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A Study on Realistic Energy Storage Systems for the Privacy of Smart Meter Readings of Residential Users

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ABSTRACT The introduction of smart meters sparked concerns about privacy breach through real-time monitoring of electric power consumption. Valuable private information about occupancy, behaviour, health, religion and wealth can be extracted from the user's power profile which urges measurements to protect the integrity of the user. One physical mitigation technique to assure privacy is explored using energy storage systems. Real energy storage technologies are limited in their energy capacities and power capabilities, which have to be appropriately sized to fulfil their role. This paper analyses and compares different energy storage technologies (li-ion, lead-acid, electric double layer capacitor and flywheel) for the protection of residential users by estimating the minimal required capacities and costs for both single and multiple user cases. The analysis is based on actual measured user data from the *REDD* data set. The results show that the integrity can be protected with reasonable capacities and investments ranging in the margin of market available products.

INDEX TERMS Energy storage system, privacy, smart meters, residential user.

I. INTRODUCTION

Smart meters (SMs) are the next generation of electricity meters enabling near real-time monitoring of electric consumption and generation at the customers' premises. They have been introduced with the purpose of improving the electric network reliability and efficiency, and allowing greater control and feedback over the user's own consumption. The integration of such Information and Communication Technologies (ICTs) has opened up new possibilities and services such as accurate consumer billing through dynamic pricing or valuable real-time information for grid operators [1]. However, the interconnectivity and accessibility of such devices gave rise to concerns regarding cybersecurity and privacy.

Especially, the real-time monitoring of the user's electric energy consumption via SM reveals private information such as occupancy, behaviour and wealth. The potential privacy breach has sparked public interest on various media: especially, the potential abuse of such information. The leaked information can go so far to expose the use of individual home appliances [2], [3] and even the TV program being watched if a sufficient data sampling rate is available ($\geq$0.5 Hz) [4]. In short, the power consumption of the TV varies with changing brightness. A person with prior knowledge of the power consumption patterns of certain TV programs or movies can deduce the content being viewed on the TV based on the non-intrusive load monitoring method (NILM) as applied in [4]. Identifying information about health and religious affiliation is also not too far-fetched if, for example, patients are using medical equipments (e.g., heart monitoring) or religious festivities take place (e.g., fasting period with less cooking practices). Similarly to the TV all that is required is an adequate estimate of the power consumption profiles of the individual appliances: in this case the cardiac monitor or the cooking appliances such as a stove, a kettle, and a microwave etc.

This issue creates a conflict of interest between the consumer and the grid utility over the disclosed data. Several solutions and methods have been investigated in achieving a compromise between both factions by guaranteeing safety (encryption) and use of only necessary information (legislations) [1]. However, the aim of this paper does not focus on either option, but instead explores the idea of manipulating the electric consumption profile measured by the SM through

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energy storage systems (ESSs). In fact, the ESS is utilized to alter the power profile in such a way that the least amount of information about the user can be deduced: i.e. a constant power profile. In [3] and [5] the idea was studied to use ESS to mask the user's profile or, more specifically, what mitigation impact an ESS can potentially have on privacy. Please note, that in this study it is assumed that the ESS is isolated, i.e., disconnected from the internet and free from other surveillance. The latter focuses on identifying the minimum required storage capacity and power capabilities of an ESS needed to fulfil the task. However, a real ESS is bound by constraints limiting its output or capacity. For example, battery energy storage systems (BESSs) feature limited power output due to their restrictions of discharging current. Similar restrictions apply to other energy storage technologies as well such as flywheels, where a maximum rotational speed marks the upper limit of safe operation. Furthermore, real ESSs exhibit losses and delayed responses to sudden input changes, which affect the storage's overall performance and efficiency. Here, this translates to important information leakage. Hence, the results in [5] provide an initial picture of the requirement for an ESS to comply with the demand for privacy. But, further investigation is required to transfer previous conclusions to real ESSs.

Providing privacy via ESSs is the main focus of this study. In this study an experimentally verified circuit model of ESSs is applied to residential power consumption profiles to judge what ESS capacities are appropriate to maintain privacy. A set of four different ESSs (li-ion, lead-acid, electric double-layer capacitor (EDLC), flywheel energy storage (FES)) are compared for their suitability in this particular application. In addition, this paper uses actual measured user data from the *REDD* data set [6] (date, load power consumption etc.).

The paper follows the structure of first introducing the model approach used to analyse ESSs in Section II-A. Section II-B describes the parameters and assumptions made for the ESS model. Then, a reference point for the ESSs and the measure of privacy level is defined (Section II-C). A brief description of the load profiles is provided for the used *REDD* data in Section II-D. Next, four different ESSs are investigated and discussed for single users (III-A), followed by a comparison of capacity and cost for different levels of privacy protection (III-B), and finally an analysis for multiple consumers (III-C). A short summary of the findings and concluding remarks are given in the Sections IV and V.

II. ENERGY STORAGE FOR PRIVACY

A. ENERGY STORAGE MODEL

In [5] ESSs have been investigated to protect the user's privacy by masking the user load profile as a constant flat power profile. The premise of the aforementioned study is based on the postulate that a constant profile leaks the minimum amount of information. Hence, the ESS's task is to store and absorb power in accordance to the user's behaviour to obtain the desired flat profile. In other words the momentaneous power to be handled by the ESS is the power difference P_Δ between the instantaneous power consumption of the user P_z and the desired (and reported by the SM) power $P_i = k$ (see Fig. 1).

