Enhancing Privacy Through Time Aggregation of Load Profiles in Energy Management

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***Abstract*—Demand side management (DSM) applications rely on the exchange of load profiles to effectively manage the operation of energy systems. However, sharing detailed energy profile data raises substantial privacy concerns, such as potential misuse of personal information. To mitigate these concerns, we investigate the potential of time aggregation (TA), which involves merging multiple samples of a profile into a single value representing multiple intervals. TA reduces data exchange and computational requirements in energy management and helps preserve user privacy by reducing granularity of user data. We show that, for an effective implementation of TA in energy management, it is important to make the right choice of TA method. We compare and evaluate seven different TA methods. Furthermore, we perform TA across various time frames using an optimization based DSM approach. Our findings reveal that if we aggregate load profiles from 15 minutes to 4 hours, we obtain both enhanced privacy and a 21% decrease in the required number of iterations with the investigated DSM method, albeit at the cost of a 15% decrease in objective value performance. Based on this, we conclude that depending on the application needs, TA with a carefully selected aggregation method has the potential to bring value to energy management, even when aggregating to a considerable extent.**

***Index Terms*—Load profiles, Energy management, Demand side management (DSM), Time series aggregation (TSA), Privacy**

I. Introduction

The large-scale integration of renewable energy sources (RES) in the electricity grid, necessary to reach the European Commission's carbon emission targets for 2050, requires sustainable flexible assets to temporally shift their load to time frames where energy is available [1]. To provide this flexibility, a lot of different technologies can be considered. Energy storage is one of the core means to provide this flexibility, but alternatives from the field of energy management such as demand side management (DSM) and demand response (DR) also show potential [2].

As an example showing this potential, it was found in 2016 that in Germany, "DR can economically substitute up to 10 GW of power plants" [3]. For the operation of DSM, appropriate modeling of energy systems is required, which by itself requires accurate energy production and consumption data. However, the use of such highly accurate data raises significant privacy concerns, a problem that gained significant regulatory attention with, e.g., the introduction of the GDPR by the EU in 2016. To mitigate such concerns, Hoepman [4] introduces data aggregation as a strategy aligning with the principles of *privacy by design* [5].

In the field of data aggregation, various methods are employed to handle complex data sets efficiently. Müller [6] has identified four distinct methods of time series aggregation (TSA) that can reduce computational resource requirements in grid planning. These methods include downsampling (reducing temporal resolution), heuristic selection (selecting days based on predefined criteria), clustering (selection of representative days), and optimization (selecting days by minimizing an error indicator). Other research has explored the effectiveness of TSA methods in grid planning [7]. Our focus differs from this work as we concentrate on TSA not for long-term grid planning, but for privacy enhancement and complexity reduction in DSM.

Erkin and Tsudik [8] make the distinction between two types of TSA for smart meter power consumption: spatial and temporal (time) aggregation. Spatial aggregation (SA) is the aggregation of the profiles of multiple devices, or multiple households, into one combined profile. Time aggregation (TA) is the aggregation of a given profile into a profile with lower time resolution (i.e., downsampling). In recent literature, such as [9], [10], research on SA of profiles is presented. Additionally, e.g. [11], [12] present approaches that apply TA to aggregate profiles to a timespan of entire years for billing purposes. Bollen *et al.* [13] implement dynamic TA in optimization based DSM by averaging energy profiles in a battery planning algorithm. In their implementation, the specific TA method they chose reduces the execution time of their DSM algorithm while minimizing the loss of the objective function. However, to the best of our knowledge, no literature has specifically considered the general effect of TA on DSM performance. Moreover, the effect that different *TA methods* can have on DSM performance has not been evaluated. While Bollen *et al.* use an averaging method in their study [13], other approaches, such as using instantaneous power measurements (e.g., a sample at the beginning of an interval), are also used frequently. We are not aware of literature considering the consequences of choosing one of

