Impact of Smart Electric Thermal Storage on Distribution Grid

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***Abstract*—The paper presents a preliminary assessment on impact of smart electric storage heating on distribution grid in comparison to conventional electric heating if heating electrification is partly introduced. Real-world data of electric load, heating demand, electricity prices and ambient temperature was used for simulations to conclude that while a small penetration of smart storage heating can facilitate efficient usage of the existing distribution grid, larger penetrations can require grid reinforcements due to a significantly increased electric load. These effects could be partly mitigated using smart charging algorithms for storage heaters. From the economic point of view, smart storage heating provides cheaper energy for end-users and lower cost of distribution losses for the system operator.**

Keywords—distribution grid; electric heating; smart control; thermal storage.

I. Introduction

The growing usage of renewable energy sources for power generation requires additional energy storage capacities. One of technologies that can be used for energy storage and heating electrification is smart electric thermal storage (SETS) which combines storage with demand response. SETS (smart heating) is a local small-scale sensible heat storage system [1] which consumes electricity, converts it to heat and stores thermal energy.

In comparison to other storage technologies, heat storage has much lower costs [2]. Besides, EU strategies suggest that electrification of heating sector could increase energy efficiency and facilitate decarbonisation [3], [4]. At the same time, switching to electricity changes the demand profile and requires smart solutions for optimal grid utilisation so as to avoid grid reinforcement costs [4].

SETS devices are equipped with smart control at the aggregate electric power system level while ensuring that end-user comfort requirements are maintained [5]. It allows to decouple the electricity demand from the expected heat output. Consequently, the whole electricity supply chain can potentially benefit from SETS by using a number of services the aggregated load can offer such as demand shifting and demand response, congestion management and deferral of capital investments into the network [2], [6]–[8]. At the same time, as a result of electrification of the heating sector, total electric consumption will increase. However, since SETS devices are controllable at the power system level, the demand profile could potentially be adjusted so as to not interfere with the existing grid structure.

A major challenge for flexible demand response is the lack of understanding of its potential benefits due to a lack of methodologies for the quantification of costs and benefits [7]. This paper aims to assess how heating electrification with SETS might impact the distribution network by comparing it to electric resistance heating without storage (conventional electric heating). It is based on a case study of Latvia where currently electric heating is not widespread.

The assessment was done through simulations of electric load based on a large database of end-user loads from which a number of end-users were randomly chosen. Several heating control strategies were examined and a simplified radial distribution network topology was modelled which allows to draw general conclusions on the potential impact of SETS. When designing an actual network, the same modelling approach can be applied considering the specific topology and parameters of the grid and end-user characteristics.

The potential impact of smart heating versus conventional electric heating was quantified using several indicators, such as maximum power and current, load factor, voltage deviation, cost of distribution losses and cost of electricity for heating. The results allow to evaluate the benefits and potential issues that might arise as a result of heating electrification with or without heat storage.

II. Methodology

Nomenclature

d, D; j, J	index and set of days and hours
i, I	index and set of end-user types
$c^{d,j}$	electricity market price on day d, hour j (€/MWh)
f	fraction of end-users with electric heating
h	time step, equal to one hour
l	length of distribution line (m)
n_i	number of end-users of type i
E	total storage capacity of SETS (MWh)
$P_{\text{heat}}^{d,j}$	electric heating demand (MW/m^2)
P_{input}	maximum input power for charging of SETS (MW)
$P_{\text{total heat}}^{d,j}$	total active power of heating on day d, hour j (MW)

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$P^{d,j}_{\text{total base}}$	total active power of the base load on day d, hour j (MW)
$Q^{d,j}_{\text{total base}}$	total reactive power of the base load on day d, hour j (Mvar)
S_i	average heated space of end-users of type i (m^2)
$T^{d,j}$	ambient temperature on day d, hour j

In our model, the existing base load is supplemented with electric heating (Fig. 1) thus simulating heating electrification. Since SETS allows storing thermal energy for later use, it is obvious that, on the one hand, end-users would be willing to store heat during periods of cheapest electrical energy. Accordingly, charging of SETS would depend on real-time market prices.

