Load Profile Negotiation for Compliance with Power Limits in Day-Ahead Planning

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***Abstract*—The variability of electrical energy prices at the spot market incentivizes cost-optimized load scheduling. Based on day-ahead price forecasts, energy costs can be considerably reduced by shifting energy-intensive processes to times with lower energy prices. While the mechanism of the market match demand and supply, they currently do not consider technical limitations of the electrical power grid. A large number of consumers scheduling electrical loads according to the same price forecast could result in congestion in the transmission or distribution systems.**

We propose a mechanism for day-ahead scheduling that enables negotiation of load profiles between multiple consumers and an aggregator in compliance with overall power limits. We present two mechanisms for an aggregator without knowledge about internal details of the participants to achieve this goal and compare the performance to the results of a centralized scheduler with global knowledge.

***Index Terms*—Smart grids, demand-side management, scheduling, virtual power plant.**

I. Introduction

The increasing share of weather-dependent renewable power generation leads to a large intraday variability of wholesale energy prices. Shifting loads to times with lower energy prices can considerably reduce energy costs and helps to increase the use of renewable energy by improving the match of demand and supply. Schedules of multiple consumers optimized for the same price forecast can lead to extreme load peaks. The mechanisms of the energy markets match the demand peaks and the production peaks, so the optimization of schedules based on price forecasts could be beneficial for both the generation and consumption domains. However, it can lead to problems in the transmission and distribution domains as there is no guarantee that the physical grid is capable of transporting the purchased energy volumes from generators to the consumers.

We proposed a distributed control architecture for virtual power plants [1] where participating enterprises locally optimize their load schedules according to price forecasts provided by an aggregator. The aggregator trades energy at the spot market on behalf of the participating enterprises. However, if the combined load profiles of a set of enterprises violate any constraints, the aggregator needs to negotiate re-scheduling with the affected enterprises.

In this work we propose mechanisms for a set of business units to negotiate load profiles that reduce energy costs while avoiding the violation of restrictions imposed by bottlenecks in the power grid.

This paper is structured as follows. Section II discusses related work. In Section III we present the context for the optimization and an abstract model for enterprises with load shifting capabilities. Section IV proposes two mechanisms for load profile negotiation. In Section V we shows the scenario and parameters for the evaluation and in Section VI we evaluate the performance of the negotiation mechanism and compare its results to an centralized scheduling approach with global knowledge. Section VII concludes the paper.

II. Related Work

Ibars et. al. present a distributed load management using dynamic pricing [2]. The approach is based on a network congestion game. The authors show that the system converges to a stable equilibrium. Biegel et. al. [3] describe a receding horizon control approach for moving shifting loads to minimize costs for balancing energy while avoiding grid congestion. Huang et. al. [4] propose a congestion management method for distribution grids with a high penetration of electrical vehicles and heat pumps. They use a decomposition-based optimization. In [5] they present a real-time approach for congestion management using flexible demand swap. Boroojeni et. al. [6] propose an oblivious routing economic dispatch approach for distribution grids. Bagemihl et. al. [7] describe a market-based approach to increase the capacity of a distribution grid without physical grid expansion. Hazra et. al. [8] propose a demand-response mechanism for grid congestion management using ant colony optimization. Sundström and Binding [9] propose a method for the optimization of charging schedules for electric vehicles while avoiding grid congestion.

Most work in the area of grid congestion management is based on actual grid topologies and focuses on global optimizations to avoid grid congestion. This paper uses a simplified approach, limiting congestion to a single bottleneck and focuses on interactive negotiation without global knowledge.

III. Model

In this section, we present the use case. We explain the concept of load profiles and define the parameters for the consumer model.