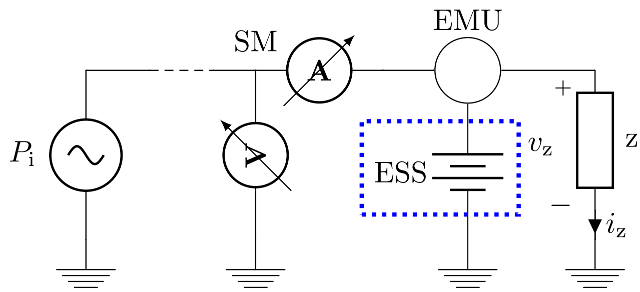

FIGURE 1. Schematic of the electric power supply from the utility (left), denoted as P_i, to the consumer z. The smart meter SM measures the power consumption from the utility to the user. The Energy management unit (EMU) monitors and controls the power in-/outflow between load and ESS.

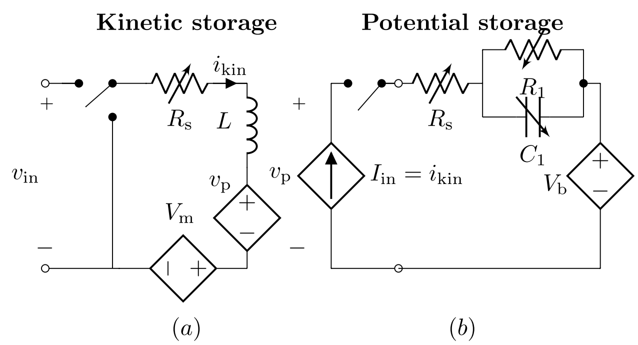

FIGURE 2. Equivalent circuit models for (a) kinetic and (b) potential storages.

$$P_\Delta(t) = P_i(t) - P_z(t) = k - P_z(t) \quad (1)$$

A real ESS may only uphold P_Δ to a limited degree since efficiency, self-discharge and delayed response affect the ESS's overall performance. Thus, this paper applies a more realistic modelling of ESS to privacy protection schemes. The model used in this context has been adopted from [7] (see Fig. 2). The lumped model encompasses the dynamic behaviour these ESSs display in form of the electrical equivalent components resistance, capacitance, inductance as well as dependent sources. Depending on the type of ESS different parts of the model apply. The potential storage part in Fig. 2 (b) represents the li-ion, lead-acid battery or EDLC. Here, the EDLC is treated as a pure capacitor with the voltage source V_b omitted, and for the batteries two series RC-branch instead of one are used here. More components can be added for better dynamic response behaviour. The flywheel is sufficiently modelled by the kinetic storage part only in Fig. 2 (a). Depending on the nature of storage technology some components vary with the storage's state. For example V_b changes with the state-of-charge (SoC) of the battery or R_s with the rotational speed of a flywheel. The model is verified in [8], and a more detailed description of the components can be found in [7].

TABLE 1. ESS circuit model parameters and constraints.

	ESS parameters						ESS constraints						
ESS type	R_s [Ω, Nm · s]	L [H, kgm^2]	$R_{1,2}$ [Ω]	$C_{1,2}$ [F]	V_b [V]	V_m [mV]	SoE_0 [%]	SoE_{min} [%]	SoE_{max} [%]	I_{min} [A]	I_{max} [A]	V_{min} [V, rad/s]	V_{max} [V, rad/s]
Li-ion	0.113	-	0.041 0.019	1027 58880	3.7	-	50	20	100	-1.75	1.75	3.1	4.2
Lead-acid	0.018	-	0.063 0.072	558 32586	6	-	50	20	100	-6	6	5.2	6.6
EDLC	0.014	-	227.4	50		-	50	20	100	-1	1	0.25	2.5
FES	1.041e-06	0.871	-	-	-	85.39	50	20	100	-13.75	13.75	280.9	628.31

Note, in this study ageing effects of the ESSs have been neglected partly due to the fact that the studied time frame is short (24 hr) where ageing is deemed negligible. However, for longer time periods (>months) degradation is crucial for a realistic representation of the ESSs, and time dependent components have to be adopted (e.g., $R_s(t)$).

B. ENERGY STORAGE PARAMETERS AND ASSUMPTIONS

Four different storage technologies, namely a li-ion battery [9], a lead-acid battery [10], a EDLC [11] and a FES driven by a permanent magnet synchronous machine (PMSM) [12] have been analysed.

Table 1 summarizes the storage parameters and assumptions made for the models. Note, the table lists only the initial values during the start of simulation. Some parameters such as series resistance R_s or V_b can change over the course, dependent on the condition of the ESS during operation (e.g., R_s(SOC), R_1(SOC), R_2(SOC), C_1(SOC), C_2(SOC) and V_b(SOC) for the li-ion and lead-acid batteries). The data used for the li-ion and lead-acid battery has been established from data sheets [9], [10] and through experimental testing [8]. EDLCs are also electrochemical devices similar to batteries which can also display non-linear characteristics [13], [14]. In this study, however, the EDLC is simplified as a pure capacitor (i.e., constant parameters) which is an acceptable approximation seen in [8] and pointed out in [15]. The FES is a flywheel system enclosed in a vacuum chamber and stabilized by magnetic bearings. The dominant loss factor is attributed to the bearings where V_m and R_s represent a constant and a speed dependent torque loss respectively.