On the other hand, charging of a large amount of SETS simultaneously can potentially overload the distribution grid. To prevent that, flexibility of SETS can be employed to decrease the peak load and distribution losses. Accordingly, the charging schedule of SETS can be formed dependent on the total network loading. To implement the aforementioned objectives, charging of SETS needs to be optimised based on the forecasts of ambient temperature, electricity market price and network loading. These operations are to be carried out by an aggregator equipped with hardware and software for communication and feeding-in data from the system operator, power exchange, weather service and end-users of SETS. Based on the forecasts, the aggregator optimises charging of SETS and sends respective control signals to each device.

When describing the respective optimisation problem mathematically, it obviously involves several random time-dependent parameters such as the total base load without heating and the additional heating load, electricity price and ambient temperature. Moreover, all of these parameters are somewhat correlated with each other. This leads us to a stochastic optimisation problem which is expressed as minimisation of the expected costs of heating energy (C_{heat}), total electrical energy ($C_{\text{total en.}}$) or expected network losses (C_{loss}):

$$\begin{aligned} &\mathrm{E}\left[C_{\text{heat}}\right] = \varphi\left(P_{\text{total heat}}, P_{\text{total base}}, T, c, X\right) \rightarrow \min, \\ &\mathrm{E}\left[C_{\text{total en.}}\right] = \varphi\left(P_{\text{total heat}}, P_{\text{total base}}, T, c, X\right) \rightarrow \min, \\ &\mathrm{E}\left[C_{\text{loss}}\right] = \varphi\left(P_{\text{total heat}}, P_{\text{total base}}, T, c, X\right) \rightarrow \min, \end{aligned} \tag{1}$$

where X is the set of grid and end-user parameters (lines and transformers, end-user type and heated space etc.).

An aggregator optimises the daily operation of a large number of SETS and the number of end-users can reach several hundreds or even thousands. Correspondingly the number of optimisation variables would typically reach several thousand considering that each end-user can have several controllable appliances installed and that optimisation is done with a planning horizon of at least one or several days. This increases the computational burden of the aggregator.

In addition to that, to estimate the expected value of functions involving stochastic processes (1), one needs to know the respective probability distributions [9]. Meanwhile, there is a large variety of end-users in a single network with different base loads and distinct heat energy demand patterns that needs to be considered. To decrease the computational effort, this paper presents an approach that allows to simplify the optimisation of SETS charging to estimate its potential impact on the distribution grid.

Real-world historical data of electric base load was used which characterises common types of end-users in Latvia. This data has been previously collected from smart meter measurements of end-user consumption. A random number of each type of end-users was selected and assigned to each of the nine feeders (Fig. 3) to form the total electric base load. Load data covers a whole year, and an hourly time step was used for this study. The total load of end-users was obtained by combining the historic base load time series with estimated heating load for each end-user type dependent on their heated space.

The heat demand of buildings was averaged for the whole ensemble of end-users based on their heated space. This was done to avoid the necessity to model different types of buildings. To model the required heating energy, relationship between the ambient temperature and heating demand was derived based on the historic data of district heating consumption and the respective heated space in Riga, Latvia at the right bank of River Daugava during the months of January–April and November–December, 2015. The daily average consumption was then related to the ambient temperature to establish a linear expression with a coefficient of determination 0.93 (Fig. 2). Additionally, the maximum and minimum heating load was constrained:

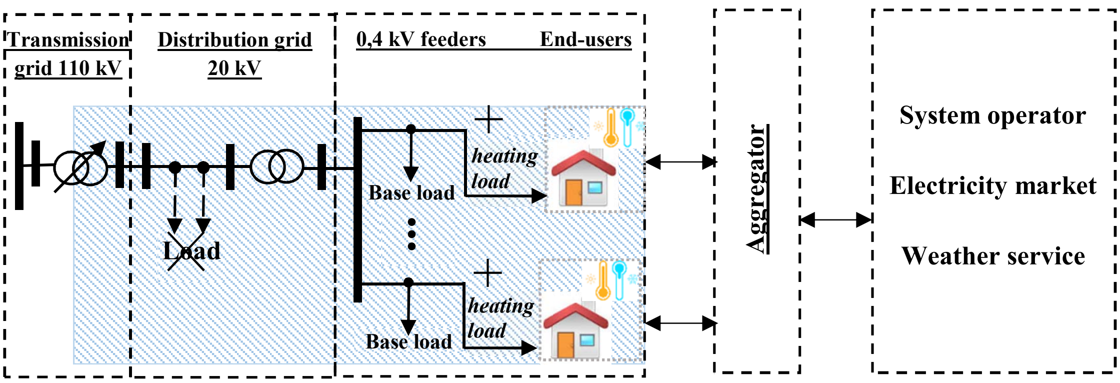

Fig. 1. The object of study (highlighted)

$$P_{\text{heat}}^{d,j} = \begin{cases} \left(-1.6857 \cdot T^{d,j} + 26.244\right) \cdot 10^{-6} \\ \qquad\qquad \text{for } -29.8°\text{C} \le T^{d,j} \le 15.5°\text{C} \\ 76.5 \cdot 10^{-6}\ \text{MW/m}^2 \qquad \text{for } T^{d,j} < -29.8°\text{C} \\ 0\ \text{MW/m}^2 \qquad\qquad \text{for } T^{d,j} > 15.5°\text{C} \end{cases} \tag{2}$$

Though this relationship implies some simplifications and approximations, it is sufficient to estimate the overall impact of heating electrification.

Assumptions on the average space of premises for each type of end-users were made and for load simulations it was assumed that a particular share (5, 10 or 20%) of the total heat demand is supplied by electric heating in the form of conventional electric heaters without storage or smart electric thermal storage (SETS).

The actual hourly power consumed by conventional heaters was calculated based on the derived relationship (Fig. 2) multiplying it by the total space of end-users with electric heating:

$$P_{\text{total heat}}^{d,j} = P_{\text{heat}}^{d,j} \cdot f \cdot \sum_{i=1}^{I} n_i S_i. \tag{3}$$

To limit the computational burden of optimisation, three main control strategies of SETS were examined. SETS were assumed to provide the same total amount of heating energy over the day (24 hours) as conventional heaters, but given the storage possibilities and smart control of SETS, three different ways of charging were assumed, thus achieving different electricity consumption profiles: (A) charging at maximum input power during the hours when the base load of the particular feeder is lowest; (B) charging at maximum input power during the hours with the lowest electricity market prices; (C) charging of SETS distributed equally over seven hours with the lowest electricity market prices (usually during the night):

$$\begin{cases} (\text{A}): \ \sum_{j=1}^{J} P_{\text{total heat}}^{d,j} + P_{\text{total base}}^{d,j} \to \min, \quad P_{\text{total heat}}^{d,j} = \left\{0, P_{\text{input}}\right\}; \\ (\text{B}): \ \sum_{j=1}^{J} P_{\text{total heat}}^{d,j} \cdot c^{d,j} \to \min, \quad P_{\text{total heat}}^{d,j} = \left\{0, P_{\text{input}}\right\}; \\ (\text{C}): \ P_{\text{total heat}}^{d,j} = \sum_{j=1}^{J} P_{\text{heat}}^{d,j} / 7; \\ (\text{A})-(\text{C}): \ \sum_{j=1}^{J} P_{\text{heat}}^{d,j} \cdot h \cdot f \cdot \sum_{i=1}^{I} n_i S_i = \sum_{j=1}^{J} P_{\text{total heat}}^{d,j} \cdot h \le E. \end{cases} \tag{4}$$

In our case study, SETS devices were selected so that 7 hours would be mostly enough to accumulate the necessary amount of energy even during the coldest days of the year. Additionally, SETS are equipped with a boost element that can provide additional heating if not enough heat has been stored. In our case study, boost was used on some of the coldest days. The average installed storage capacity of SETS was assumed 150 W/m^2, which was then upscaled based on the heated space of each end-user type to obtain the total storage capacity.