A. Use Case

The grid connection of a consumer is limited in electrical power by technical or contractual means. We denote this limit as l_c where c is a consumer. Due to limitations in the distribution grid, similar restrictions apply to groups of consumers, e.g., urban districts. As the sum of all individual power limits can be larger than the limit for the group, a group of consumers could exceed the group power limit L while still complying with their individual limits, i.e., $\sum_{c \in \mathcal{C}} l_c > L$ where $\mathcal{C}$ is a set of consumers. This problem becomes more severe in presence of price-optimized day-ahead planning when loads of all flexible consumers are scheduled for the times with the lowest energy price forecasts. However, day-ahead planning usually involves an aggregator providing the forecasts and trading at the energy markets. As an aggregator requires load forecasts of all aggregated consumers, we propose a mechanism for day-ahead demand-side management (DSM) within the group the aggregated consumers.

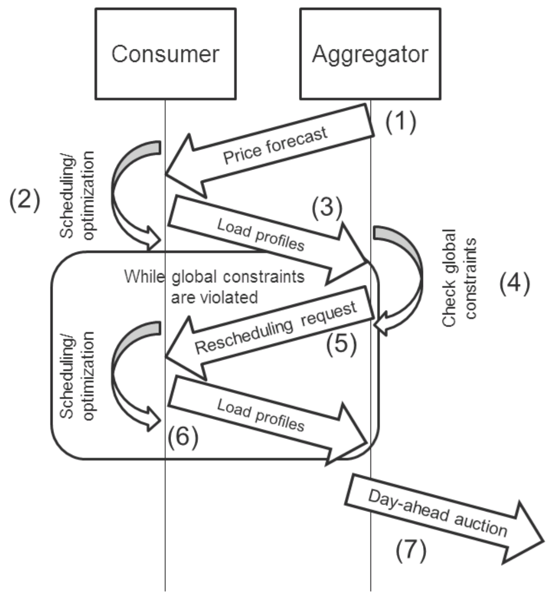


Fig. 1: Negotiation process between enterprise and aggregator during day-ahead planning.

Figure 1 shows the negotiation process to ensure that limitations for a group of consumers are complied with. The aggregator distributes price forecasts for the day-ahead energy market to the aggregated consumers (1). Each consumer computes price-optimized schedules based on their model parameters using the price forecast received from the aggregator (2). After the best schedule is selected, the consumers send the load profiles to the aggregator (3). After receiving load profiles from the consumers, the aggregator checks global constraints (4). An example for a global constraint is a cumulative power limit for a group of participants imposed by the grid operator. If such a constraint is violated, the aggregator sends a rescheduling request to the affected groups or individual participants (5). The affected consumers perform planning and optimization based on additional information provided by the aggregator and submit new load profiles (6). Steps (4)–(6) are repeated until the global constraints are no longer violated. Finally, energy is traded at the day-ahead market (7).

B. Consumer Model and Load Profiles

A load profile is a time series of electrical load over a given period. As we focus on day-ahead optimization, we chose a period of 24 hours and a granularity of one hour. A time slot is denoted as t and the set of the time slots of a day is defined as $\mathcal{T} := \{0, \ldots, 23\}$. We denote the load profile of a consumer c as e_c^t, $t \in \mathcal{T}$, with an energy demand for each hour of a day. The total energy demand of all consumers in time slot t is limited by the group power limit L^t.

For our study we use an abstract model of a business consumer with flexibility for load shifting. We do not consider internal organization and dependencies among processes within a consumer, but limit the model to energy and cost parameters. The consumer is defined by a daily demand of electrical energy E_c, a power limit l_c^t, and operational costs A_c^t. The objective is to find a set of load profiles $e_c^t, t \in \mathcal{T}$, that satisfy the following conditions.