The ESS's operation is limited by the constraints listed on the right side in table 1. Here, we characterize the level of energy reserve of an ESS by the state-of-energy (SoE) instead of the more commonly used term of state-of-charge (SoC) used in batteries. The reason stems from the more intuitive use of this metric for the alternative storage technologies. The SoC expresses the ratio of accumulated electric charge measured in Coulomb (or Ah) to the nominal charge capacity, which is not directly transferable to ESSs of different physical nature such as flywheels or pumped-hydro stations.

All ESSs start with 50 % SoE and cannot be discharged below 20 % state-of-energy (SoE).[1] Note, the assumed initial SoE for the real ESSs differs from the initial SoE (0 %SoE) of the later described ideal ESS (Section II-C). This reduces the direct comparability between the real and ideal ESS. But, it is a necessary adjustment to represent real ESSs based on the minimum and maximum limitations. Otherwise, an initial empty (SoE = 0 %) or fully charged ESS (SoE = 100 %) would limit its use if further discharge or charge is requested while its SoE lies below SoE_{min} or would rise above SoE_{max}. Choosing either one initial condition for the real ESS leads to a reduction of privacy protection. Hence, for that reasoning we choose 50 % SoE_0 to give leeway for the ESS's operation range. Note though, that this assumption entails that the real ESS needs to be oversized based on the restricted SoE range (SoE_{min}-SoE_{max}) and initial starting point (SoE_0). Furthermore, the BESS's and EDLC's operation is limited by the minimum and maximum allowed voltage and current input. The FES is similarly constrained in the input current to the PMSM and by the allowed rotational speed range (rad/s).

[1]The minimum and maximum SoE is equal for easier comparison, even though some storage technologies can utilize deeper discharge levels.

C. IDEAL ENERGY STORAGE AND COVERAGE FACTOR

The main objective is to protect the user's privacy by not leaking valuable information on the user's behaviour based on their electric power consumption. A constant power consumption reported by the SM is postulated to guarantee protection as described earlier in equation (1). However, this has to be achieved with the least effort, i.e., the smallest possible ESS. In this sense, the power k ($P_i(t) = k$) is chosen in such a way to minimize the storage capacity (see (2)). Furthermore, we assume that the energy $W(t)$ in the ideal ESS is empty at the beginning (i.e., $W(0) = 0$) and demand that $W(t) \geq 0\ \forall t$ (see (3)). W_{max} denotes the maximum energy stored in the ESS during the course of the studied time period t ($W_{max} = \max(W(t))$). Depending on how k is determined the ESS is charged and discharged differently with different outcome in size. An example can be seen in Fig. 3 where P_Δ must be met by the ESS at all times to achieve $P_i = k$. The peak point of $W(t)$ marks the maximum needed energy capacity of the ESS.

$$\underset{k \in [0,\infty]}{\arg\min}\{W_{max}\} = \underset{k \in [0,\infty]}{\arg\min}\{\max(W(t))\} \tag{2}$$

$$W(t') = \int_0^{t'} P_\Delta(t)dt = \int_0^{t'} (k - P_z(t)) \tag{3}$$

The ideal ESS can serve as a reference point for real ESSs. A smaller ESS is not able to provide the necessary capacity to absorb and deliver sufficient energy. An oversized ESS is underutilized, introduces higher self-discharge losses

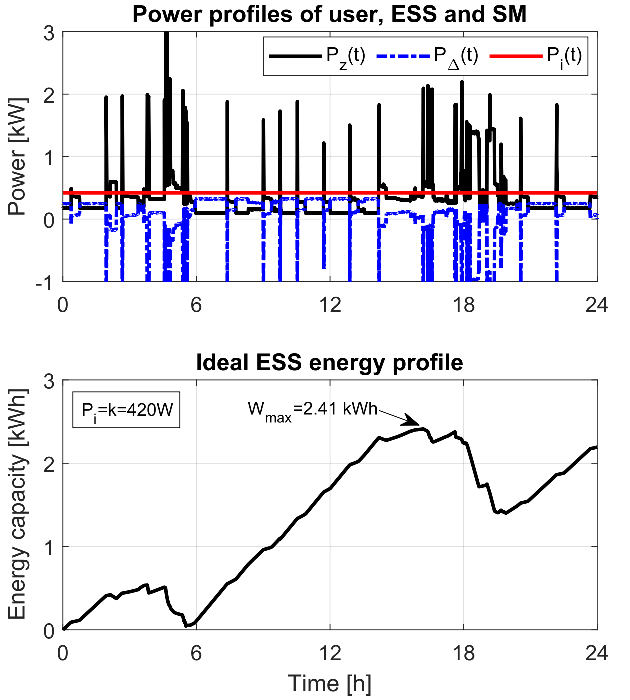

FIGURE 3. Power and energy profile of an ideal ESS ($W_{max} = 2.41$ kWh) to fulfil privacy requirement ($P_i(t) = k = 420$ W) from the *REDD* dataset [6]. The SM reports the constant P_i instead of the real consumption.

