Peak Load Reduction of Multiple Water Heaters: Respecting Consumer Comfort and Money Savings

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***Abstract*—Demand Response programs can allow residential electricity consumers to cut their energy bills. However, in case of contingencies in the energy system when the guaranteed peak load reduction is needed, comfort of consumers can be significantly deteriorated and they can choose to opt out. This paper investigates the possibility of peak load reduction and yet highly respecting consumers' comfort by coordinating a group of electric tank water heaters.**

The proposed peak shaving mechanism accounts for interests of both utility companies and their customers. It employs two optimization models tailored to the needs of both sides to optimally schedule individual water heaters. The suggested Simulation results show the potential of the proposed mechanism to provide the guaranteed peak load reduction thus contributing to the stability of the electrical grid, while transparent balancing between comfort-money and comfort-energy incorporated in the control scheme is of interest and use to green consumers.

I. Introduction

In light of the European objective to achieve 20% reduction of energy consumption and to lower greenhouse gas emissions by 2020, enhancement of the current ways of generation, transmission, and distribution of electric energy is becoming of paramount importance. Demand Response (DR) is currently recognized by the European Commission as a backbone instrument for increased energy efficiency and stability of the electrical grid [1]. DR can be identified as a set of measures "designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" [2].

By practicing DR, utility companies can benefit from a more optimal utilization of transmission and distribution electricity networks as well as generation assets, resulting in increased reliability of the power supply and reduction of the final consumption on the aggregated level. Energy consumers, in turn, can get the reduced outages, more transparent and frequent billing information, which they can use to cut their electricity bills [3].

Utility equipment faults and switching on unplanned large loads can cause system disturbances such as short-term voltage sags and longer undervoltage which can result in disruption, damage and downtime of home devices [4]. The heavy drop of voltage can induce cascade blackouts, if not timely handled. To prevent the power supply from halting completely provided that system voltage is decreasing, a utility typically regulates reactive power by throttling up nearby sources and/or buys power from remote sources. As the last resort, the utility can dim (brownout) or even shed the loads to recover the voltage. These traditional control options require a real-time work of grid operators. Another and more automated approach to mitigate energy deficit situations that can be planned off-line in advance is offered by DR programs.

There exist two types of DR distinct in the way consumers are involved in the energy reduction process. Whilst the first type allows consumer response to high energy prices set by utility companies to diminish the peak loads, the second type yields load reduction by shutting consumers' loads or by scheduling their operation times. Although many experts argue in favor of using price-based programs, and in particular dynamic pricing, as the most straightforward and efficient DR measures [5]–[7], such programs are becoming unacceptably risky to rely on when a *guaranteed* load curtailment is critical. For instance, price-based steering of consumer loads cannot deal with real-time scenarios when utilities have to wrestle with unexpected peak-demands or when near-real time DR is of vital necessity [8]. Dynamic pricing may also result in overloading of cables and voltage problems, if a majority of consumers responds to high price by shifting their demand to the same period of low prices [9], [10]. In contrast, a utility can achieve a guaranteed load reduction during the peak demand hours when exercising the second type of DR programs, e.g., by directly shutting down (or cycling) residential loads (e.g., Direct Load Control) or by shifting demand to the off-peak hours for flexible loads.

Tank electric water heaters for domestic hot water activities (WHs) is a good example of such flexible loads. Once hot water is stored in the tank, they can be disconnected from the grid for some time without leading to substantial drop of user comfort. In addition, extra reserve of thermal energy can be created in a WH by pre-heating the unit to higher temperatures than operating setpoints to ensure user comfort during the shut-off period [11]–[13]. It reveals the whole flexibility of WHs to shift their electricity demand to times preceding the peak demand periods in the grid, and to satisfy comfort of residents, on the other hand, and thus is of special interest to us. However, if load shifting is done on a consumer level, i.e. without awareness of other loads present in the grid, new peaks may appear in the system. It brings the necessity to coordinate the scheduling of loads on the aggregated (e.g., district) level.

Approaches for coordination of groups of loads can be categorized into centralized [10], [14] and distributed [9], [15] based on whether scheduling is derived on the utility side or both on the consumer and utility sides. Each of these has

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its own benefits and downsides. Amongst the key difference points are privacy, autonomy, simplicity of communication links and scalability. On top of all, consumers are expected to care about the impact of DR on their comfort [3], hence user comfort is becoming a cornerstone to consumer acceptance of DR, and thus it is of utmost importance to adaptation of DR in practice.