$$\sum_{t \in \mathcal{T}} e_c^t = E_c \;\forall c \in \mathcal{C} \tag{1}$$

$$e_c^t \leq l_c^t \;\forall t \in \mathcal{T}, c \in \mathcal{C} \tag{2}$$

$$\sum_{c \in \mathcal{C}} e_c^t \leq L^t \;\forall t \in \mathcal{T} \tag{3}$$

Each load profile is associated with costs. F^t is the energy price forecast for time slot t. A_c^t gives the additional (non-energy) operation costs of a consumer c in time slot t. The total costs C_c for a consumer c are given by

$$C_c = \sum_{t \in \mathcal{T}} e_c^t \cdot F^t + A_c^t. \tag{4}$$

IV. Mechanisms

In this section, we present a linear program that computes load profiles for each participant resulting in the lowest total costs while complying with the group power limit. The linear program needs global knowledge, i.e., it requires information about internal details such as cost structures of all participants to compute the solution. However, aggregator operation without such global knowledge of internal details about the participating enterprises is an explicit goal of [1]. Therefore, we propose two methods for load profile negotiation that work without global knowledge. The sequential approval method is based on a first-come-first-serve approach combined with a compensation for swapping time slots. The simultaneous approval method requests multiple load profiles per participant to find an acceptable combination of load profiles.

A. Load Optimization Using Global Knowledge

The load profiles $e_c^t, t \in \mathcal{T}, c \in \mathcal{C}$ consist of continuous variables that can be determined by the following linear program.

$$\begin{aligned}
\text{minimize} \quad & \sum_{t=0}^{23}\sum_{c\in\mathcal{C}} F^t e_c^t + A_c^t \\
\text{subject to} \quad & \sum_{c\in\mathcal{C}} e_c^t \le L^t, && t\in\mathcal{T} \\
& \sum_{t=0}^{23} e_c^t = E_c, && c\in\mathcal{C} \\
& e_c^t \le l_c^t, && t\in\mathcal{T}, c\in\mathcal{C} \\
& e_c^t \in \mathbb{R}, && t\in\mathcal{T}, c\in\mathcal{C}
\end{aligned}$$

B. Sequential Approval of Load Profiles

For the sequential approval method, each submitted load profile is individually approved after submission unless its load combined with the previously approved load profiles would exceed the group power limit. To resolve the violation, all participants with acknowledged energy demand in the respective time intervals compute alternative load profiles avoiding the overloaded time slots $t \in \mathcal{T}'$. They submit load profiles annotated with the additional costs resulting from higher energy prices or increased operation costs in alternative time intervals. The aggregator selects the combination of load profiles with the lowest total additional costs. The process is repeated until a load profile for each participant is approved.

A linear program is used to find an appropriate combination of load profiles. The load profiles are selected such that the sum of the additional costs, i.e., the differences between the respective cheapest load profiles, of all enterprises is minimized. If every consumer c hands in n_c load profiles, let x_c^i be a binary variable which is true iff the i-th schedule of enterprise $c \in \mathcal{C}$ is selected. Furthermore, let $e_c^{t,i}$ be the energy demand of load profile i of consumer c in slot t, C_c^i the total cost of consumer c for load profile i and L^t the group power limit of slot t.

$$\begin{aligned}
\text{minimize} \quad & \sum_{c\in\mathcal{C}}\sum_{i=1}^{n_c} (C_c^i - C_c^1)\cdot x_c^i \\
\text{subject to} \quad & \sum_{i=1}^{n_c} x_c^i = 1, && c\in\mathcal{C} \\
& \sum_{c\in\mathcal{C}}\sum_{i=1}^{n_c} e_c^{t,i} x_c^i \le L^t, && t\in\mathcal{T} \\
& x_c^i \in \{0,1\}, && c\in\mathcal{C}, i=1,...,n_c
\end{aligned}$$

The inequations ensure that every consumer has exactly one schedule approved and that the group power limit is not exceeded in any time slot.

The participant triggering the violation compensates additional costs for participants with approved load profiles or selects a different load profile if costs are lower compared to the required compensation. While a participant can exaggerate the additional costs to generate additional revenue from rescheduling, higher costs lead to a lower chance for a load profile to be selected by the aggregator or accepted by the participant that triggers the violation.

C. Simultaneous Approval of Load Profiles

For the sequential approach the order of load profile submissions is important. Therefore late submissions of load profiles are penalized and the cost increase is distributed unevenly among the participants. This might lead to acceptance problems and prevent some enterprises from participating.