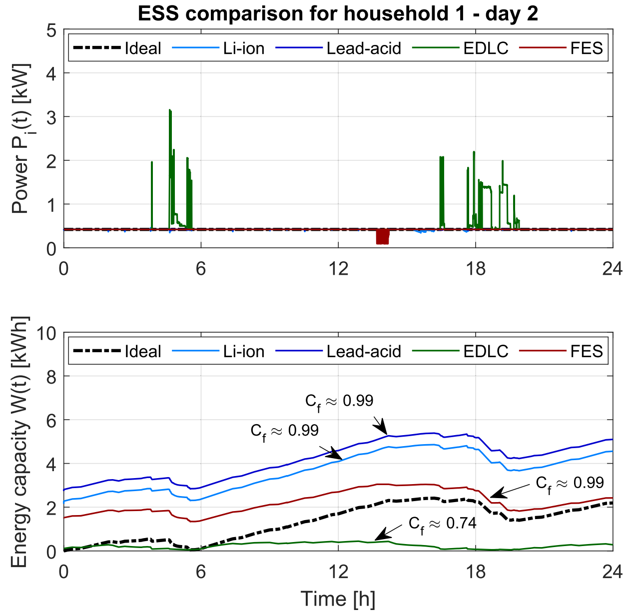

FIGURE 4. Comparison between the ESSs' performance for a single day of household 1. The minimum required capacity of the ESSs to fulfil $P_i = k$ as best as possible for this particular day is the maximum peak of respective $W(t)$.

and investment effort. Since real ESSs feature losses and technical constraints (e.g., minimum or maximum allowed SoE, current or voltage levels etc.) they are bound to deviate from the ideal case. The interesting question to answer is what type and size of different storage technologies is required.

If we understand a breach of privacy by not keeping $P_i(t)$ constant then we can loosely define that the degree of lost privacy is measured by the ESS not satisfying $P_\Delta(t)$. In [16] a coverage factor (C_f) was introduced to measure the degree of overlap between the ESS's actual power performance (P_{st}) and a reference power profile. There, C_f is used to optimally size ESSs to just follow the demanded reference curve. This approach is also applicable in this study, where the demanded reference curve is P_Δ the ESSs have to satisfy. A C_f of 1 indicates that the ESS is fully able to provide $P_{st}(t) = P_\Delta(t)\ \forall t$ which means 100% privacy protection. On the other hand if C_f is 0 the ESS does not provide any power equivalent to having no ESS and 0% privacy protected. It is noteworthy that the C_f factor does not scale proportionally to the percentage of protected privacy as some leaked power peaks may contain more or less information. For example, the ESS may only partially cover a peak power and revealing a portion of actual user consumption. However, more information will be exposed in case the ESS is fully depleted or charged preventing further operation, and, thus, exposing the original profile.

$$dp(t) = P_\Delta(t) - P_{st}(t)$$
$$C_f = 1 - \frac{\int_0^T |dp(t)|dt}{\int_0^T P_\Delta(t)dt} \tag{4}$$

D. USER LOAD PROFILE FROM REDD DATA

In this study the *Reference Energy Disaggregation data* set (*REDD*) [6] is used to investigate the privacy focused application of real ESS. The data set measures close to three weeks worth of data on the power usage of six different households. Unfortunately, as it has been pointed out in [5] interruptions in measurements occur throughout the data set, where only a few complete 24 h sets of continuous data are available (i.e., $24 \cdot 60 \cdot 60 = 86400$ consecutive data points). Additionally, interruptions below 60 seconds are neglected by filling the missing data points with a constant power from the previous data point. With these assumptions a total of 27 full 24 h sets divided between the six households are available.

As a side note, the profiles seen for the individual households can vary significantly from each other even within the same household. This coincides with the notion in [17] that examined possible factors contributing to the variation within household energy consumption. There, it is inferred that the behaviour of the occupants is the dominant factor on the variability of consumption which means that the conclusions drawn for one household are only to a limited extent transferable to other households. In our case, the optimal size of the ESS to protect the privacy has to be uniquely defined for each household and cannot necessarily be understood as a general rule of thumb for all residential buildings.

III. OPTIMAL STORAGE CAPACITY

A. REAL CAPACITY REQUIREMENT FOR SINGLE USER PROFILE AT MAXIMUM PRIVACY

In this section the minimum required capacity of the ESSs for the different households is estimated. The example in Fig. 4

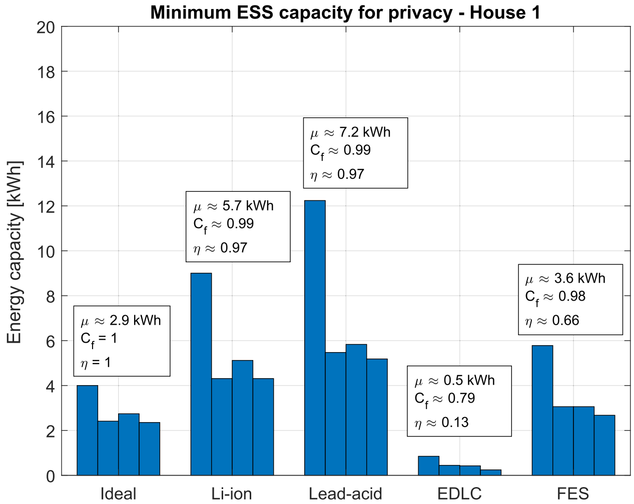

FIGURE 5. ESS comparison household 1 with 4 independent days of data.