In this paper we propose a distributed approach for coordinating a group of WHs. We apply a recently introduced concept of profile steering [9] that employs ready-to-use profiles to schedule the loads (contrast to energy prices), so that a desired flattened power demand curve can be attained on some level of the grid hierarchy. In the profile steering of a community of consumers, the utility side collects consumers' demand profiles obtained based on their consumption preferences for a day ahead and aggregates them to verify if the aggregated profile fits the desired flat profile, and if necessary it modifies the initial profiles to send them back to the customers.

A coordination scheme suggested in this paper schedules a group of WHs, while highly respecting user comfort. For this purpose, we utilize two scheduling models to create schedules for individual WHs, namely the energy model (EnM) [12] and the price model (PrM) [13]. While the EnM allows to minimize electricity consumption for water heating while minimizing user comfort disruptions, the PrM given the tariff plans the WH demand with respect to minimum money expenses for heating and maximum user comfort. We differentiate between consumers present in a community who can tolerate some discomfort (comfort elastic) and thus can offer more flexibility and those who have rigid comfort preferences.

At the first step of our scheme, the controller of each WH obtains a day-ahead forecast of hot water usage, computes the WH power demand profile based on the EnM and PrM, and sends them to the aggregator. At the second step, the aggregated profiles are checked for the utility power threshold(s) violation. If violation is found, the aggregator attempts to satisfy the resulting aggregated demand by combining the received profiles. If the wanted combination is not found among the submitted profiles, the aggregator initiates the algorithm of guaranteed peak load reduction (GPLR). The GPLR algorithm requests the customers to re-optimize their profiles posing a hard constraint on the switch on times of their WHs. At the final, the consumers get the updated profiles and are obliged to follow them which ensures the guaranteed peak demand reduction.

Section II gives a brief overview of the approaches to schedule groups of residential loads. In Section III we provide the background on the the energy and price models to schedule individual WHs. We outline our approach for peak demand reduction in Section IV. Section V gives further considerations of our approach for the case of a single WH, while Section VI presents our distributed scheme for multiple WHs and the algorithm for guaranteed load reduction. The evaluation of the approach is presented in Section VII together with our findings and discussion.

To sum up, the contributions of this paper are:

- a distributed scheme for peak load reduction of a group of WHs which highly respects user comfort and utilizes the profile steering concept (Section VI);
- an algorithm for guaranteed peak load reduction (Section VI-A).

II. State of the Art

Scheduling of groups of electrical loads to flatten daily energy demand curves requires interaction schemes between the energy provider (a utility company) and consumers.

A centralized model predictive control of a group of heat pumps was proposed in [14]. The prediction and scheduling of individual heat pumps at each house is done on the aggregated level based on the information about the states of charge of thermal storages (SoCs), desirable room temperatures and occupancy schedules from the houses. This scheme allows the heat pump controllers to perform only simple tasks such as real-time correction of steering signals due to possible errors in the forecast, whereas the major duty of forecasting and control is delegated to the central controller located in the grid. In [10] the authors propose another centralized control scheme where an aggregator schedules a group of heat pumps only based on house comfort priorities represented as lower and upper bounds of electricity demand sent from the underlying level houses. This scheme requires the lower-level home controllers to handle the demand forecasting duties and to calculate the flexibility margin.enough to understand to what degree inhabitants are ready to sacrifice their comfort to determine the lower bound of energy demand.

A distributed approach for load scheduling is under investigation of the Mas2tering project [15]. Focused rather on the price incentives to trigger load reduction the project highlights the multi-agent communication scheme between the individual houses and a 'flexibility manager' on the utility side. In this scheme home controllers (or agents) compute various scenarios of shifting home energy demand subject to flexibility constraints imposed by deferrable loads available in a house and user preferences. These scenarios are further forwarded to the flexibility manager that re-schedules the loads, pursuing his own objective to reduce the peak-load. The agents updated with the new price signals re-compute their demand profiles, then the process repeats until both sides reach an agreement on demand and cost of energy. A profile steering approach to manage consumer loads on all levels of the grid hierarchy is presented in [9]. A desired flattened power demand curve is attained by calculating the deviation of aggregated profiles from the desired flat profile. The profile steering algorithm then re-schedules all the loads to find 'the best profile candidates' to reduce the deviation of the aggregated profile from the desired one.