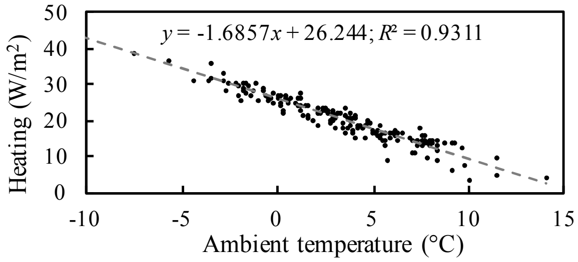

Fig. 2. Required heating as a function of ambient temperature

To compare the cost of distribution losses between the two types of heating and different charging modes of SETS, the cost of line losses was calculated by subtracting base load losses from the total losses with heating included, thus obtaining the estimated cost of losses due to the additional load of heating:

$$C = \sum_{d=1}^{D} \sum_{j=1}^{J} \left(R_0^{d,j} + X_0\right) \cdot l \cdot \left(c^{d,j} + c_{\text{TSO}}\right) \cdot h \cdot \\ \cdot \left({P_{\text{total load}}^{d,j}}^2 + {Q_{\text{total load}}^{d,j}}^2 - \left({P_{\text{total base}}^{d,j}}^2 + {Q_{\text{total base}}^{d,j}}^2\right)\right) \Big/ U_{\text{nom}}^2 \tag{5}$$

The losses are calculated based on the actual resistance dependent on the ambient temperature $R_0^{d,j}$ (Ω/km), inductive reactance X_0 (Ω/km) and length of the line l (km), and evaluated using the hourly electricity market price, $c^{d,j}$, and a constant transmission system tariff, c_{TSO} (€/MWh). Similarly, transformer losses are calculated and compared. Other indicators such as maximum current and voltage deviation were calculated based on a classic *RL* line model.

Simulations of electric load were run with an hourly time step for the four types of heating scheduling. Main results are presented in the next section.

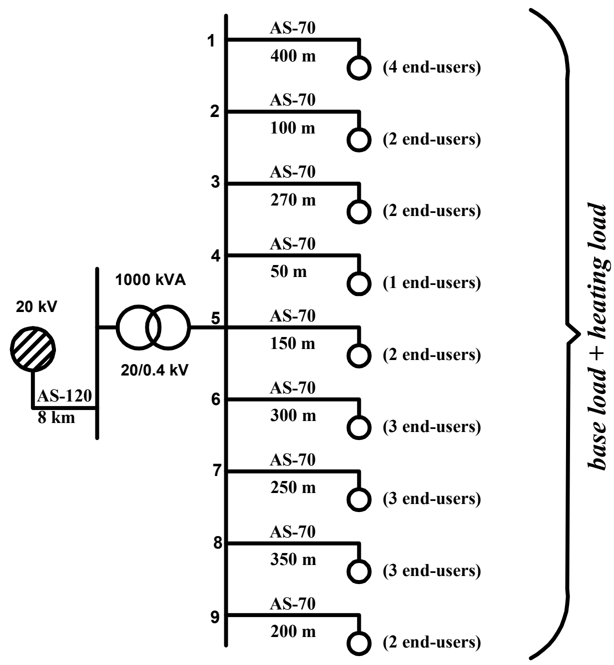

Fig. 3. Topology of the distribution grid under study

III. RESULTS AND DISCUSSION

For the assessment of impact of SETS on the distribution grid versus the impact of conventional electric resistance heating, a simplified radial distribution grid was considered with a 20 kV distribution line (120 mm^2 cross-section), distribution transformer (20/0.4 kV) and nine radial 0.4 kV feeders (70 mm^2 cross-section) (Fig. 3) with randomly chosen, but typical lengths of 0.4 kV lines varying from 0.05 to 0.4 km. Assuming that a transformer with automatic on-load tap changer is used to step down from 110 kV to 20 kV, the voltage of the distribution line was assumed to be constant 22 kV. For the 0.4 kV feeders, it was assumed that a constant voltage of 400 V is maintained at the beginning of each feeder

