Exploring household's flexibility of smart shifting atomic loads to improve power grid operation and cost efficiency

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Abstract— **This paper explores the possibilities of shifting certain household consumer-based loads in time, to reduce unnecessary load peaks to the grid which again can cause challenges for Distribution System Operators (DSOs). Historical measured data on household consumption and the consumption profile of certain household appliances (dishwashers, washing machines and dryers) that can be shiftable in time are being used in an optimization model to investigate the potential that shifting these loads may have on the overall grid consumption of aggregated groups of households. The results indicate that such a model is a viable approach to effectively lower the peak load with respect to these appliances, even with consumer behavior and the inconvenience to perform these shifts accounted for. However, the contribution of the considered household appliances is arguably modest with respect to the total load of the household.**

***Index Terms*-- household flexibility, consumer demand, shiftable atomic loads, smart grid, optimization model**

I. INTRODUCTION

Distribution System Operators (DSOs) face increasing challenges maintaining a balanced and sustainable grid network due to a number of reasons, such as the introduction of non-dispatchable renewable production, volatile consumer consumption patterns and new appliances causing the peak load (the hour of the day with the highest load) to increase more than the energy consumption. The objective of this work is to assess the load smoothing potentials from shiftable atomic loads, such as washing machines, dryers and dishwashers. Atomic loads can be shifted in time, but once running they need to finish the process before they can stop. Consequently, their load profiles are fixed and cannot be interrupted after they start operating.

Based on empirical data on timing and load consumption of atomic loads, atomic load profiles and operation patterns are characterized in [1]. They describe a method for estimation of load shifting potential from the atomic loads of 100 households independent of the overall household loads. All atomic loads within a given time interval are jointly delayed to the same succeeding time interval, showing a load smoothing potential but at the risk of a rebound effect. Several studies address more general load scheduling problems, such as [2] who address scheduling of residential appliances including atomic loads. They emphasis that load scheduling are influenced by multiple incentives: minimization of electricity cost, peak load reduction and consumer behavioral preferences. An optimization model is used to assess how the balancing of these incentives affect load scheduling of 1-3 households.

The study presented in this paper uses an optimization model to schedule the atomic loads as part of the total load of 102 households. We estimate the load smoothing potential from atomic loads relative to the overall household loads in high load periods and assess how consumer preferences affect this potential. After the nomenclature, the following section describes the method used, including the data and optimization model. Next, the case study and the results are described, discussed and concluded upon.

II. NOMENCLATURE

TABLE I - INDICIES

a	Atomic load a	$\forall a \in A$
c	Consumer c	$\forall c \in C$
h	Hour h	$\forall h \in H$
d	Day d	$\forall d \in D$
y	Year y	$\forall y \in Y$
s	Time step s of atomic load a	$\forall s \in S_a$

TABLE II – SETS AND RANGES

A	Set of atomic loads	$A = 1,..,\|A\|$
C	Set of consumers	$C = 1,..,\|C\|$
H	Range of hours	$H = 1,..,\|H\|$
D	Set of days	$D = 1,..,\|D\|$
Y	Set of years	$Y = 1,..,\|Y\|$
S_a	Duration of atomic load a [h]	$\forall a \in A, S_a = 1,..,\|S_a\|$

TABLE III - VARIABLES

$l_{shifted}^{c,h,d,y}$	The new shifted load in hour h, day d, year y	kWh
$l_{total}^{c,h,d,y}$	The total load in hour h	kWh
$l_{peak}^{d,y}$	The peak load hour for all h in H, day d, year y	kWh
$\beta_{shifted}^{a,c,h,d,y}$	A binary indicator of atomic load a from consumer c shifted to start in new time step h, day d, year y	{0,1}
$p_{inconvenience}^{d,y}$	The penalty on the inconvenience of shifting atomic load for all atomic loads by all consumers in day d, year y	-
$l_{shifted}^{c,h,d,y}$	The new shifted load in hour h, day d, year y	kWh