Similar to [9], our approach utilizes the deviation of the aggregated demand profile of multiple loads (WHs) from the desired flat profile to steer the loads for the peak demand reduction. However, the profile steering algorithm in [9] is proven to be NP-hard and requires multiple re-scheduling of all the loads to find the new profiles with the 'the largest improvement' of that deviation. As opposed, this paper considers a case where a *guaranteed* demand reduction down to to a certain threshold is required. Moreover, our approach for profile steering does not re-schedule all the WHs, but rather it immediately enables the maximum number of profiles from those initially submitted to the utility and which do not violate the threshold, and re-schedules only the residual WHs.

III. Background on WH Control

In general, utilities are more focused on stability of the energy system, which can be sustained by minimizing the peak loads and flattening daily electricity demand curves. Consumers, on the other hand, are more interested in getting maximum comfort at the minimum cost for water heating. In our previous studies [12], [13] we tailored two optimal control models for a domestic WH, each of which being able to support either of these two objectives.

A. Energy Model (EnM)

The EnM [12] is basically an optimization algorithm to schedule power demand of a WH along the daily timescale while simultaneously satisfying two conflicting objectives, namely minimization of energy consumption for water heating and minimization of user comfort disruptions.

The input for the EnM is a day-ahead forecast of hot water usage, the thermodynamic model of the WH including the cold water temperature in the main pipe, and temperature of the surroundings. In order to fulfill user comfort, the model also requires an input about their comfort preferences provided in the form of the comfort model. Based on these inputs, the multi-objective optimization algorithm plans power injections into the water tank to minimize total daily energy consumption with respect to minimum user discomfort. Since users may desire to sacrifice some level of comfort to reach extra energy savings, the outcomes of the model are multiple trade-offs between energy and comfort that form a Pareto front.

B. Price Model (PrM)

Similar to the EnM, the PrM [13] schedules electricity demand of a WH for a day ahead by solving a multi-objective optimization problem. However, unlike the EnM, the PrM aligns the two conflicting objectives of minimization of money expenses for water heating while minimizing the user discomfort.

Apart from the inputs required for the EnM, the PrM additionally also needs information about the energy prices. As well as for the EnM, to quantify the user dissatisfaction with the tap water temperature, the PrM utilizes the comfort modeling approach described in [13]. Similar to the EnM, the PrM returns multiple alternatives associated with different user comfort requests and expressed as trade-offs on Pareto front.

IV. Our Approach for Peak Load Reduction

Our approach for peak demand reduction of a group of WHs is based upon the profile steering concept [9], wherein consumers provide an aggregator with the desired profiles that

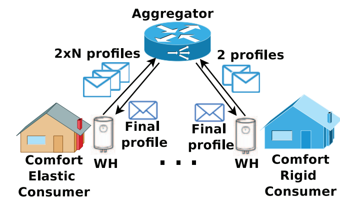


Fig. 1: Two groups of consumers.

meet their comfort and money preferences. After a certain load shifting policy applied, consumers retrieve the final profiles which they have to follow the next day on a contractual basis. Contrast to [9], our approach highly concerns about the effect of such profile steering on users' comfort.

Comfort preferences, money that residents are ready to pay for water heating together with parameters of WHs determine the consumer flexibility to reduce electricity demand and can vary from one household, i.e. consumer, to another. To attain a desired peak load reduction, it makes sense for a utility to account for different consumer potentials to shift their demand during DR based on their flexibilities. Since DR program participants can choose to sign out if the control actions severely degrade their comfort, the role user comfort becomes of paramount importance when considering consumers' flexibilities. In our approach we presuppose that two groups of residential consumers can be present on the community level in the grid. The first group consists of comfort-elastic consumers who allow a utility to downgrade their comfort to a certain level for the sake of a stable power supply of the entire community. Their flexibility for load reduction can be determined by discomfort tolerance, desire to benefit financially from using to the price model (PrM), intention to save energy to reduce environmental footprints by means of the energy model (EnM) and by parameters of their heating units. The second group includes rigid-comfort consumers who have fixed comfort preferences that cannot be deteriorated due to some reasons (e.g., people with chronicle illness). Thus their flexibility for load reduction is limited only to switching between the energy and the price models and determined by characteristics of their WHs.