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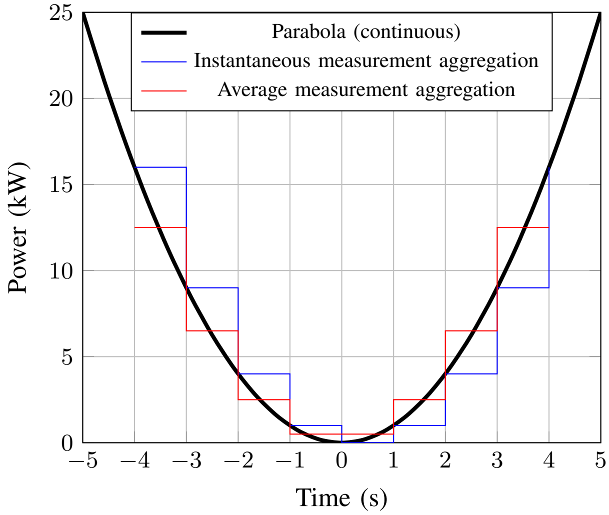


Fig. 1. Example of two time aggregation methods on a parabolic profile.

these TA methods over another in energy management.

TA has the potential to address privacy concerns in energy management, and simultaneously improve performance from a computational perspective. This paper explores this potential, and aims to find which TA method can be applied best for energy management applications. We investigate the trade-off between the performance loss in the considered optimization process objective and the computational performance benefits for different TA methods.

The main contributions of this paper are:

- A comparison of TA methods for load profiles.
- An analysis of the impact of TA on device scheduling decisions.
- Recommendations on TA methods for DSM.

The remainder of this paper is organized as follows. In Section II, we formally define methods for TA of load profiles. We describe a test framework for TA methods for DSM in Section III, and evaluate the obtained results in Section IV. We finally draw conclusions and present directions for future work in Section V.

II. Time aggregation

In this section, we provide a definition for TA, and discuss different methods to implement it.

A. Time discretization

For many applications in the energy domain, the power flow over time $x(t)$ is an important input for decision making or analysis. Since this data needs to be measured, transmitted, stored and processed by algorithms, for technical and efficiency reasons some form of time discretization is needed. This in general implies that the given time horizon $\mathcal{I}$ is subdivided into N intervals $I_1, \dots, I_N$. We denote the length of an interval $n \in \{1, \dots N\}$ by $T_n := |I_n|$, and the power used within the interval by x_n, implying that the vector $\vec{x} = (x_1, \dots, x_N)$ is the power profile for the given time horizon.

The discretization implies that a single value x_n is used to represent the power values $x(t)$ of the whole interval I_n, thereby reducing many (possibly infinitely many) values to a single value. We call this process *time aggregation* (TA) of the power flow. For this, two commonly used approaches are (i) using an instantaneous power measurement (e.g., a sample at the beginning of an interval), or (ii) using averages (e.g. by measuring the energy e_n in the interval and using that to calculate the average power by $x_n = \frac{e_n}{T_n}$). In Fig. 1 a graphical representation of these two approaches is given. Note that besides the two mentioned approaches, numerous alternatives exist.

TABLE I
Aggregation methods $f(x, I_{\tilde{n}})$ considered in this paper

Method name	Description
mean	Takes the mean of an interval
median	Takes the median of an interval
max	Takes the highest value of an interval
min	Takes the lowest value of an interval
first	takes the first value of an interval
last	takes the last value of an interval
random	takes a random sample from an interval

B. Merging intervals

In many practical applications, the starting point for time discretization is not a continuous power signal, but a given high(er) frequency representation by values $x_1, \dots, x_N$ and the goal is to reduce the resulting data volume by going to a lower frequency $\bar{x}_1, \dots, \bar{x}_{\tilde{N}}$ with $\tilde{N} \ll N$. Commonly the relatively high frequency data is reduced to frequencies on minute scale, for example reducing to 30 minute data.

This frequency reduction is a reduction of an (already) discrete power profile $x_1, \dots, x_N$ by merging K consecutive intervals to a single interval $\bar{x}$ using TA. The result is a profile $\vec{x}$ of length $N = K\tilde{N}$.