A straightforward implementation of an order-agnostic negotiation method consists of iterative energy price increases for the overloaded time slots and requests for new load profiles from all participants. However, this approach leads to artificially high energy prices and experiments showed that it fails to resolve violations for low group power limits while the sequential approval method still succeeds. Therefore, we propose a simultaneous approval method that works without modified price forecasts.

The aggregator checks for limit violations after all participants have submitted load profiles. In case of a limit violation the aggregator requests an alternative schedule from all participants, indicating the affected time slots $t \in \mathcal{T}'$. With the original load profiles and the alternative load profiles, the aggregator computes a combination not exceeding the limits. If such a combination does not exist, the aggregator repeatedly increases the number of requested load profiles per participant until there is a combination of load profiles that complies with the limits. The participants annotate the list of submitted load profiles with a preference.

The optimal selection of load profiles is computed using a linear program. If every consumer hands in n load profiles, let x_c^i be a binary variable which is true iff the i-th schedule of enterprise $c \in \mathcal{C}$ is selected. Furthermore, let $e_c^{t,i}$ be the energy demand of load profile i of consumer c in time slot t, C_c^i the total cost of consumer c for load profile i and L^t the group power limit of slot t.

$$\begin{aligned}
\text{minimize} \quad & \sum_{c\in\mathcal{C}}\sum_{i=1}^{n} i\cdot x_c^i \\
\text{subject to} \quad & \sum_{i=1}^{n} x_c^i = 1, && c\in\mathcal{C} \\
& \sum_{c\in\mathcal{C}}\sum_{i=1}^{n} e_c^{t,i} x_c^i \le L^t, t\in\mathcal{T} \\
& x_c^i \in \{0,1\}, && c\in\mathcal{C}, i=1,...,n
\end{aligned}$$

The weighting of load profiles by the number i gives the load profiles a preference by the order of submission. The consumer $c \in \mathcal{C}$ indicates that a load profile $e_c^{t,i}$ is preferred over a load profile $e_c^{t,i+1}$.

V. Evaluation Model

In this section we describe company-specific operational costs and day-ahead forecasts used in our experiments. Finally, we point out how load profiles are calculated for companies that participate in the negotiation processes described in Section IV-B and Section IV-C.

A. Operational Cost Factor

In the model described in Section III-B operating costs A_c^t can be given per time slot for each consumer. For our evaluation, we model the A_c^t as a dependency of the energy demand e_c^t and an operating cost factor $f_{o,c}^t$. We model the operational cost factor $f^t o, c$ of a consumer c using an interval of primary business hours and two intervals of secondary business hours. The primary business hours start at time slot t_c^p and its duration is d_c^p time slots. The secondary business hours are d_c^s time slots before and after the the primary business hours. During the primary business hours the operational cost factor is $f_{o,c}$ and $2 \cdot f_{o,c}$ during the secondary business hours. Outside of primary and secondary business hours operational costs are infinite, so business operation is not possible. The additional operational costs are given by the operational cost factor and the energy demand in the respective time slot: $A_c^t = f_{o,c}^t \cdot e_c^t$.

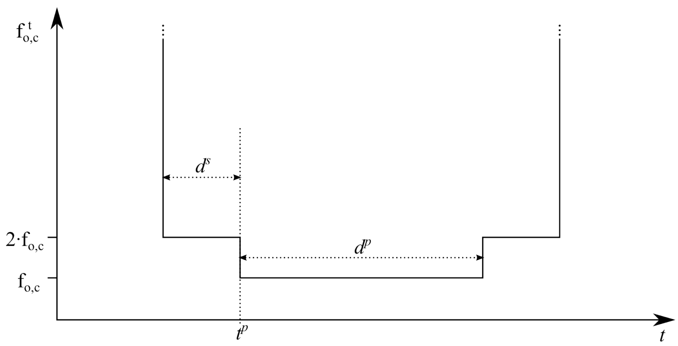


Fig. 2: Operation cost factor $f_{o,c}^t$ defined by parameters t_c^p, d_c^p, d_c^s, and n.