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TABLE IV - PARAMETERS

$L_{initial}^{c,h,d,y}$	The initial load in hour h, day d, year y	kWh
$L_{fixed}^{c,h,d,y}$	The fixed part of the initial load in hour, h, day d, year y	kWh
$L_{atomic}^{a,s}$	Atomic load a in period s	kWh
$A_{initial}^{a,c,h,d,y}$	Number of initial starts of atomic load a by consumer c in hour h, day d, year y	$\mathbb{Z}$
$H_{allowed}^{h}$	A binary indicator of allowed hours to start atomic loads	{0,1}
$P_{inconvenience}^{a,c,h}$	A constructed penalty on the inconvenience of shifting atomic load a for consumer c in hour h	-

III. METHOD

A. Data

1) Historical household consumption data

Electricity consumption at more than 100 individual consumers in a town in Mid Norway has been metered on an hourly basis, for a duration of six years (from 2007-2012). After removal of consumers where measurement errors could be suspected or where the patterns were clearly not in line with the electricity consumption of households, 102 time series constitute the household data used in this study. We believe this provide an extensive and trustworthy representation of the usage of power from households both individually but also as an aggregated group in the same regional area. As the study focus on peak load reduction, we have used the workdays from the week with the highest average aggregated consumption from each of the years, corresponding to 30 days. See Fig. 10 in the appendix for a graphical overview of this data.

2) Household appliance data

Based on the same empirical data set on atomic loads (dishwashers, washing machines and dryers) as presented in [1] the daily and hourly probability of start for each of the atomic loads are calculated, see Fig. 1.

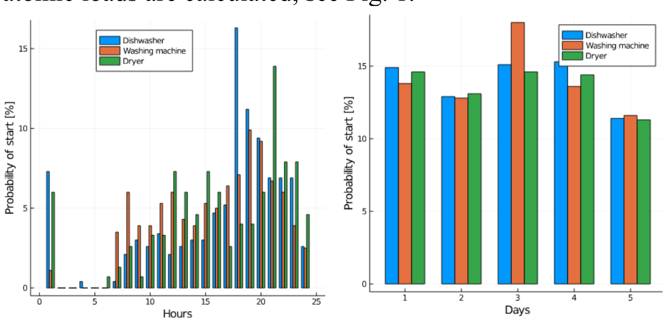

Fig. 1 - Daily and hourly probability distributions of household appliances

[3] and [4] have conducted comprehensive studies of consumer behavior for cloth washing and drying and dishwashing, respectively, based on surveys in selected European countries. [3] find that the average number of washing cycles per week in Sweden, which we assume is most closely comparable with Norway, is 3.5. During winter, 31% of the drying cycles are done with tumble dryer, giving 1.1 drying cycles per week. [4] find the number of dishwashing cycles per week to depend on the number of persons in the household. Interpolating from their numbers using the average household size in Norway, which is 2.16 according to [5], gives 4.2 dishwashing cycles per week. We use the average load profiles of atomic loads in Table V, which are taken from [1] and aggregated to hourly resolution.

TABLE V - AVERAGED HOURLY CONSUMPTION DATA OF ATOMIC LOADS

Hour	Atomic load [kWh]		
	Dishwasher	***Washing machine***	***Dryer***
1	0.801117	0.63815	1.044
2	0.26815	0.142133	0.32375

B. Sampling and identifying atomic loads from data

One of the motivations for investigating the potential of reducing aggregated household's peak load by shifting atomic loads is illustrated in Fig. 2, where we see a clear correlation between the peaks of load consumption for aggregated household scenarios and the distribution of probabilities for starting the atomic household appliances.

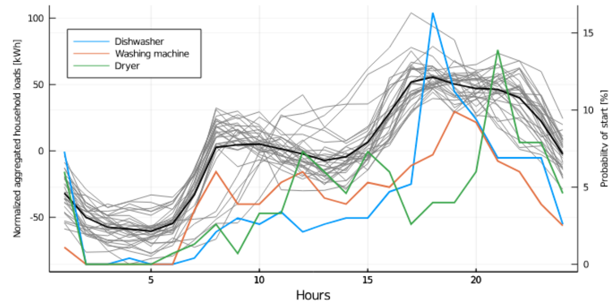

Fig. 2 - Normalized aggregated household loads vs. hourly probability distribution of household appliances

We use the data on household appliance use patterns to randomly sample an initial state of atomic load starts that yield a possibly shiftable load. The initial load is then divided into a fixed part and a shiftable part, the latter to which the optimization model can change to another hour or not.