In this connection, we illustrate how a utility can search for solutions to reduce peak demand of a group of WHs considering the above two types of consumers. Together, these actions concentrate on how each of the players can benefit from using the EnM and PrM in the scenario where an energy system is under stress and guaranteed peak load reduction is required.

V. Single Water Heater

In this section we illustrate how an individual consumer with a WH can react to specific limitations posed by the need to reduce its energy demand. We assume that a WH is equipped with a controller that can schedule its power demand based on a desired consumer's objective either to save energy [12] or to save money [13] for water heating, respecting user comfort. To do so, the controller utilizes the energy

(EnM) and price (PrM) models, which result in a consumer-desired power demand profile. Because the comfort-elastic and comfort-rigid consumers have different flexibilities as discussed earlier, outcomes of the EnM and PrM as well as the consumer response to load reduction request will be different too. To discriminate between the two consumer categories, we further describe a case where the utility aims at lowering the power demand, first, of a single elastic consumer, and then of a single rigid consumer, during a certain period of peak demand.

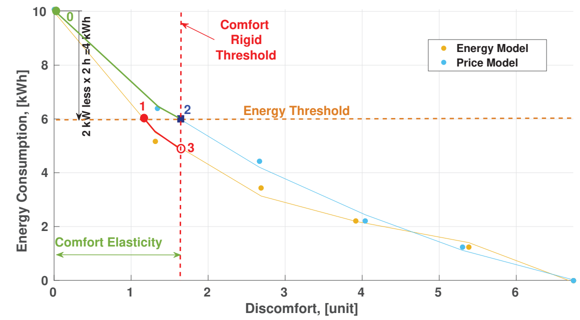
A. Comfort-Elastic Consumer

An *elastic* consumer is ready to sacrifice some comfort to contribute to the peak load reduction for the sake of a stable power supply of a community. Even though comfort of such a consumer can be deteriorated, there is a predefined discomfort threshold beyond which the consumer might decide to sign out from the DR program, hence it should not be violated, as shown in Fig. 2.

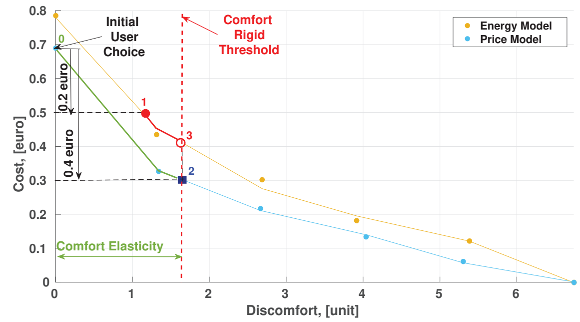
The energy and price-oriented calculations are applied to derive a pair of solution vectors $\mathbf{X}^{\{1,2\}}$, which describe binary state (on/off) of the WH $x_k = \{0, 1\}$ at every interval $k \in [1, N]$ on a discrete day-ahead timescale [12]. More precisely, the user comfort request might change over time, thus each of the models outputs a set of solutions $\{\mathbf{X}_i\}^1$ and $\{\mathbf{X}_i\}^2$ that a user can choose from. To make it possible, every $\mathbf{X}_i$ in a set relates to a pair of values, that signify a certain level of comfort $D_i \in [D_{min}, D_{max}]$ and some level of energy consumption $E_{\mathrm{e},i} \in [0, E_{max}]$ for the energy model (EnM) or monetary expenses $C_i \in [0, C_{max}]$ for the price model (PrM). The pairs of solutions $\{D_i, E_{\mathrm{e},i}\}$ and $\{D_i, C_i\}$ form a Pareto fronts for two models which are understandable by a consumer as illustrated in Fig. 2.

In case of an elastic consumer, the number of power profiles represents a subset of $\{\mathbf{X}_i\}^1$ and $\{\mathbf{X}_i\}^2$ bounded by the minimum and maximum user-allowed comfort thresholds. Consider, for example, an elastic consumer who can tolerate up to 25% of comfort decline with the initial choice for getting maximum comfort at the lowest cost. Such preference corresponds to a set solutions of the PrM in between of the points "0" and "2" in Fig. 2(b). Assume, the utility aims to reduce power demand of an elastic consumer by 2 kW during a certain period of 2 hours, this reduction can be mapped to 4 kWh energy reduction on the daily timescale, as shown in Fig. 2(a). Due to this change, the user has to match the utility's threshold and thus sacrifice his comfort.