An example of operating costs over time defined by those parameters is given in Figure 2. The operating costs are twice as large during secondary business hours compared to primary business hours. During nonproductive hours, operating costs are infinite.

For our evaluation we chose $t_c^p \in \{7, \ldots, 11\}$, $d_c^p = 8$, and $d_s^c = 2$. We define four classes of consumers by $(E_c, f_{o,c})$, $E_c \in \{1200\,\text{kWh}, 3000\,\text{kWh}\}$ and $f_{o,c} \in \{500\,€/\text{MWh}, 1000\,€/\text{MWh}\}$. The individual power limit l_c^t is set to $\frac{E_c}{6}$ in all time slots. Each starting time slot t_c^p is used once per class resulting in a group size of 20.

B. Day-Ahead Price Forecast

The prices shown in Figure 3 are used as day-ahead price forecast. While the actual prices are fictitious, the price level and the development over the 24 hour period are typical for the German day-ahead energy market.

C. Local Load Scheduling

The total costs of a schedule arise from the energy costs associated with the load profile and the operation costs. The price forecast is given as F^t, $t \in \mathcal{T}$, where F^t is the predicted price per MWh during time slot t.

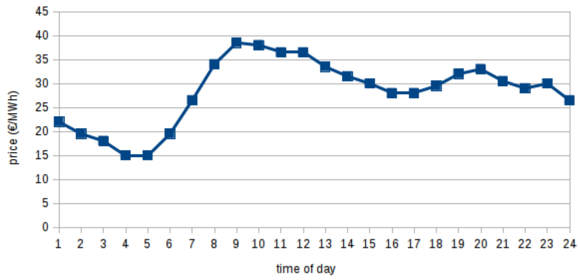


Fig. 3: Day-ahead energy price forecast.

Data: T_c^t for $0 \leq t < 24$, l_c^t, E_c
Result: e_c^t for $0 \leq t < 24$
$t[] :=$ list of times sorted ascending by value of T_c^t
$i = 0$
$E := E_c$
while $E > 0$ **do**
  if $E > l_c^t$ **then**
    $e_c^{t[i]} := l_c^t$
    $E := E - l_c^t$
  else
    $e_c^{t[i]} := E$
    $E := 0$
  $i := i + 1$
end

Algorithm 1: Cost-optimized local load scheduling.

As the hourly operation costs A_c^t in our scenario depend on the energy consumption the algorithm for producing cost-optimized schedules is straightforward. The scheduling is implemented using a greedy approach as shown in Algorithm 1. A scheduler first computes the total operation costs per kWh $T_c^t = F^t + f_{o,c}^t c$. At the time t with the lowest T_c^t, energy consumption e_c^t is set to the maximum allowed by l_c^t, proceeding with the second-lowest T_c^t and so on until $\sum_{t=0}^{23} e_c^t = E_c$. The total cost C_c of a schedule i is computed according to Equation (4).

For the computation of alternative load profiles, the consumers repeat Algorithm 1 with selectively reduced l_c^t for the affected time slots $t \in \mathcal{T}'$. For the sequential approval method, the consumers use $l_c^t = 0, \forall t \in \mathcal{T}'$. For the simultaneous approval method, the consumers reduce l_c^t for the affected time slots $t \in \mathcal{T}'$ by 1% iteratively.