C. Aggregation methods

TA reduces a profile of N intervals into a $\tilde{N}$ intervals wherein $\bar{x}_i$ ($i \in \{1, \dots, \tilde{N}\}$) represents the i-th time aggregated interval. More formally, we define TA as:

$$\bar{x}_{\tilde{n}} := f(x, I_{\tilde{n}}), \tag{1}$$

where $f(x, I_{\tilde{n}})$ is a TA function aggregating the K values of the profile x corresponding to interval $I_{\tilde{n}}$. In this paper, we consider the methods described in Table I for aggregation of the x-values of an interval $I_{\tilde{n}}$. The next section explains the implementation of these methods in our simulation framework.

III. Test framework

In the following, we describe the use of TA in DSM. We first present the optimization goal that we aim to achieve with DSM. Then, we discuss the used DSM algorithm, after which we introduce alterations made to this algorithm to implement the TA methods of Section II.

Note that the use of TA within DSM to achieve privacy benefits comes at a cost: it will generally have a negative impact on DSM objective value performance, since the algorithm only has $\tilde{N}$ data points to make decisions for $N = K\tilde{N}$ intervals. However, as we show later, TA can have a significant positive influence on the computational performance of DSM, since it causes a direct reduction of the size of the optimization problem. This gain in computational performance, combined with the privacy benefits, may be worth a slight decrease in the objective value.

A. Optimization goal

To analyze the performance of our algorithm, we consider a scenario where the goal is to obtain a load profile that is as flat (close to zero) as possible. Thus, we analyze DSM performance in terms of the Euclidean norm $\|x\|_2$ of the power profile x, defined as:

$$\|x\|_2 := \sqrt{\sum_{n=1}^{N} x_n^2}. \qquad (2)$$

Note that we evaluate over N intervals of the original profile and not on the time aggregated profile $\tilde{N}$. While the goal of TA is to make (parts of) a DSM algorithm run based only on information of the aggregated intervals (since this better aligns with the principles of *privacy by design* [4]), the evaluation should still be done on the original N intervals for a fair comparison between aggregation with different values of K.

B. DSM algorithm

To investigate the effect of TA on the performance of optimization within energy management, we use a DSM method that uses communication to minimize the negative impact of the resulting power profile on the grid. To this end, we use the profile steering (PS) heuristic [14] as DSM algorithm, which is a method to steer flexible devices using a desired profile (e.g., a flat profile) instead of prices. The standard implementation of PS applies spatial aggregation, while in [13] effects of TA with scheduling of batteries within PS have been investigated. We extend this implementation of TA in PS to include any type of device, and compare various alternatives for applying TA. As PS assumes multi-layer bi-directional communication, it is well suited to demonstrate the effect of TA on communication and optimization in a DSM context. What follows is a description of the core of the algorithm.

For scalability, PS works in a hierarchical structure, as presented in Fig. 2. The flexibility of devices is coordinated in PS by controllers on various hierarchical levels, e.g., at a household or neighborhood level. By default, the algorithm steers a group of devices to minimize the Euclidean norm of the difference between the group profile x and a target profile p.

To indicate how the (global) profile needs to be adopted, a parent controller communicates its desired profile changes d (the difference between x and p) to its M child controllers. Each child controller m determines its own target profile p^m from the received profile d and its own profile x^m. Subsequently, it optimizes its flexible assets and proposes a new profile $\hat{x}^m$ that minimizes the distance $\|\hat{x}^m - p^m\|_2$. The child controllers communicate the improvement e^m of their proposed new profiles $\hat{x}^m = (\hat{x}^m_1, \ldots, \hat{x}^m_N)^T$ back (possibly consisting of the improvement of the child controllers below them). The parent controller then picks the child controller that can provide the largest improvement and the parent profile x is updated. After this, the algorithm repeats these steps until it converges (i.e., the improvement is less than a convergence criterion ϵ and thus no significant improvement is provided to the objective anymore), or a maximum number of iterations has passed. The algorithm is explained in more detail in Algorithm 1, adapted from [14].