In our approach, the user has two options how to proceed. The first option is to lower electricity consumption by switching to the EnM. By sacrificing 1.2 unit of comfort a consumer can get 0.2 € money savings (point "1" in Fig. 2(a)). In fact, the user might select any solution in between the points "1" and "3" (red line) because it is allowed by his discomfort threshold. The second option is to remain using the PrM and get 0.4 € cost reduction with 1.6 unit of comfort decrease. These two options are shown by points 1 and 2 respectively in Fig. 2(a) and Fig. 2(b).



(a)



(b)

Fig. 2: Consumer response to limited energy request (user comfort with respect to (a) energy consumption, (b) cost for water heating).

The two points describe two boundaries that inform about the users choice how to meet the utility's request. The user can also choose some intermediate solutions within these boundaries as depicted in Fig. 2(b). The most right point on the EnM curve (point 3) in Fig. 2(b) is probably the less advantageous for the user, because he has to pay more for the same level of comfort as compared to the PrM (point "2").

B. Comfort Rigid Consumer

Unlike a comfort elastic consumer, a comfort rigid consumer does not allow a utility to lower his energy consumption by lessening user comfort. The possible actions suitable for a rigid consumer are restricted to switching from one model to another but at the same comfort level. For instance, switching a rigid consumer to the EnM when a desired comfort level is at the rigid comfort threshold in Fig. 2, i.e. switching from the point "2" to point "3", can result in 1.1 kWh energy reduction. As follows from Fig. 2, it is not always possible to get energy reduction from such switching, as for example at the user maximum comfort request.

VI. Multiple Water Heaters

As several users are grouped within a community, the role of the utility becomes more prominent. The concern becomes how to simultaneously deal with a number of water heating patterns.

Let us consider a more realistic case in which a utility triggers a load shifting of a group of M WHs to reduce their load within the interval of peak demand. For simplicity assume that all the WHs are of a cyclic type and that their capacities are equal. The communication between the utility and the users can proceed as follows. At the first step, based on the contract with the utility, each of the M customers provides a fixed n-number of points decoded as $2 \times n$ binary profiles $\{\mathbf{X}\}^{\{1,2\}}$ from two Pareto fronts that are derived by means of the two models for a day ahead. The day-ahead timescale represents evenly spaced time intervals $\Delta t_k, k \in [1, N]$. For the m-number of comfort-elastic consumers the points can be extracted from the customer's Pareto fronts based on the maximum discomfort level the users can tolerate. For the $(M-m)$ of comfort rigid consumers the number of such profiles boils down to two $n = 1$ as shown in Fig. 1.

At the second step, the controller on the utility side aggregates $(M \times n) \times 2$-number of the received profiles into the two binary 3-d matrices $\mathbf{Pr}_{[N \times M \times n]}$ and $\mathbf{Enr}_{[N \times M \times n]}$ that store the solutions of the price model (PrM) and energy model (EnM) respectively. Further, the task is to find M profile combinations in $\mathbf{Pr}[:, j, :]$ and $\mathbf{Enr}[:, j, :]$ for $j \in [1, M]$ that meet the predefined threshold Thr, e.g. imposed by the maximum allowed power flows in the distribution line. Since all the WHs have the same maximum power demand, Thr can be expressed as a number of WHs allowed to be turned on at every slot Δt_k. Then the solution of the search task can be expressed as the best combination $\mathbf{Sol}$ of vectors $\mathbf{X}_{j,p}^{\{1,2\}}, \forall j \in [1, M], p \in [1, n]$ in matrices $\mathbf{Pr}$ and $\mathbf{Enr}$ such that $\sum_{j=1}^{M} Sol[k, j] \leq Thr, \forall k \in [1, N]$, i.e. the threshold is matched at every k-th time-slot. Performing this task directly is hardly possible due to its complexity.