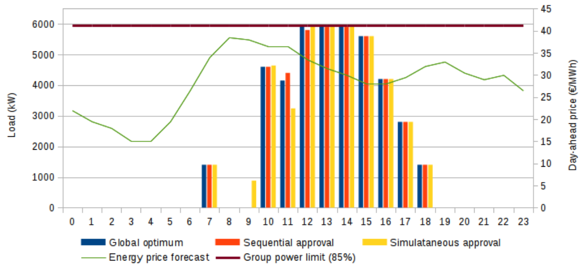
VI. Results

In this section we present the results of the evaluation. We show the load profiles resulting from sequential and simultaneous approval and compare them to the global optimum. In the evaluation scenario described in Section V, the sum of all individual power limits is given by $\sum_{c \in C} l_c^t = 7000\,\text{kW}\ \forall t \in \mathcal{T}$. We use relative group power limits of 85%, 65%, and 55%, corresponding to $L^t \in \{5950\,\text{kW}, 4550\,\text{kW}, 3850\,\text{kW}\}$ for all time slots. We show the cost increase compared to each

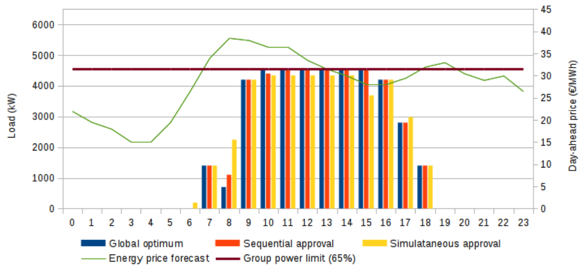
TABLE I: Relative total cost increase.

	Group power limit		
	5950 kW (85%)	4550 kW (65%)	3850 kW (55%)
Global optimum	0.03%	0.15%	4.40%
Sequential approval	0.07%	0.23%	6.01%
Simultaneous approval	0.04%	1.02%	12.12%

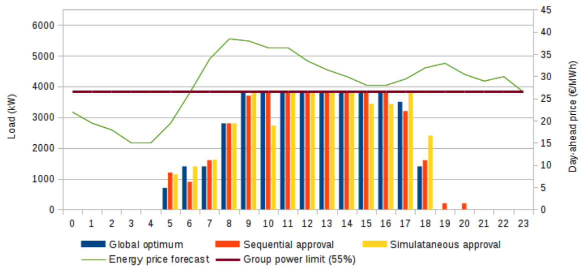
consumer's preferred load profile, which would be possible with a group power limit of $L^t = 7000\,\mathrm{kW}$. Finally we give an overview on the scheduling overhead caused by both mechanisms.



(a) Results for 85% relative group power limit.



(b) Results for 65% relative group power limit.

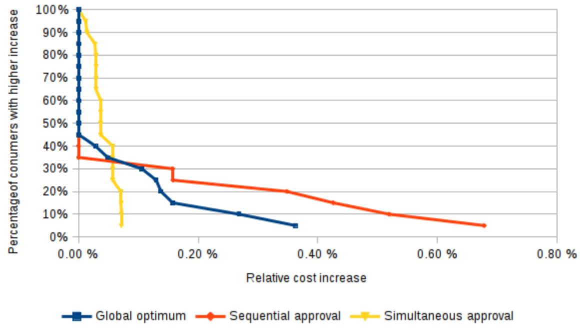


(c) Results for 55% relative group power limit.

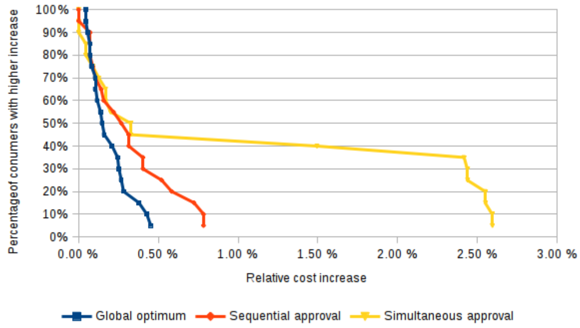
Fig. 4: Load profiles resulting from simultaneous approval, sequential approval, and global optimization at different group power limits.