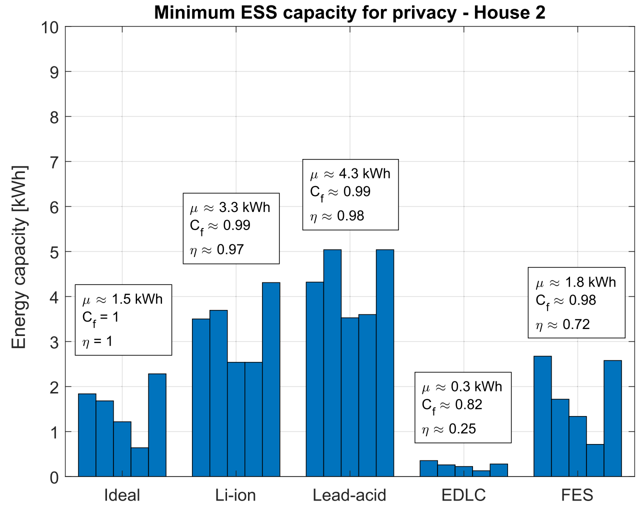

FIGURE 6. ESS comparison household 2 with 5 independent days of data.

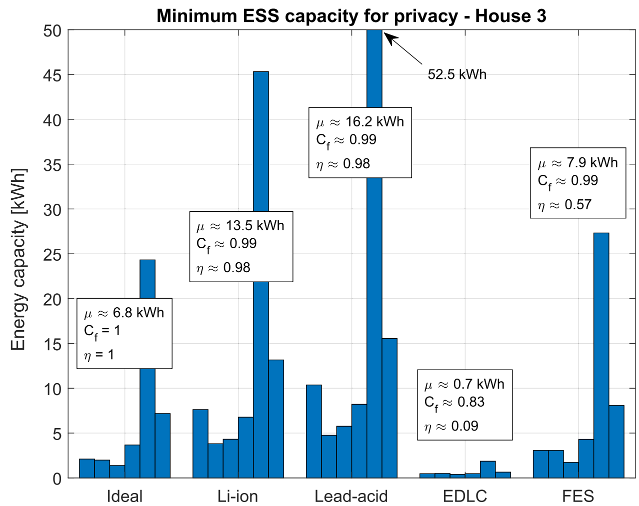

FIGURE 7. ESS comparison household 3 with 6 independent days of data.

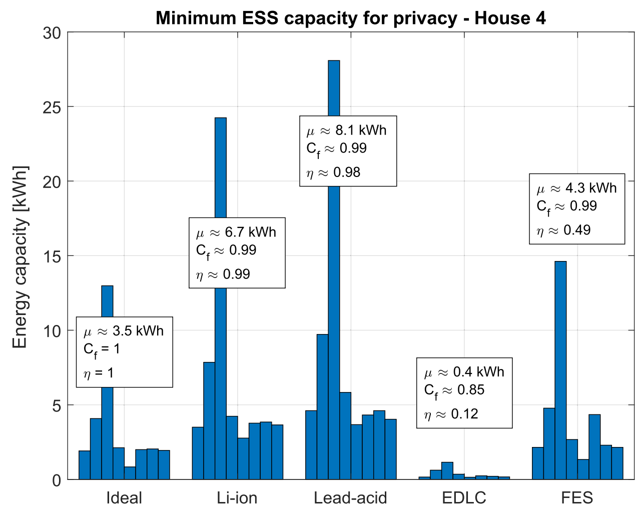

FIGURE 8. ESS comparison household 4 with 8 independent days of data.

shows the comparison between power and energy profiles of the different ESSs for household 1 day 2. The black dashed line represents how an ideally suited ESS operates with the corresponding energy capacity needed. Discrepancies in P_i reveal that not all ESSs are fully able to provide P_Δ, manifesting itself as $C_\mathrm{f} \neq 1$. This is especially visible for EDLC (see Fig 4). The desired constant power consumption seen by the utility is therefore not guaranteed. Furthermore, taking a closer look to the energy curves reveals different necessary storage capacities to fulfil this task. The batteries and the FES are considerably oversized (up to 230 % of $W_\mathrm{max,ideal}$). The necessary flywheel size is slightly above the ideal case (130 % of $W_\mathrm{max,ideal}$) but lacks in efficiency compared to the batteries. In this particular case, the EDLC's C_f maximizes at 0.74, which results in a storage size of less than one-fifth of the necessary capacity. The EDLC system depletes exponentially dependent on its time constant[2] hinting to a considerable energy loss of 99 % within 8 hours. Paired with the charge and discharging losses the EDLC system is barely able to uphold energy levels above the minimum SoE, and, thus, low C_fs are obtained even with increasing the capacities. From this it can be concluded that EDLC are unsuited for this application and timespan. The batteries and the FES are technically feasible with li-ion system as the most promising option due to the lower in generally required capacity compared to lead-acid, and higher efficiency than the FES.