The load was simulated for a whole year by assuming three different shares of electric heating: 5, 10 and 20%. Load profiles for all the three shares of heating are presented in Fig. 4–6 for some of the coldest winter days (January 9–11, 2016) and in Fig. 7–9 during warmer spring weather (April 1–3). In Fig. 4 we can notice that the largest peaks come from load with smart heating C and B followed closely by conventional heating. During the day (generally from 7 until 22) the load with smart heating is equal to the base load, since SETS are charged mostly during the night when the lowest prices or smallest base load occurs.

In contrast, on April 1–3 the total load is less and the largest peaks arise from smart heating B which is charged based on price signals. With smart heating A and C there are generally less peaks than with conventional heating for 5% share of electric heating, whereas for larger shares of heating the load with all types of SETS exhibits higher peaks than that with conventional heating. This is particularly pronounced with smart heating B. At the same time, this type of charging provides cheaper cost of electrical energy for the end-user. This is evaluated in more details later.

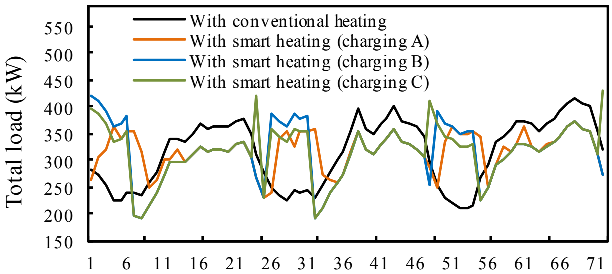

Fig. 4. Total electric load on January 9–11, 2016 (**all feeders**) with **5%** share of electric heating

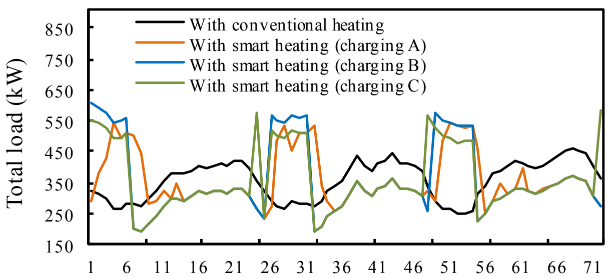

Fig. 5. Total electric load on January 9–11, 2016 (**all feeders**) with **10%** share of electric heating

Alternatively, SETS could be controlled with more elaborate algorithms so as to respond not only to price signals but also to other signals from the power system to trade-off between the interests of end-users and those of the distribution operator. Otherwise network reinforcements might be required to accommodate large shares of electric heating.

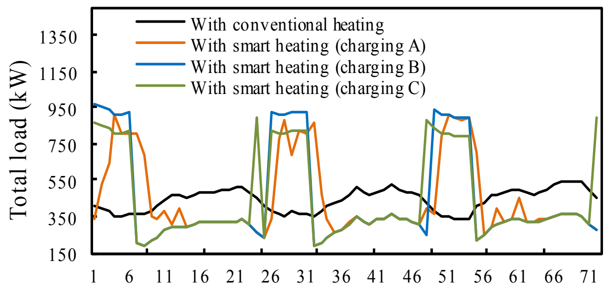

Fig. 6. Total electric load on January 9–11, 2016 (**all feeders**) with **20%** share of electric heating