A naive search approach to traverse all the received profiles results in $m^{2n} \times (M-m)^2$ total number of profile permutations of comfort-elastic and comfort rigid consumers and seems daunting. A more focused and practical search approach is to apply a greedy algorithm that attempts to switch off the minimum number of WHs at every interval $[t_{k1}, t_{k2}]$ with the threshold violation. At any Δt_k the number of WHs to be shut off will be $Num_k = \sum_{j=1}^{M} \mathbf{X}[k, j] - Thr$. Switching even one single WH can let the total demand to match the threshold, thus the number of combinations at Δt_k is equal to $\sum_{m=1}^{Num_k} C_M^m$. Having N_{viol} number of violated intervals, the total number of combinations increases to $\prod_{k=1}^{N_{\text{viol}}} \sum_{m=1}^{Num_k} [C_M^m]_k$. Importantly, these combinations are only potential candidates, since only a few of them, if any, might match with the received power demand profiles in matrices $\mathbf{Pr}$ and $\mathbf{Enr}$. Therefore, it is needed to verify their presence in these matrices starting from the entries associated with the highest user comfort and gradually moving towards the lowest comfort of comfort-elastic consumers. If multiple alternatives are found, then only one combination of $\{\mathbf{X}\}_j, \forall j \in [1, M]$ should be selected, for example, based on the following rule: take as many as possible of $\{\mathbf{X}\}_j$ from $\mathbf{Pr}$, the rest $\{\mathbf{X}\}_j$ replace with the ones from $\mathbf{Enr}$ - this rule allows to keep the maximum number of WHs on the PrM satisfying some user preferences for cost-money, while switching the residual WHs to the EnM which more of an interest to the utility.

At the third step, M final demand profiles from the found combination $\mathbf{Sol}$ are sent back to the consumers, who have to accept them as shown in Fig. 1.

It is important to emphasize that the above search approach may not provide a guaranteed peak load reduction, the aggregator can fail to find the needed combination in the received profiles. If this is the case, at the final step the aggregator executes the guaranteed load reduction optimization algorithm.

A. Guaranteed Peak Load Reduction Algorithm (GPLR)

The algorithm comes to the stage in case the aggregator fails to retrieve the wanted profile combination $\mathbf{Sol}$ in the received profiles, or if only comfort-rigid consumers are present in a community. In the latter case there can be only a limited $(M-m)^2$ of profile combinations possible. Additionally, if all the comfort-rigid consumers desire the maximum comfort setting, there might be no flexibility to reduce their peak demand as mentioned in Section V-B.

One part of the GPLR algorithm is implemented at the aggregator, while the rest is executed at the consumer side in a distributed way.

Firstly, the aggregator's part of the GPLR algorithm selects the maximum $G < M$ number of the consumers whose desired profiles do not violate Thr $\mathbf{P}_G = \sum_{j=1}^{G} \mathbf{X}[k, j] \leq Thr, \forall k \in [1, N]$. Then G group of consumers is allowed to perform based on these selected profiles and is taken out from further consideration. The aggregator algorithm sends vector $\mathbf{P}_G$ to the first consumer from the set $M \setminus G$ of the remaining consumers. Secondly, a consumer who received $\mathbf{P}_G$ updates either his preferred PrM or EnM by adding additional constraint, that prohibits switching on his WH at time-slots Δt_k where $\mathbf{P}_G[k] = Thr$. The updated model is re-optimized to satisfy that added constraint. In case of the PrM, the new optimization problem for the j-th consumer can be formulated as:

$$\begin{cases} min[F_1] = min[\mathbf{1} \times \mathbf{D}^T], & (1) \\ min[F_2] = min[\boldsymbol{\lambda} \times \mathbf{X}^T], \text{s.t.} & (2) \end{cases}$$

$$F_1(\mathbf{X}) \leq F_1^*, F_1^* \in [F_{1,min}, F_{1,max}] \quad (3)$$

$$T_{\text{cw}} \leq T_{\text{WA}} \leq T_{\text{wh,max}}, \forall k \in [1, N] \quad (4)$$

$$\sum_{k \in K_{P\ \text{prev}}} \mathbf{X}[k] = 0, \quad (5)$$

where $\mathbf{1}_{[1 \times N]}$ is a row vector of "ones"; $\mathbf{D}^T$ is the column vector of size $[N \times 1]$ of the thermal discomfort experienced by a user at any step k on the day-ahead timescale; $\boldsymbol{\lambda}_{[1 \times N]}$ is the price vector; $\mathbf{X}^T$ denotes a binary vector $[N \times 1]$ that decides whether to switch the WH off or on at any control step; F_1^* stands for the solution of (1) that is imposed as a constraint to (2); $T_{\text{cw}}, T, T_{\text{wh,max}}$ signify the cold water temperature, temperature inside the WH tank and maximum

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safety allowed temperature in the tank respectively; $K_{P\,\text{prev}}$ are the indices of the time-slots where $\mathbf{P}_G[k] = Thr$.