A. Negotiation Results at 85% Relative Group Power Limit

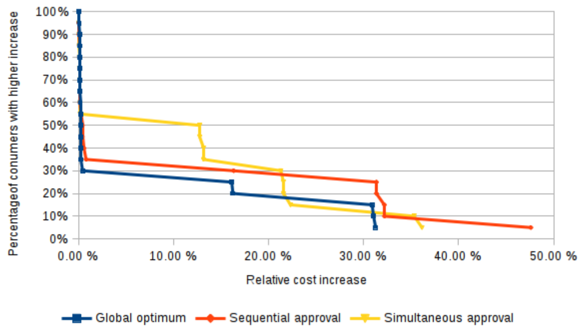
The results for the load profile negotiation at a group power limit of 5950 kW are shown in Figure 4(a). Both the sequential and simultaneous approval methods yield load profiles similar to the global optimum. The only major difference can be seen at the 9:00 time slot which is only selected in the simultaneous approval method. However, Table I shows only minimal differences regarding the increased costs. While the difference is negligible, the simultaneous approval method actually leads



(a) Results for 85% relative group power limit.



(b) Results for 65% relative group power limit.



(c) Results for 55% relative group power limit.

Fig. 5: Percentage of consumers with higher relative cost increase at different group power limits.

to lower increased costs compared to the sequential approval method. Figure 5(a) shows that no cost increase occurs for more than 50% of the consumers with the global optimum and the parallel approval method. With the simultaneous approval method, cost increase occurs for all consumers, while no consumer suffers from cost increase of more than 0.1%.

B. Negotiation Results at 65% Relative Group Power Limit

Figure 4(b) shows the results for the load profile negotiation at a group power limit of 4550 kW. While in most time slots the load is similar to the global optimum, larger differences can be seen at 6:00, 8:00, and 15:00. The sequential approval yields increased costs close to the global optimum as shown in Table I. While the increased costs caused by the simultaneous approval method exceed the optimum by a factor of 7, with approximately 1% they are still very low. However, according to Figure 5(b) the simultaneous approval method does not only lead to the highest cost increase but also to the most uneven distribution of the cost increase among the consumers.

C. Negotiation Results at 55% Relative Group Power Limit

The results for the load profile negotiation at a group power limit of 3850 kW are shown in Figure 4(c). The low group power limit compared to the total energy demand forces the consumers to shift more energy demand to the secondary business hours. Due to the additional costs, this leads to higher total costs. In Table I we can see that even the global optimum leads to an increase of approximately 4% compared to the preferred load profile of each consumer. The sequential approval method leads to an increase of 6%, and the simultaneous approval leads to an increase of approximately 12%. Figure 5(c) does not show a significant difference regarding the evenness of the distribution of the cost increase.

D. Scheduling Overhead

Table II shows the average number of load profiles that a consumer computes before the violation of the group power limit is resolved. The sequential approval method requires the computation of slightly less load profiles compared to the simultaneous approval method.

TABLE II: Average number of load scheduling cycles per consumer.

	Group power limit		
	5950 kW (85%)	4550 kW (65%)	3850 kW (55%)
Sequential approval	17	53	90
Simultaneous approval	18	63	122

VII. CONCLUSION

Optimized load scheduling based on day-ahead energy price forecasts may lead to demand peaks that cannot be satisfied due to grid limitations. In this paper, we proposed approaches for load profile negotiation that do not require knowledge of internal enterprise details at the aggregator. The results for the given scenario are close to the optimum computed using global knowledge. For lower group power limits compared to the sum of all individual power limits, the sequential approval method yields a lower increase of total costs compared to the simultaneous approval method.

Due to the simplified model, the results cannot be generalized. However, the results show that it is possible to use

The first-come-first-serve property of the sequential approval method leads to penalties for late submissions and can be considered unfair. However, the expectation that the simultaneous approval method leads to a more even distribution of cost increase does not hold for low group power

load profile negotiation to comply with power limits in a day-ahead price optimization scenario. The cost increase is higher compared to a central optimization using global knowledge, but except for very low group power limits (see Section VI-C) the total cost increase is quite small.
limits. Additionally, for the simultaneous approval method an incentive for submitting the requested number of different load profiles and a distance metric to quantify the degree of difference between submitted load profiles are required.

Opportunities for future research include investigations with more complex mechanisms and more elaborated consumer models.

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