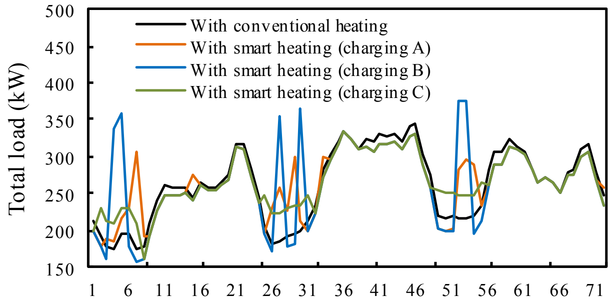

Fig. 7. Total electric load on April 1-3, 2016 (**all feeders**) with **5%** share of electric heating

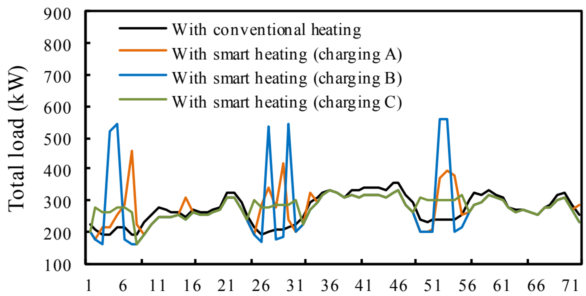

Fig. 8. Total electric load on April 1-3, 2016 (**all feeders**) with **10%** share of electric heating

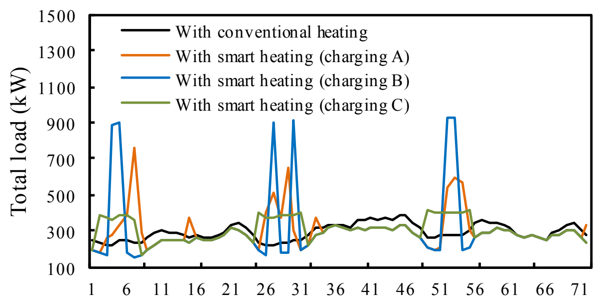

Fig. 9. Total electric load on April 1-3, 2016 (**all feeders**) with **20%** share of electric heating

TABLE I. PARAMETERS OF THE BASE LOAD AND TOTAL LOAD WITH DIFFERENT SHARES OF ELECTRIC HEATING

Parameter / share of electric heating		Load type				
		Base load (no el. heat.)	*Load with conv. heating*	*Load with smart heating (three types of charging)*		
				A	*B*	*C*
Maximum load (kW)	5%	548.57	569.50	548.57	664.52	562.58
	10%		596.08	737.78	871.16	714.62
	20%		662.28	1160.78	1307.32	1138.07
Load factor	5%	0.50	0.5108	0.5322	0.4394	0.5188
	10%		0.5182	0.4224	0.3579	0.4354
	20%		0.5213	0.3041	0.2703	0.3084

Table I summarises the maximum load and load factor at the beginning of the 20 kV line for different shares of electric heating and three SETS charging modes. Distribution line and transformer losses are also included. Among all the cases, the largest peaks and worst (smallest) load factor occurs with SETS B when charging takes place during the lowest price periods. SETS A and C both have fairly similar peaks which are even little less than those of conventional heating for 5% share of electric heating. Meanwhile, with larger shares of electric heating the maximum load of SETS A and C, and more so SETS B, becomes much greater than that of conventional heating. This clearly shows that to accommodate a significant amount of electric storage heating more sophisticated algorithms for SETS charging should be developed for more efficient utilisation of the existing grid and less peaks.

To evaluate how the additional load from electric heating impacts network congestions, we estimated the hourly voltage deviation for each 0.4 kV feeder (overhead distribution line with steel-cored aluminium conductors). Fig. 10-12 shows the maximum voltage drop observed over the year for 5, 10 and 20% share of electric heating. It should be noted that in Latvia the allowable voltage deviation is +10%/–15%. Thus, both with 5% and 10% share of electric heating the voltage drop is within the permissible range since it does not exceed 15%. The largest voltage drop is observed on feeder No. 1 and 8, which can be attributed to the longest lines compared to other feeders (0.4 and 0.35 km). However, with the 20% share of electric heating the voltage drop does exceed the 15% limit during a few hours. As detailed in Fig. 13 for the worst case (feeder 1, SETS B with 20% share of el. heat.), the voltage drop is above 10% for many hours when SETS are being charged. The results demonstrate that the voltage deviation should also be accounted for when developing control strategies of storage heaters so that the power quality is maintained.