Similar results are observed when we take a look at the other households and days. Figure 5-9 show the corresponding storage sizes for the different households where each bar represents one day of the respective house. It becomes apparent that even within one household electricity consumption can vary substantially, where different storage sizes are required to satisfy privacy issues. It is unwise to customize ESS for a single day, but this highlights the high variability in the user's consumption patterns (visible peaks in household 1, 3, 4 and 6). Overall, the results seen in Fig. 5-9 and summarized in Table 2 coincide well where li-ion battery systems are 190-220 %, lead-acid battery systems 230-290 % and FES

[2] $\tau = (R_1 C_1)/2 \approx 1.58$ h when considering the relation $W = 0.5\, C_1 V^2$

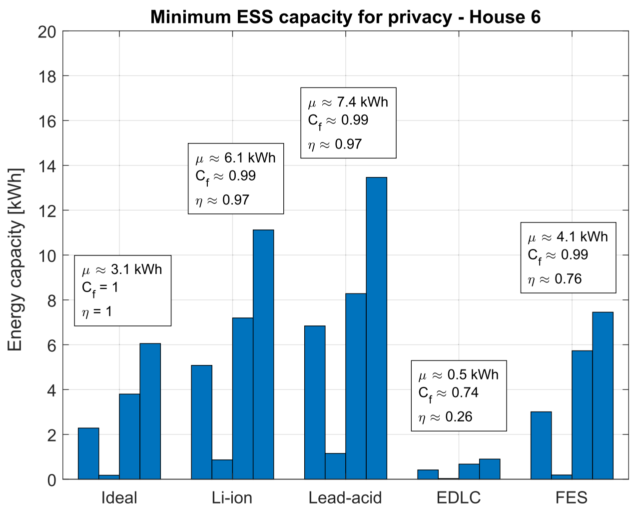

FIGURE 9. ESS comparison household 6 with 4 independent days of data.

TABLE 2. Average capacity requirement for single household.

	W_{max} [Wh]	C_f [-]	η [-]	% larger/smaller than ideal energy [%]
Ideal	3705	1	1	0
Li-ion	7350	0.99	0.98	100.6
Lead-acid	8962	0.99	0.97	148.7
EDLC	466.6	0.81	0.15	-85.7
FES	4513	0.99	0.62	23.5

115-140 % the size of the ideal storage. The EDLC are only 10-20 % of the size of $W_{max,ideal}$ due to the fact that larger EDLC sizes do not improve C_f. The variance in percentage is explained by the required power capability in the application. Some profiles exhibit high short term power spikes (up to 10 kW in seconds/minutes intervals) unfavourable to battery systems due to their limited power capabilities. As compensation the BESS size has to be further increased, as dictated by the theory of Ragone plots [18], which leads to redundant capacity just to fulfil power demands. The opposite is true for EDLCs which, in contrary to BESS, feature high power in exchange for low energy capacity per unit.

The results show that the necessary (mean) storage capacities to preserve privacy lie within the margin of existing products on the market. For example, the Tesla Powerwall (5 kW/ 13.5 kWh) [19], the RESU10H (5 kW/ 9.8 kWh) from LG Chem [20] or the Varta element 12 (4 kW/ 13 kWh) from Varta [21] are few examples of viable market available lithium-ion based products. On the other hand EDLC and FES have so far not experienced any residential use, but have potential use in grid focused applications and services such as voltage control, power quality, and smoothing of intermittent power generation of renewable energy sources [22], [23].

B. ENERGY STORAGE SIZE AND COSTS VS PRIVACY

Another crucial aspect to consider is the potential costs for investing in a system for privacy purposes alone, especially answering the question what storage sizes and total costs are expected for different levels of privacy. For example, in exchange for a part of the user's privacy a smaller sized ESS can be a compromise between privacy and necessary investment.

TABLE 3. Main cost items of energy storage systems from [24], [26]. *The $C_{OM,v}$ and C_{RC} for EDLC are not available and assumed 0 €/kWh and 229 €/kW (equal to C_{TCC}) respectively.

	Capital		O&M		Replacement
	c_{PCS} [€/kW]	c_{SV} [€/kWh]	$c_{OM,f}$ [€/kW]	$c_{OM,v}$ [€/kWh]	c_{RC} [€/kW]
Li-Ion	463	795	6.9	2100	369
Lead-acid	378	618	3.4	370	172
FES	287	2815	5.2	2000	151
	c_{TCC} [€/kW]		$c_{OM,f}$ [€/kW]	$c_{OM,v}$ [€/kWh]	c_{RC} [€/kW]
EDLC	229		4.4	0*	229*

The total costs c_{TC} for an ESS are estimated based on capital, operation and maintenance (O&M) and replacement costs (see (5)). The capital costs divide into two parts: The procurement of the storage vessel (c_{SV} [€/kWh]) and the power conversion system (c_{PCS} [€/kW]). The O&M costs comprise of a fixed ($c_{OM,f}$ [€/kW]) and variable cost factor ($c_{OM,v}$ [€/kWh]). A one time replacement cost (c_{RC} [€/kW]) is also included although this study investigates only a 24 hours time period.[3] The individual costs are calculated based on the rated capacity (W_{st}) and rated power (P_{st}) of the ESS at specific C_f values. Table 3 lists the cost assumptions given in [24]. Information on the EDLC are only available for the total capital costs C_{TCC} and the fixed O&M costs.