C. Consumer behaviour assumptions

In a DSO perspective, with the incentive to minimize the peak to average load ratio, the optimal load shifting could be found by an automated, central dispatch planner. In order to model a real-life environment however, we need to introduce certain assumptions regarding consumer behavior.

1) Unavailable hours

Firstly, [4] find some reluctance to run dishwashers during night due to disturbance. This observation can also be found for all appliances in Fig. 1. We conclude that hours 2-6 are considered as too inconvenient to shift load onto, thus we mark them as unavailable. The sampled initial atomic starts are also highly unlikely to be allocated to this period due to the probability of start close to zero

2) Inconvenience as a function of initial start deviation

Secondly, we also assume a certain inconvenience factor for the consumer for shifting their loads. [2] represent this with an inconvenience index counting the number shifted loads. We use a similar idea, but assume the inconvenience not only depends on whether a shift is taken, but also how many hours the load is shifted. We model a linear inconvenience function where the inconvenience to shift the load increases linearly with a factor of 0.1 per hour away from the initial start hour.

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D. Mathematical formulation of optimization model

The optimization model that follows is generically defined in order to iterate over dy scenarios, where d is the number of weekdays consisting of H hours, and y the number of years consisting of D days. This means it is applicable for both a single instance of one day, but also able to produce aggregated results. We will utilize both aspects of this when analyzing the results.

$$\min l_{peak}^{d,y} + \sum_{\forall a\in A,\forall c\in C,\forall h\in H} P_{inconvenience}^{a,c,h}\,\beta_{shifted}^{a,c,h,d,y} \qquad \forall d\in D,\forall y\in Y \tag{1}$$

The objective function (1) aims to minimize the peak load of the aggregated load by all consumers for each daily scenario, taking a penalty on the consumer's inconvenience load shifting into account.

$$l_{total}^{c,h,d,y} = L_{fixed}^{c,h,d,y} + l_{shifted}^{c,h,d,y} \qquad \forall c\in C,\forall h\in H,\ \forall d\in D,\forall y\in Y \tag{2}$$

Equation (2) makes sure not to alter the total load during the day, summing up the pre-calculated fixed part of the initial load with the new, optimized shifted atomic loads.

$$l_{shifted}^{c,h,d,y} = \sum_{a\in A,\forall s\in S_a} L_{atomic}^{a,s}\,\beta_{shifted}^{a,c,(h-s+1),d,y} \qquad \forall c\in C,\forall h=S_a,\ldots,H,\ \forall d\in D,\forall y\in Y \tag{3}$$

(3) ensures that the atomic load is distributed correctly over its two-hour period.

$$l_{shifted}^{c,h,d,y} = \sum_{a\in A,s=1,\ldots,|H|} L_{atomic}^{a,s}\,\beta_{shifted}^{a,c,(h-s+1),d,y} + \sum_{a\in A,s=1,\ldots,|H|} L_{atomic}^{a,|S_a|}\,\beta_{shifted}^{a,c,|H|,d,y} \qquad \forall c\in C,h=1,\ \forall d\in D,\forall y\in Y \tag{4}$$

Because we consider a 24-hour time period but we have atomic loads that lasts two hours with the possibility of starting the load at hour 24, (4) creates a cyclic link that places the second hour of the atomic load in hour 1, should it be defined to start in the last hour of the day.

$$\sum_{\forall h\in H} \beta_{shifted}^{a,c,h,d,y} = \sum_{\forall h\in H} A_{initial}^{a,c,h,d,y} \qquad \forall a\in A,\forall c\in C,\ \forall d\in D,\forall y\in Y \tag{5}$$