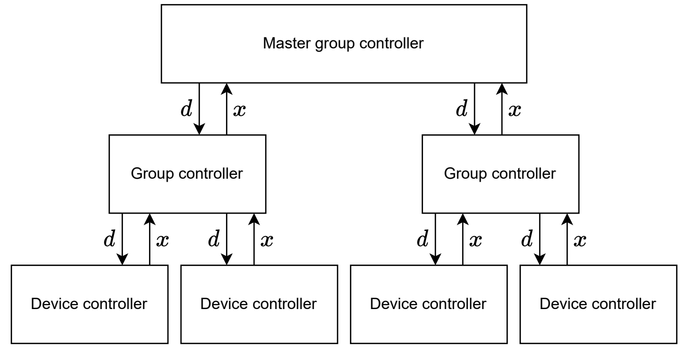


Fig. 2. An example of the hierarchical structure of controllers in PS. A master group controller on top of the hierarchy steers towards a flat profile. Below each group controller, (child) device controllers can be connected (or another layer of group controllers). Each controller sends its load profile x upwards, and its parent controller sends their desired profile d downwards.

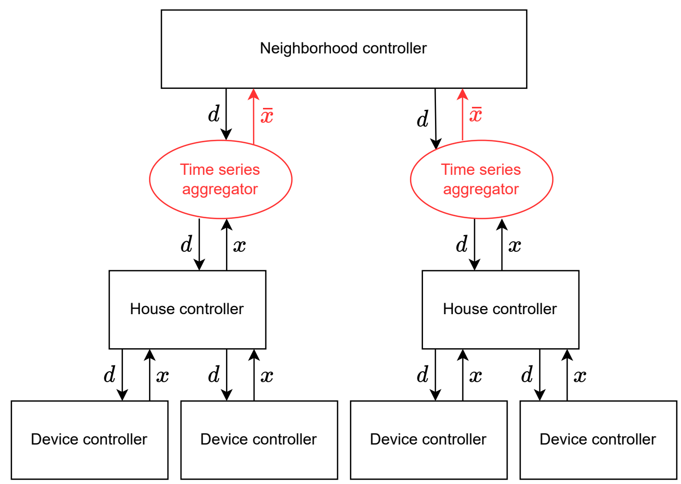


Fig. 3. The implementation of PS hierarchy with the time series aggregation components added in red. The time series aggregators aggregate a profile x to a profile of lower temporal resolution $\bar{x}$.

PS has shown to be able to significantly reduces grid losses compared to optimization through regular dynamic pricing [14]. However, to achieve this, it requires communication of power profiles both upwards and downwards. This means that a neighborhood controller obtains access to privacy sensitive precise power profiles of households connected to it. Additionally, the algorithm must evaluate complete profiles on every iteration. Therefore, a reduction of the profile data granularity would result in a lower complexity, thereby increasing computational performance. Summarizing, we aim to improve PS performance in terms of privacy and processing time by TA of the power profiles shared by households.

Algorithm 1 Hierarchical profile steering algorithm. Parts printed in grey are added to integrate TA.

Request each child $m \in \{1, \dots, M\}$ to minimize $\|x^m\|_2$.
if parent is neighborhood controller **then**
  $x := \sum_{m=1}^{M} \bar{x}^m$ ▷ Apply TA for total consumption
else
  $x := \sum_{m=1}^{M} x^m$ ▷ Total consumption (parent)
end if
repeat
  $d := x - p$ ▷ Difference vector
  for $m \in \{1, \dots, M\}$ **do**
    $p^m = x^m - d$
    Let child m find a planning $\hat{x}^m$ that minimizes $\|\hat{x}^m - p^m\|_2$
    $e^m = \|x^m - p^m\|_2 - \|\hat{x}^m - p^m\|_2$ ▷ Flexibility m
  end for
  Find the child m with the highest contribution e^m
  if parent is neighborhood controller **then**
    $x := x - \bar{x}^m + \bar{\hat{x}}^m$ ▷ apply TA, update parent
  else
    $x := x - x^m + \hat{x}^m$ ▷ Update parent consumption
  end if
  $x^m = \hat{x}^m$ ▷ Update profile of child m
until $e^m < \epsilon$ ▷ Repeat until insufficient progress