$$c_{TC} = W_{st} * \left(c_{SV} + c_{OM,v}\right) + P_{st} * \left(c_{PCS} + c_{OM,f} + c_{RC}\right) \quad (5)$$

Figure 10 illustrates how the ESS sizes and corresponding total costs increase in average with higher requested privacy. The size is detailed as a ratio between the actual compared to the ideal ESS size (W_{st}/W_{ideal}). The BESS are in average more than two times (li-ion 2.24, lead-acid 2.71) the ideally required size when considering 100 % privacy. Reducing the requirement slightly significantly decreases the storage sizes, where the highest reductions are achieved at the top 10 % C_f (around 80-100 % capacity savings for batteries). The FES has an advantage over the BESS due to its lower necessary storage size even at near 100 % C_f (≈130 % of W_{ideal}). However, we keep in mind that the FES is in general less efficient (η ≈62 %) than the BESSs. The EDLC rarely reaches C_f values over 80 %. Higher C_f values are only achieved in cases where the ESS is dominantly charged over the time period. On first impression, this seems positive in regard to the small storage size. But, with an low efficiency ($\eta \approx 15$ %) this equates to wasting rather than storing energy even though useful if only concerning the privacy preservation [25]. In this sense the EDLC only works as load without being able to

[3]Long-time investigations (> several years) may require several replacements.

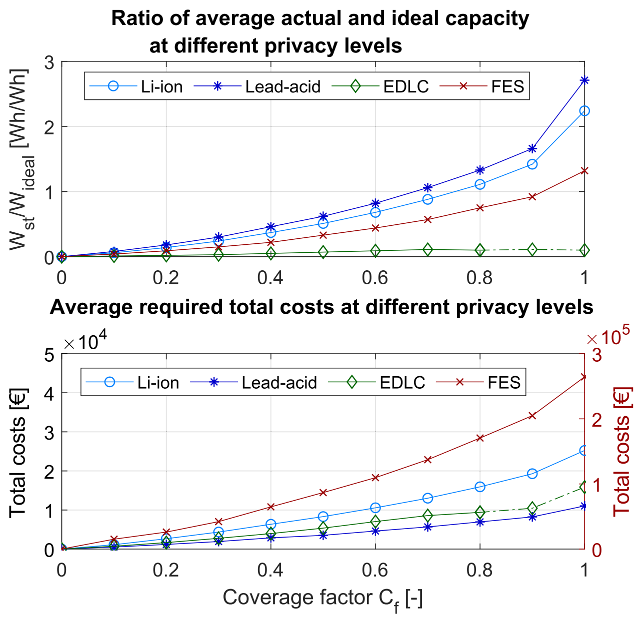

FIGURE 10. Top: Required average storage capacities to fulfil different levels of privacy. Bottom: Total cost estimation for various ESS at different levels of privacy. (left axis: li-ion, lead-acid, EDLC; right axis: FES.). Note, high levels of C_f for EDLC are only obtainable under specific conditions (dominantly charging).

return the energy which has already been lost through charging and self-discharge. Ultimately, a small storage capacity is sufficient since only a fraction of the input energy is retained.

Now, taking a closer look at the required costs for different C_f the result is reversed where FES, even though close in size to the reference, features the highest total costs in average ($\approx$ 260000 €) (Fig. 10). This is ten times higher compared to the other ESS alternatives, where li-ion amounts to roughly 25000 €, followed by EDLC ($\approx$ 16000 €), and lead-acid as the cheapest option ($\approx$ 11000 €). The FES is significantly oversized in terms of power capabilities (5.5 kW/unit) due to the fact that the residential application is dominantly energy rather than power focused, which ultimately stacks up the costs for C_{PCS} and C_{SV}. The high specific power of FESs (400-1500 W/kg) compared to BESSs (75-300 W/kg) favours their usage in short term high power applications (up to few hours) such as power quality and voltage regulation control in the power grid [22]. In applications with long discharge times over several hours the advantages of FESs diminish due to significant self-discharge losses similar to the EDLC. Hence, FESs commonly find application in conjunction with other ESS [22], e.g. batteries, to compensate each other's shortcomings if both high power and high energy capacity is demanded.

The cost calculations favour the lead-acid over li-ion battery due the overall low costs for all cost items (Table 3). This is unsurprising with regard to the short time frame, where major differences in performance remain negligible. However, a long-term analysis, and also including ageing processes over several years will reveal differences due to the distinct lifetimes of the technologies. In general, the expected lifetime of lead-acid batteries is commonly 200-500 cycles dependent on its operation regime compared to 1000+ cycles for li-ion batteries [22], [27]. In niche applications with short term high power demands, i.e. short discharge durations with immediate recuperation, FESs can surpass BESSs in terms of expected lifetime (20000+ cycles [22]). Therefore, this cost calculation does not deliver a full economic evaluation, but an initial picture instead. As previously the EDLC is deemed unsuited in performance and in economy with occurring costs higher than lead-acid.