Equation (5) ensures that there is exactly the same amount of atomic loads between the initial sampling and the optimized results for each household appliance, consumer, hour, day and year.

$$l_{peak}^{d,y} \geq \sum_{\forall c\in C} l_{total}^{c,h,d,y} \qquad \forall h\in H,\forall d\in D,\forall y\in Y \tag{6}$$

(6) enforces the variable in the objective function, declaring that the total load for each hour should be considered as a possible peak load.

$$\beta_{shifted}^{a,c,h,d,y} \leq H_{allowed}^{h} \qquad \forall a\in A,\forall c\in C,\forall h\in H,\forall d\in D,\forall y\in Y \tag{7}$$

Finally, constraint (7) ensures that only the allowed hours are used when shifting the atomic loads, i.e. not at night.

IV. CASE STUDY

The data discussed in chapter III.A is the basis for the case study. However, as we are considering 30 different days worth of data over 6 different years with no direct coupling in time, we choose to run the model iteratively over these 30 individual scenarios, and to mainly look at the aggregated results and trends not on a single scenario, but on the scenarios combined. Nevertheless, we choose also to investigate certain behavior on a single scenario to better understand the results.

A. Benchmark case

To establish a benchmark of the theoretical potential for peak reduction by load shifting, we define an initial setting of model parameters that do not consider consumer preferences, such as their inconvenience when rescheduling their atomic loads and which hours that are likely to be considered unavailable.

B. Practical case

After the initial benchmark is defined, we introduce the parameters of consumer preference, which in term give insight to the potential such a model can actually have if implemented in practice.

C. Individual case

Lastly, in order to observe the details of a single scenario (i.e. a single day), we choose the practical scenario with the most reduced peak load to further investigate individual behavior of the model before they get aggregated and averaged.

V. RESULTS

A. Theoretical peak reduction potential (benchmark case)

When considering the optimal potential of atomic load shifting without any user constraints, we observe a high level of shifted load from the initial sampled starts based on probabilities described in section III.A.2). See Fig. 3, including a yearly output.

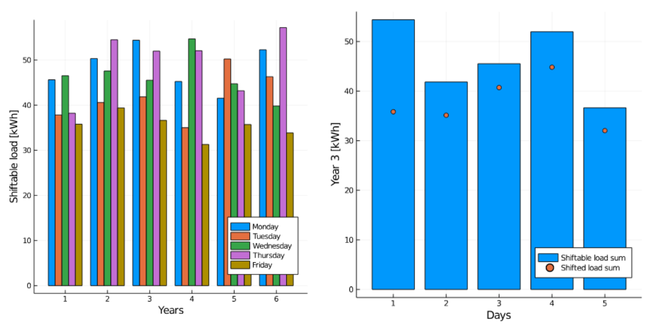

Fig. 3 - Shiftable loads from all initial load scenarios and the portion of the shifted load from days in year 3 for the benchmark case

We calculate an average daily shiftable load of 44.33 kWh, whereas an average of 36.49 kWh are shifted per scenario. This translates to shifting 82.32% of the initial sampled atomic loads into new suggested start times. If we look at the initial peak load of the system compared to the peak load after the optimal re-ordering of atomic loads, we see a reduction in all scenarios as displayed in Table VI.

TABLE VI - PEAK LOAD REDUCTIONS FOR ALL BENCHMARK SCENARIOS

Peak load reduction	**Mon**	**Tue**	**Wed**	**Thu**	**Fri**
Average [kWh]	3.39	3.23	4.56	4.14	4.07
Total [kWh]	16.96	16.14	22.79	20.73	20.35
Max [kWh]	5.03	4.52	5.43	6.07	4.06

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On average, we calculate a daily peak load reduction of 3.23 kWh which translates to 1% of the initial load. There are no clear differences between the weekdays, supporting a more or less uniform behavior from Monday to Friday. When investigating where the atomics load shift from and to, there is a clear trend to shift almost all load to the first hours of the day, as assumed, given the objective of the model is to minimize the peak load, illustrated in Fig. 4.