The constraints (3) and (4) are described in detail in [13]. The constraint (5) ensures the WH of the each j-th consumer to be turned off at times $k \in K_{P\,\text{prev}}$, which guarantees the peak load reduction for a group of WHs. Once the problem (1)-(4) is solved for the consumer j, the resulting demand profile is sent to the aggregator who adds consumer j in G and re-calculates $\mathbf{P}_G[k]$. The re-optimization continues for the rest of consumers $M \setminus G$.

VII. Performance Evaluation

To evaluate the proposed scheme in terms of guaranteed load reduction, we perform simulations based on the illustrative and simplified scenario with the community of 10 houses each equipped with the similar WHs having 2.95 kW power demand. In this scenario, all houses initially preferred to schedule their WHs for the next day based on the price model (PrM) with the maximum comfort settings, i.e. consumers desired to get maximum comfort at the minimum cost. Given the double-price tariff with the period of high prices from 6:30 to 23:00, such situation resulted in that all WH loads were shifted to the morning period before 6:30, which caused the maximum power threshold (20.65 kW) violation identified by the aggregator.

After the aggregator has performed a search of profile combinations, possible solutions were splitted into the three different cases: (a) the power demand profiles of the PrM in the matrix $\mathbf{Pr}$ with reduced user comfort, (b) the profiles from matrix $\mathbf{Enr}$ related to the EnM with the lowered comfort, and (c) the profiles that allow to maintain the initial comfort of all consumers at the expense of the higher costs.

Finally, we lowered the utility power threshold down to 17.7 kW to demonstrate the quality of solutions of the GPLR algorithm. First, we grouped six WHs in a group that can follow their initial profiles. Second, we recursively solved the optimization problem (1)-(4) while updating $\mathbf{P}_G[k]$ and re-computing $K_{P\,\text{prev}}$ for each new consumer who is not yet in group G.

A. Simulation Results

The simulation results that meet the aforementioned cases (a) and (b) of profile steering are represented in Fig. 3, which depicts the power demand (kW) and energy consumption (kWh) for the considered WHs. The vertical red lines show the beginning and the end of the high-price period.

The results of our simulations related to the case (c) are illustrated in Fig. 4.Vertical stem bars in Fig. 4 show the power demand after switching WH1 and WH5 from the original price model (PrM) to the energy model (EnM).

Resulting values of total energy consumption, total discomfort and total cost before and after the profile steering are presented for the community of 10 houses in Fig. 5. The first group of bars shows the results of the original PrM initially selected by the consumers. Whereas the second and the third groups of bars relate to the case (a) and (b) respectively and the forth group relates to the case (c) shown in Fig. 4.

The total power demand and energy for the case where the GPLR algorithm is applied for a group of 10 WHs are shown in Fig. 6.

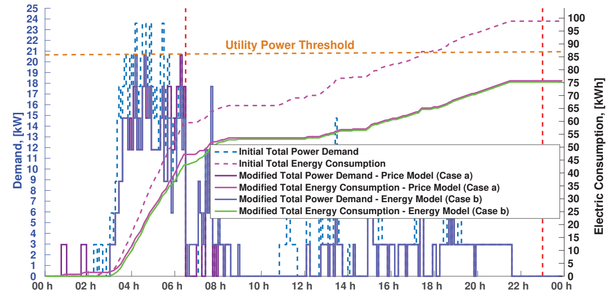

Fig. 3: Cases (a),(b). Peak reduction by comfort reduction via the price and energy models.

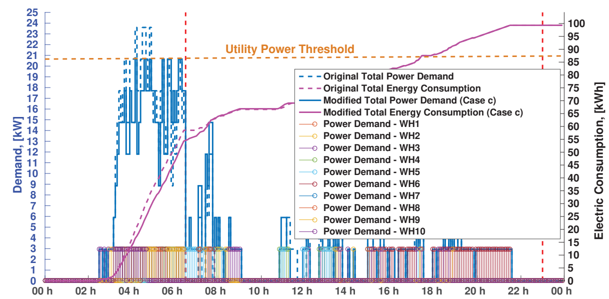

Fig. 4: Case (c). Peak shaving by purely switching the houses to the energy model.