Additionally, the cost of electricity used for heating was calculated (Table II). To compare different types and shares of electric heating, it shows the heating cost for end-users based on their hourly consumption of electricity and the respective hourly market price. Obviously, the least cost is achieved with SETS B for all shares of heating since the heaters were charged during the lowest price periods. It is followed by SETS C, SETS A and conventional heating the cost of which is larger by 4%, 7.2% and 39.5% respectively in relation to SETS B. Comparing the cost of conventional resistance heating with that of SETS, the latter provides savings for the end-user, namely 23.2–25.5%.

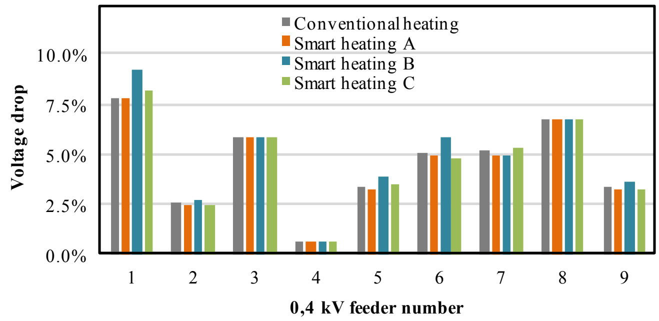

Fig. 10. Maximum voltage deviation at the end of each feeder (**5%** share of electric heating)

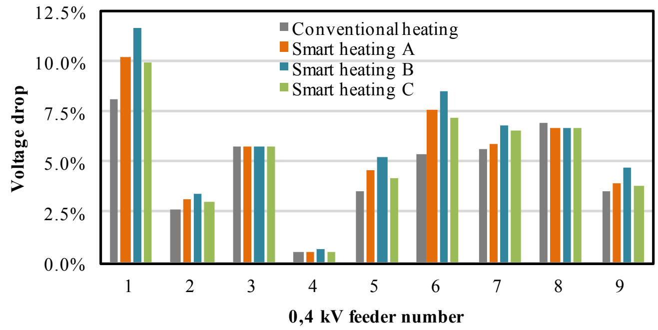

Fig. 11. Maximum voltage deviation at the end of each feeder (**10%** share of electric heating)

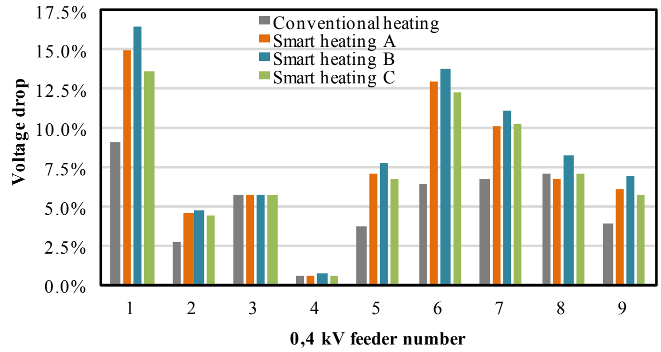

Fig. 12. Maximum voltage deviation at the end of each feeder (**20%** share of electric heating)

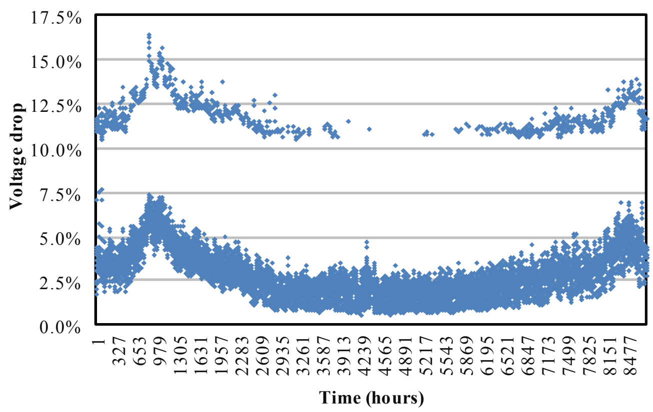

Fig. 13. Hourly voltage deviation at the end of 0.4 kV feeder No. **1**, **SETS B** (**20%** share of electric heating)