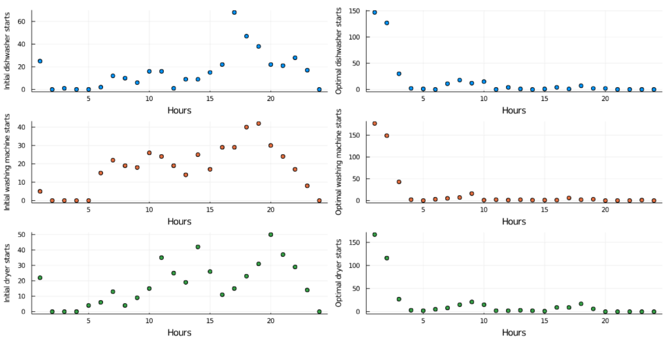

Fig. 4 – Initial and optimal starts of atomic loads for the benchmark case

This is explainable by the shape of the aggregated load curve for all scenarios in Fig. 2, which has its lowest value in the first hours of the day. The reason it does not necessarily fill up the hours with the very lowest load is simply that it does not matter to the model, as long as the peak load has been reduced. The model has sampled 1238 initial atomic starts whereas 1111 of them has been changed, translating to 90% of all initial starts.

B. *Peak reduction potential with consumer inconvenience penalty and hours unavailable to shift to (practical case)*

To model assumed consumer preferences, we need to introduce certain restrictions to the model. Thus, we enforce that atomic loads cannot start in hours 2-6. Additionally, we introduce an inconvenience function that penalizes the model's objective linearly with respect to how far apart the atomic load is shifted from its initial position. With an inconvenience penalty and restrictions on hours, we observe the total shifted load to decrease to 412.61 kWh (68.76 kWh on average weekly and 13.75 kWh on average daily), whilst the percentage of the total shifted load from the total shiftable load is reduced to 31.02%, as per Fig. 5, which also includes a yearly selection.

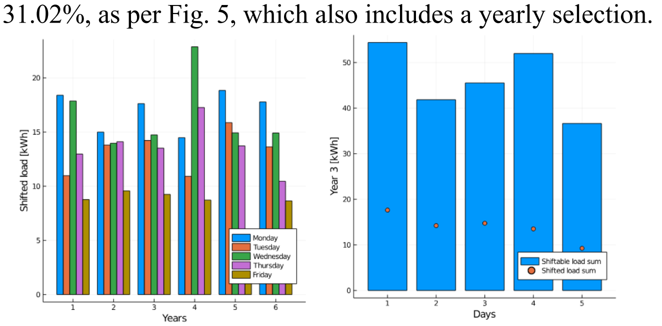

Fig. 5 - Total shifted load for all scenarios and the comparison towards the shiftable load for year 3 for the practical case

In *Fig. 6* we also identify a clear difference between the runs when comparing the optimal new starts of the atomic loads, yielding a more reasonable and balanced distribution of the loads over the hours allowed to be shifted towards. Out of the 1238 sampled initial atomic loads, 622 where shifted, equaling exactly 50.0%. However, the peak load reduction is unchanged from the less restricted solution, resulting in the same amount of reduction for all scenarios. This is due to it being enough capacity in the allowed hours for the atomic loads in peak hours to be shifted.

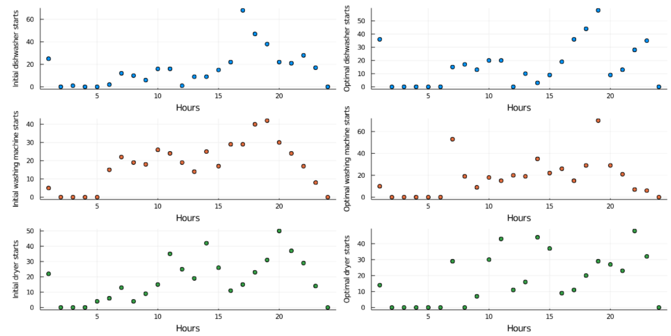

Fig. 6 - Initial and optimal starts of atomic loads for the practical case

C. *Single result of day with most reduction in peak load (individial practical scenario)*

Looking at the scenario with the most reduction in peak load (year 3, day 4, equivalent to Thursday, 31.12.2009), we observe that the new total load has decreased compared to its initial level. See Fig. 7.