C. Aggregation implementation

To improve privacy and processing time of household power profiles using TA in PS, the (privacy sensitive) profile x that is sent upwards by the controllers to the neighborhood controller is time aggregated by the methods described in Subsection II-C. We introduce a separate time series aggregator component, which time aggregates the profiles sent upward. The component receives a profile x updated by a child and transforms it into a time aggregated profile $\bar{x}$ before sending it to the parent. The described implementation of aggregation is presented in red in Fig. 3. In this figure, the components printed in black represent the basic version of the implementation of PS. The additions made to the algorithm of PS to include TA when sharing data with a neighborhood controller, are highlighted in grey in Algorithm 1. Note that we only apply TA on the upward profiles, but not the downward profiles d. As we mainly apply TA for privacy reasons, and d is already spatially aggregated, we deem it unnecessary to apply TA to d. We note that the application of TA on the upward profiles decreases the quality of the input for the house controller and hence also its decisions (as d is iteratively altered based on the received $\bar{x}$, it is ultimately also affected by the implementation of TA). However, the results presented in Section IV show that the objective value performance gain of applying our DSM algorithm remains significant.

IV. Evaluation

In this section we evaluate the impact of TA on the performance of PS when we aggregate x into $\bar{x}$. We first describe the scenario we use for the evaluation, after which we present and discuss the results.

A. Evaluation scenario

To evaluate the performance of PS with TA, we simulate a neighborhood of 20 households using the open-source simulation software DEMKit [15], which includes PS. House load profiles are generated using the open-source Artificial Load Profile Generator (ALPG) [16]. Our aim is to show how TA affects the performance of the DSM algorithm.

Zakeri et al. [17] show that coordinated operation of storage assets has the most added value for prosumers that have only PV or only battery storage, while benefits decrease when they have combinations of these technologies themselves. Thus, to emphasize the effect of the implemented TA methods, we consider a neighborhood that has a very heterogeneous distribution of (flexible) appliances. The appliances are distributed as follows:

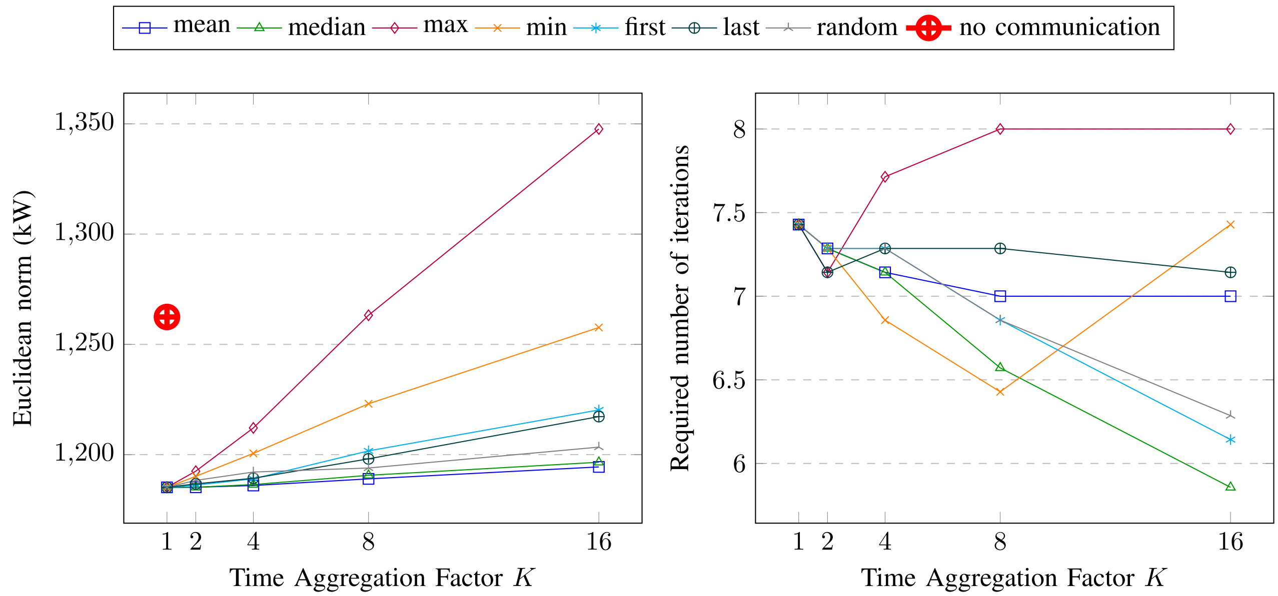
- Houses 1-5 have a PV installation.
- Houses 6-10 have a heat pump.
- Houses 11-15 have an electric vehicle.
- Houses 16-20 have a home battery.