TABLE II. COSTS OF HEATING AND LOSSES THEREOF WITH A 5% SHARE OF ELECTRIC HEATING

Parameter / share of electric heating		Yearly cost of heating (EUR)			
		Conv. heating	*Smart heating (three types of charging)*		
			A	***B***	***C***
Heating cost for end-users	5%	5556.66	4267.78	**3982.24**	4139.79
	10%	11 113.32	8535.56	**7964.48**	8279.58
	20%	22 226.65	17 071.12	**15 928.96**	16 559.17
Cost of distribution losses*	5%	324.97	246.39	246.09	**220.92**
	10%	692.62	675.33	675.67	**550.52**
	20%	1556.52	2088.60	2096.88	**1540.13**

* Includes losses in nine 0.4 kV feeders of different length (0.05–0.40 km, 70 mm^2 cross-section), 20/0.4 kV transformer and 20 kV line (8,0 km, 120 mm^2 cross-section)

Differing trends are observed when comparing the cost of distribution losses as a result of heating electrification (Table II). This cost was calculated by subtracting base load losses without heating from the losses of load with heating included (5). Again, the hourly electricity market price was used, plus a constant rate of transmission services payed by the distribution operator to the transmission operator for each kWh of energy transmitted. Now, the least cost is observed with SETS C for all cases. This is explained by the fact that the charging of heaters was distributed equally over seven hours with the lowest prices and thus the hourly charging power was less than for SETS B which were charged with maximum input power (and consequently required less hours of charge). As a result, the cost of losses for SETS B is 11.4%, 22.7% and 36.2% larger than for SETS C for all the three shares of heating (5, 10, 20%). The cost of losses for SETS A is almost similar to SETS B, whereas the largest amount of costs incurs with conventional heating (47.1% and 25.8% larger than for SETS C with 5 and 10% share of heating). However, for the 20% share of heating largest costs of losses occur with SETS A and B while the cost is almost equal for the conventional heating and SETS C.

While smart heating with charging strategy B is the least beneficial in terms of network loading, it provides the least cost of heating for end-users, thus setting against the interests of grid operator and the end-user. To incentivise end-users to use smart heating not only with the lowest electricity prices but also during times when it facilitates more efficient usage of the grid, this type of demand response should be rewarded by the grid operator.

Overall results show that SETS can provide benefits both for the end-user and grid operator in certain conditions depending on the penetration level of electric heating if this type of heating has not been used before and thus adds to the existing electric load. However, larger penetration of electric heating can require grid reinforcements and elaborate algorithms for control of charging.

IV. CONCLUSIONS

Electrification of heating sector needs to be considered carefully and evaluated both from technical and economical point of view. If electric heating has not been widespread before, it can add a large amount of electric load subject to the share of electric heating. The case study showed that while 5% penetration of smart storage heating (SETS) did not result in a significantly larger peak load than the existing load without electric heating, larger shares (10% and 20%) of SETS can significantly increase the maximum load and the existing distribution grid might not be able to accommodate it. In contrast, larger share of electric resistive heating results in lower peak loads than storage heating, but its energy costs are much higher for the end-user.

In order to balance the interests of the distribution system operator and the end-user, it is important to provide incentives for the end-user to use SETS for demand response, thus achieving both efficient usage of the grid and providing economic benefits for the end-user.

Future work will involve more elaborate charging control algorithms for smart storage heating and more accurate heat demand estimation for different types of buildings with varying occupancy patterns.

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