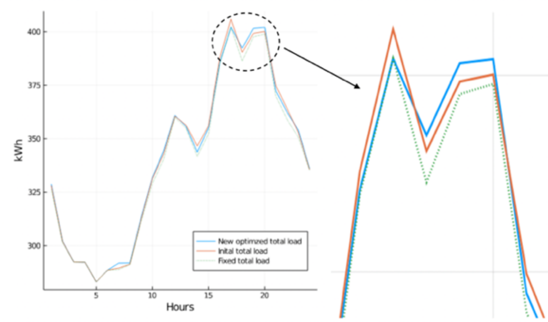

Fig. 7 – Load comparisons for the individual case (year 3, day 4)

Hour 17 is the peak hour defining the results as it is reduced to its maximum potential, which is to the level of the fixed load that hour. Fig. 8 displays all the changed hourly loads.

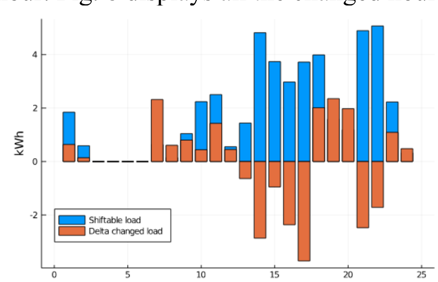

Fig. 8 – Delta changed load overlayed against the shiftable load for the individual case (year 3, day 4)

Most of the shifted load has been added to hour 15 and 23, which has been close enough to the hours with the highest load so that the inconvenience penalty is modest. Additionally, the

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movement of atomic starts for this scenario has a pattern accordingly. See Fig. 11 in the appendix for details.
Again the model does not see any difference in where to put the new load as long as the inconvenience penalty is the same and the total load for that hour does not become a new peak load itself. For this scenario, we see 15 initial starts, whereas 10 of them are shifted, yielding 67% of all initial sampled starts to be shifted.

VI. Discussion

A. Peak load reduction potential only slightly reduced by consumer preferences

The difference between the theoretical potential and a solution considering the consumer preferences are neglectable when it comes to peak load reduction. This can be a pin-point towards realizing that the right incentives towards consumers can support a realization of the peak reduction effect even though a highly centralized control mechanism is usually not applicable in real-life. This observation could be strengthened or given more nuances if empirically based knowledge was available on to what hours consumers prefer to shift their load if deviating from today's pattern.

B. Reducing the single highest peak hour is a viable strategy to a certain extent

This model's objective function is targeting minimizing the peak load for a 24 hour period, i.e. a calendar day. The consecutive hour reduced after the peak load hour is not optimally chosen by the model as long as the objective is defined as mentioned. When investigating the delta between the initial peak load hour and the initial second largest load hour for all aggregated scenarios, we observe an average value of 6.28 kWh, with most scenarios being above the average peak load reduction of 3.21kWh from the model. This observation can give insight to how much more shiftable load that it is possible to model with the current objective. See Fig. 9.

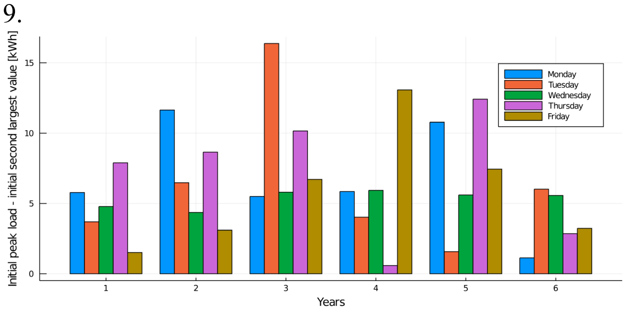

Fig. 9 – Delta between initial peak load and initial second largest value

In other words, it would in most cases be more relevant to consider the consumer's pattern of inconvenience or other equivalent factors than it would be to carefully consider which hour the new load reduced from the peak hour is shifted to (unless the hour shifted to becomes the new peak load hour, which then requires new iterations by the model).