The houses are connected to a single feeder through a single phase low voltage cable. To align the PV production of houses 1-5 with the flexibility of the other households, coordination is important. We simulate a week with weather data from June 2021 in the Netherlands, with a significant amount of PV production. The aim is to distribute this production over time and between the houses. By default, the controllers work with an electricity profile time base of 15 minutes. We apply TA using multiples of this default time base: going to 30 minutes ($K = 2$), 1 hour ($K = 4$), etc.

B. Results

To determine the effect of TA factors K on the performance of EMS, we first consider the case where there is no neighborhood controller. In this situation, there is no coordination between households and all houses only apply local PS where houses try to flatten their individual loads. This base case is plotted in red in Fig. 4.

To measure the performance of PS *with* a neighborhood controller, and thus the effect of (time aggregated) profile communication, we use two metrics: the Euclidean norm of the energy profile resulting from optimization (as explained in Section III-A) and the required number of iterations as a measure of computational complexity. The corresponding results of TA for the different aggregation methods of Section II-C are



(a) Euclidean norm.

(b) Number of iterations required for the PS neighborhood controller.

Fig. 4. Performance comparison for different time aggregation factors K. For both metrics, lower is better. Each color represents another aggregation method.

TABLE II
PERFORMANCE COMPARISON OF AGGREGATION METHODS

Aggregation Method	**Time Aggregation Factor K**[a]	**Euclidean Distance (kW)**[b]	**Number Of Iterations**[c]
min	1	1185.16 (100.0%)	7.43
	2	1190.16 (93.53%)	7.29
	4	1200.59 (80.03%)	6.86
	8	1223.07 (50.94%)	6.43
	16	1257.67 (6.16%)	7.43
max	1	1185.16 (100.0%)	7.43
	2	1192.52 (90.47%)	7.14
	4	1212.11 (65.12%)	7.71
	8	1263.21 (-1.01%)	8.0
	16	1347.66 (-110.31%)	8.0
mean	1	1185.16 (100.0%)	7.43
	2	1185.22 (99.92%)	7.29
	4	1186.02 (98.89%)	7.14
	8	1189.02 (95.0%)	7.0
	16	1194.43 (88.0%)	7.0
median	1	1185.16 (100.0%)	7.43
	2	1185.22 (99.92%)	7.29
	4	1186.43 (98.36%)	7.14
	8	1190.64 (92.91%)	6.57
	16	1196.56 (85.25%)	5.86
first	1	1185.16 (100.0%)	7.43
	2	1186.22 (98.63%)	7.29
	4	1189.05 (94.97%)	7.29
	8	1201.71 (78.58%)	6.86
	16	1220.27 (54.56%)	6.14
last	1	1185.16 (100.0%)	7.43
	2	1186.75 (97.94%)	7.14
	4	1189.29 (94.65%)	7.29
	8	1198.09 (83.27%)	7.29
	16	1217.24 (58.48%)	7.14
random	1	1185.16 (100.0%)	7.43
	2	1188.33 (95.9%)	7.29
	4	1192.11 (91.01%)	7.29
	8	1193.95 (88.62%)	6.86
	16	1203.43 (76.36%)	6.29

