83	1.83	1.83	1.80
Case 2	1.98	2.01	1.97	1.99	2.03	2.09	2.02	2.07
Case 3	2.06	2.06	2.03	2.65	2.16	2.15	2.11	2.83

of the transformer is observed as it can be seen in Table VI for both the Cases 2 and 3 when the V2H option is not available. In fact, no aging acceleration is noticed and therefore, the observed overloading may be considered acceptable.

Furthermore, the total energy procurement cost considering the availability of the V2H option is compared with the corresponding costs for the case in which the V2H option is not available and the relevant results are presented in Table VII. End-users benefit from the V2H option due to the possibility of utilizing the energy stored in the EV to cover portion of the household load during higher price periods.

This comparison indicates that even if the home owners can benefit from the V2H option and increased levels of smart grid enabling technologies, the DS may encounter detrimental results in terms of facing extra stress and aging of assets, etc., which clearly depicts that the deployment of such new technologies in power system should be carefully planned in order to balance the benefits for both end-users and energy suppliers.

C. On the Efficiency of the Pricing Mechanism

In the pricing mechanism adopted in this study, it is considered that the price of electricity is different during each hour of the day and is known to the consumer before the actual day in which the consumption takes place. Through dynamic pricing consumers are directly exposed to the variability of the cost in the wholesale day-ahead energy market. Currently, two noticeable dynamic pricing programs engaging residential end-users exist in the U.S., one by Pennsylvania New Jersey Maryland Interconnection (PJM) [28] and one by the Midcontinent ISO (MISO) [29]. In both programs the day-ahead market prices are known to the consumer one day before the actual power delivery; however, the way in which they actually price the consumers differs. In the program offered by PJM, the end-users are priced according to the real-time prices that are settled in the end of each hour in the actual dispatch day and are calculated by averaging the 5-minute prices of that hour, while in the program offered by MISO consumers are priced according to the day-ahead prices. In this paper, the pricing mechanism that is used is similar to the relevant MISO program.

Although dynamic pricing (e.g., real-time pricing) is generally considered to reflect the very short term cost of electricity, the efficiency of this pricing mechanism is often questioned mainly due to two reasons [30]: 1) residential end-users (that are the primary target group of such programs) do not necessarily follow a rational economical model as regards that consumption of electricity, i.e., a consumer may still be willing to consume electricity at peak hours, and 2) the asymmetry between the communication of the prices and the response of the end-user.

Evidently, the very short term costs of electricity are better captured by programs that price the end-user based on the prices produced by real-time markets that are cleared on a very short term basis (e.g., several minutes) rather than by those that price the end user according to the day-ahead market prices; This is the reason why the energy prices in this study, that follow the latter mechanism, do not reflect the power consumption peaks in the early morning hours due to the EV charging; however, the first type of dynamic pricing programs present the disadvantage of exposing consumers to uncertainty, since the electricity price is settled after the consumption interval. As a result, this type of programs may compromise the incentives provided to the consumers in order to motivate them to enroll, since the rationale behind dynamic pricing is that consumers would exercise price arbitrage, which in turn depends on the differences of the prices within the day, which in this case would not be known a priori. In such cases, uncertainty management techniques would be necessary in order to predict the electricity prices, which may not be justifiable for residential consumers, in terms of complexity and computational burden, because the welfare gain of their participation in dynamic pricing schemes is little.

In order to confront the deficiencies of the pricing mechanism the following are suggested:

1) Development of advanced models that predict the response of the end-users based on exogenous factors such as the weather and the time delay between the communication of the energy prices and the actual response [30].

TABLE VIII
COMPUTATIONAL STATISTICS

Equations	4281
Variables	4017
Discrete variables	568

2) Development of residential consumption coordination strategies that consider distribution system constraints [17], [31] or the interaction of the transformer management unit and the EMS [32] together with dynamic pricing mechanisms.

D. Computational Statistics

The computational statistics of each optimization subproblem are provided in Table VIII. The total solution time, considering an optimality gap of 0%, is 1 sec on a modern laptop computer (i7 at 2.4GHz, 4GB RAM, 64bit Windows).

Note that the separable form of Algorithm 1 allows for distributed computing techniques to be applied and as a result the privacy of the end-users is preserved.

As the computational capabilities of embedded systems that are needed to implement EMS and monitoring systems increase, it appears that such complex algorithms will be practically applicable even for large scale systems.

IV. CONCLUSION

In this study, an analysis of the impacts of price-incentive based DR on a neighborhood distribution transformer aging has been performed. A MILP model of a neighborhood composed of smart households with different end-user profiles was developed. The availability of a distributed generation unit, an ESS, and an EV considering also PV2H, ESS2H and V2H capabilities has been modeled. Furthermore, a thermal model of the transformer unit serving this neighborhood for transformer aging evaluation has been provided based on existing standards. The main contribution of the study was to combine the impacts of price-responsive residential end-users based DR schemes and relevant impacts on transformer aging for different case studies based on different capacities of EVs. The availability of V2H option has also been discussed in the comparative analysis. The obtained results for different case studies demonstrated the significant adverse effects of extra EV loads combined with price-based DR activities, which strive to shift as much load as possible to low-price hours. The aging of the transformer has shown a tremendous increase with the increase in the capacity of the EV. Besides, the negative impacts of V2H option on the transformer unit extra loading and the relevant increase in aging have also been comparatively demonstrated. Yet, V2H option availability provided more flexibility for EMS of each household to lower total prices by covering some portion of the household load from EVs. It can be concluded that while greater EV capacities and the availability of V2H option allowed residential end-user EMS to benefit more from price-incentive based DR schemes, these options may adversely affect DS reliability by stressing more DS assets. Thus, DR schemes can also be examined from such a perspective, that is, from DS Operator point of view. As a future study, the authors aim to provide a two-side optimization approach to investigate the appropriate balance between end-user benefits and DS operational considerations. Besides, the implementation of the proposed structure to study a greater part of the distribution system composed of multiple neighborhoods and also considering the aging effect of loading on other distribution system assets will be the topic of a future study.

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