Finally, the estimated costs for a singular household are in range of market available products. Considering only the capital costs of li-ion batteries the necessary storage size and cost is overestimated to roughly 1100 €/kWh[4] compared to the available products from Tesla (Tesla Powerwall 650 €/kWh [19]) or LG Chem (RESU10H 540 €/kWh [20]). Hence, mitigating privacy concerns through a single storage module is possible and more so if lower privacy levels are acceptable.

C. REAL CAPACITY REQUIREMENT FOR MULTI-USERS

Alternatively, multiple users can share an ESS to collectively protect their privacy to the outside observer. In this sense, the SM reports the accumulation of profiles similar to that of an apartment complex. The approach remains the same but only the combined load consumptions of all users have to be balanced.

$$P_{\Delta}(t) = k_M - \sum_{j=1}^{N} P_{z,j}(t) \tag{6}$$

Unfortunately, the data available only provides single user profiles. Therefore, in order to simulate multi-user applications this study artificially generates multiple user profiles by combining the five available household power profiles from the *REDD* data. The different profiles are summed up, analogously to a situation where these households share a SM in pairs, triplet, quadruple etc.

From Fig. 11 we can observe that the required storage capacity and total cost decrease with increasing numbers of users sharing one ESS as also noted in [5]. The greatest savings in cost are achieved by just sharing the ESS with a second user but converges to a minimum level of around 30-50 % of the initial size and costs (li-ion: 600 Wh/user, 2000 €/user; lead-acid: 850 Wh/user, 1000 €/user; EDLC: 110 Wh/user, 3200 €/user; FES: 670 Wh/user, 38000 €/user). Note, these numbers are heavily dependent on the user's consumption patterns and the ESS device tested. Nonetheless, substantial savings can be expected for groups even in small numbers.

[4] $c_{TCC} = W_{st} * c_{SV} + P_{st} * c_{PCS}$

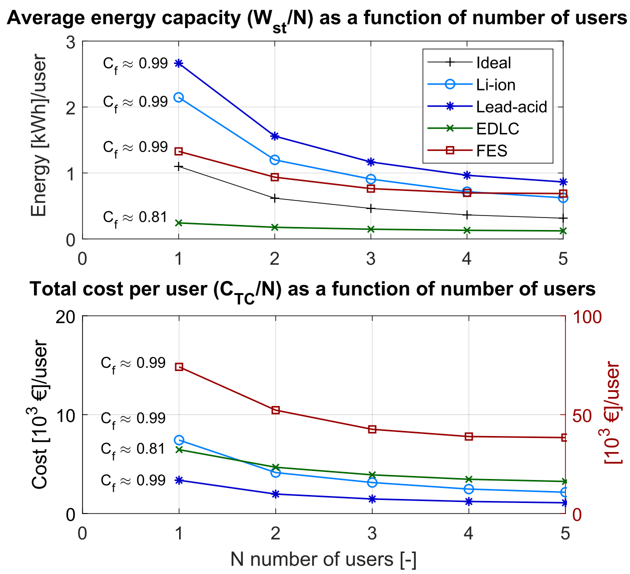

FIGURE 11. Top: Average shared ESS capacity per user with increasing numbers of users. Bottom: Total costs per user for different storage technologies. (left axis: li-ion, lead-acid, EDLC; right axis: FES.).

IV. DISCUSSION

The results from the previous sections have shown that privacy issues due to real-time monitoring of SM can be mitigated by reasonable ESS capacity sizes and costs. Market available products can be utilized to prevent leakage of private information, which can be affordable for individual users but more so for grouped users. However, the public acceptance remains to be discussed since no financial merit is gained from this investment. The results presented have to be interpreted with care. It has to be pointed out that user consumption patterns can vary heavily (e.g., seasonal changes in consumption), even within the same household, that can make appropriate sizing difficult if high levels of privacy ought to be maintained.

Furthermore, what has not been addressed in this study is what constant power $P_\mathrm{i} = k$ is suitable for a long time investigation. Here, k is chosen in such a way that yields the minimum of ESS capacity. However, this can lead to an increase of the overall electric power consumption, and thus higher cost, for the user if a constant high power has to be maintained, especially when the ESS is mainly absorbing additional energy.

Other aspects to consider for future investigations are the influence of demand-side management schemes and electric power tariffs on the ESS's required capacity. Adding further functions to the ESS creates additional value if, for example, privacy and minimization of electric power purchase are joined objectives.

Finally, the cost calculation only presents an initial picture, but is incomplete since ageing effects of ESSs are not included in the model. Significant differences become more visible in a long-term study over several years, where the lifetimes of ESSs have greater impact on maintenance and replacement costs.

V. CONCLUSION

The privacy breach through real-time monitoring of user power profiles is a valid concern and has sparked discussion about effective protection schemes. One option is to alter the consumption profiles to outside viewers by the use of ESSs. A comparison of different energy storage technologies reveals their effectiveness in this particular application and also minimum required capacity to fulfil the role. The BESS are the most suitable options in terms of cost even though considerable oversizing is necessary (up to 2-3x ideal ESS, in average 10-15 kWh). We conclude that the use of commercially available ESSs to protect privacy is possible and viable.

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