This becomes a leading strategy up until approximately twice the amount of the current reduction potential. One can analyze these results as a theoretical exercise on initial load data without applying any model or algorithms, to determine the single-hour peak load reduction potential and compare it to the magnitude of loads one wants to shift. If the sum of loads is less than this delta value, they will not alone be enough to fulfill this approach's potential, and opposite, if the sum of loads exceeds the delta value, a more extensive objective needs to be considered.

C. The impact of atomic loads on the total household load are modest

The investigated atomic load's importance with respect to the total load may be discussed, based on the values in Table VII.

Table VII – Average and max peak load vs. peak load reduction

	Average	Maximum
Peak load [kWh]	382.02	454.78
Peak load reduction [kWh]	3.21	6.07

They translate to an average reduction of the peak load of 1%, which is arguably modest considering the total load as a whole. The underlying data on both the household loads and the consumer's usage of the three considered household appliances are considered solid, concluding that in order for this method to have an increased effect on the total load, additional appliances or loads need to be considered and implemented. The willingness to delay or expedite the usage of other high power household loads normally found used in peak hours such as cooking appliances can be assumed more difficult to find sufficient incentives on as of today, but with upcoming increased resolutions on spot markets (i.e. 15 minute price blocks) and a more transparent and easily accessible way of communicating this price information in combination with ways to (smarter) control new appliances accordingly, there might still be further potential to reduce peak loads by shifting atomic and non-atomic loads in a similar way as this model proposes. Utilizing an approach comparable to this on i.e. electric vehicles is a well-proven commercialized solution already use[1] because of its larger shiftable load demand which again incentivizes the consumers and the industry to a higher degree.

VII. Conclusion

By smarter shifting atomic loads from peak load hours, taking consumer behavior and inconvenience into account through an optimization model, we are able to reduce the peak load of aggregated households in all scenarios in all our case studies. We observe that the peak load reduction potential of this model approach is approximately twice the magnitude of the current atomic load, meaning that the peak hour could be further reduced given similar household appliances that one can assume shiftable in time. At the same time, we also conclude that the impact of these atomic loads on the aggregated household load as a whole is modest.

[1] https://tibber.com

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APPENDIX

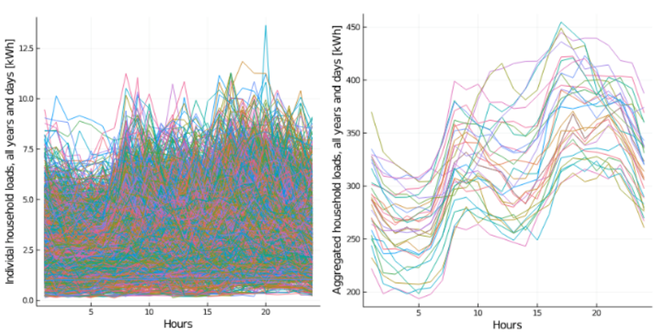

Fig. 10 - Individial and aggregated household loads for all scenarios

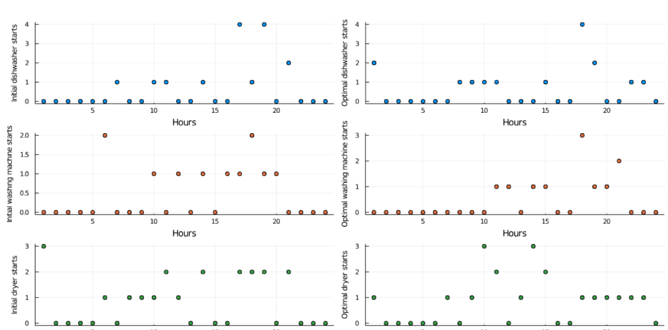

Fig. 11 - Initial and optimal starts of atomic loads for the individual case

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