[a]Notice that $K = 1$ means that no data is aggregated.
[b]Percentages represent the improvement over the base case (no communication) relative to $K = 1$ (no TA).
[c]PS uses a rolling planning horizon, replanning daily, and we simulate 7 days. The presented value is the mean of the iterations required during these planning events.

presented in Fig. 4. The results are also shown numerically in Table II. To evaluate the performance of the various methods, we compare them to the base case.

We restrict the results up to K-values of 16, i.e., aggregating up to 4 hour intervals. Aggregating further is not useful, since beyond this point, details about day/night cycles start to disappear (e.g., DSM can no longer be applied to align flexibility with solar production).

1) Euclidean norm: The results presented in Fig. 4a show the Euclidean norm of the total profile of the neighborhood. Note that for a TA factor of 1 no aggregation is done, meaning that it corresponds to regular PS, where control signals are sent every 15 minutes. If $K = 16$, this means that a new value is only sent upwards every 16 control intervals (i.e., $\tilde{N} = \frac{N}{16}$), or every 4 hours. The figure shows that all PS implementations outperform the no communication situation, with the exception of the max method for higher values of K. As a general trend, the objective value increases as K increases. This loss of performance is most profound for the min and max methods, and to a lesser extent for the first and last value methods. The mean, median, and random selection methods are less affected by the performance loss.

2) Required number of iterations: Fig. 4b shows the number of iterations PS requires on average to converge. As the value of K increases, the required number of iterations generally decreases. This shows that PS converges to a solution faster when it has to consider less data for decision making. Especially for higher K values, the required number of iterations is reduced significantly for the median, first value and random selection methods. The reduced number of iterations is a direct result of the reduced complexity of the optimization that TA provides. Because of the reduced complexity, a considerable convergence speed improvement can also be expected.

Note that the max method has outliers where the number of iterations *increases* for high values of K. Since the max method only represents the highest peak in the profile, the improvement per iteration may be slower (especially when considering a larger time interval), which means that more iterations may be required before the algorithm decides there is no longer a sufficient progress, and terminates.

C. Discussion

From the results, it becomes clear that if a proper method is chosen (i.e., the mean, median, or random selection method), the Euclidean distance remains very close to regular PS for small K values. For higher values of K, there is a small loss of performance, but this comes with the benefit of a significant reduction of the number of iterations. This shows the importance of selecting a proper method for TA in DSM.

Overall, we find that the mean, median and random selection methods provide the most consistent performance for the optimization objective, providing a comparatively low Euclidean norm regardless of the value of K.

V. Conclusion

In this paper, we show that when applying TA to power profiles in energy management for privacy reasons, it is important to choose a proper method. TA can improve both privacy and algorithm convergence time in DSM, while retaining the performance benefits of communication between house- and neighborhood controllers. However, this is only possible if a proper TA method is chosen. The mean, median and random value methods perform best for the Euclidean norm objective we evaluated. In general, performance differences between methods can be considerable, with differences between them increasing as the TA factor K increases. When applying the median aggregation method in our scenario, a TA factor of $K = 16$ (aggregating from 15 minute to 4 hour intervals) both brings considerable privacy benefits and reduces the required number of iterations by 21%, for a 15% reduction in objective value performance. Such outcomes show the potential of TA in energy management, even when aggregating to a significant extent. The presented findings indicate that knowledge of rough trends of power profiles is more important than knowledge of fine details.

In conclusion, TA decreases privacy sensitivity of shared data. Additionally, TA reduces optimization problem complexity. This not only reduces the required number of iterations of the presented DSM algorithm, but also results in an improved convergence time. Based on our results, we recommend using the mean, median or random selection method when applying TA to improve energy management implementations.

In future work, we plan to do a theoretical analysis of the suitability of different TA methods for other types of optimization problems.

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