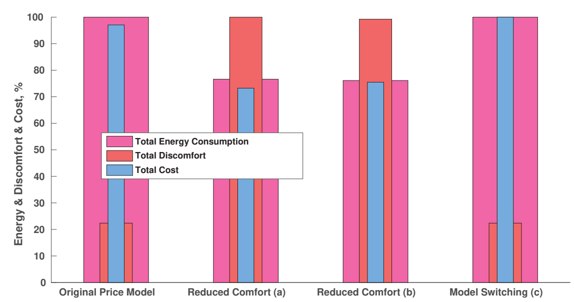

Fig. 5: Outcomes of the profile steering control of 10 WHs in cases (a)-(c).

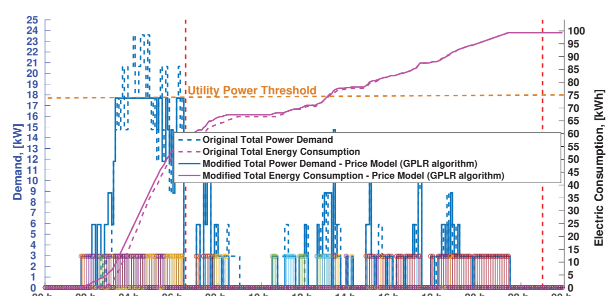

Fig. 6: Results of the GPLR algorithm for a group of 10 WHs.

B. Findings and Discussion

As it can be seen from Fig. 3 and Fig. 4, the energy model (EnM) and price model (PrM) can let the utility achieve a peak load reduction. While in cases (a) and (b) shown in Fig. 3 such peak shaving is a result of lowering consumers' comfort, case (c) highlights the opportunity to reduce the peak load by only triggering the houses to switch their demand profiles from the original PrM to the EnM as depicted in Fig. 4.

The latter case (c) is less obvious and needs more explanation. It is noteworthy that in some scenarios of domestic hot water consumption Pareto fronts derived by the EnMs and PrMs might have a potential for peak reduction without a drop of user comfort. More precisely, the EnM at the user-desired maximum comfort setting can provide less energy consumption than the PrM at the same level of comfort. Such difference can be explained by the fact that the PrM schedules the load to the cheaper price period, which in case of a day-night double price tariff coincides with the night period. If the first hot water event takes place in the high-price period and the time lag between the tariff change and that event is relatively long, then the WH should be heated up to the higher SoC (more energy will be consumed at extra cost) due to the heat losses in order to satisfy the same user comfort request as in the case of the EnM that heats up all the water right before that event regardless to the tariff. Therefore, in case the EnM yields lower energy consumption at the maximum comfort level requested by a consumer, a simple consumer switching to the EnM can contribute to the peak demand reduction as demonstrated in Fig. 4.

As follows from Fig. 5 and Fig. 3 cases (a) and (b) not only reduce the morning peak load, but also lower the total energy consumption on the community level. It can be, for instance, favorable when energy storages are available in the grid, hence the aggragator may be also interested in limiting the total energy consumption (kWh). Comparison of the first and the last groups of bars in Fig. 5 demonstrates that comfort levels of all the consumers remain unchanged, though they have to spend more money as a payoff for the peak reduction (Fig. 4), which can be explained by the fact that the WH1 and WH5 were switched to the EnMs, which are more favorable in terms of energy, but less profitable in terms of money.

As can be seen from Fig. 6, the GPLR algorithm allows to reduce the peak demand down to the requested level of 17.7 kW providing the same level of comfort and total daily energy consumption as in the initial profiles. In extreme scenarios of intense hot water usage GPLR algorithm can be tuned (via constraint (3)) to achieve the guaranteed peak reduction by lessening user comfort.

VIII. Conclusion

This paper investigates the possibilities of peak demand reduction by coordinating a group of residential tank water heaters (WHs). The proposed scheduling mechanism is based upon the profile steering concept and uses two tailored optimization models, i.e. the energy and price models, to schedule individual WHs. At the first instance, coordination of WHs is done on the aggragator level that attempts to find a combination of submitted by consumers demand profiles that reduce the total load. In case such combination is not found, the aggregator triggers a guaranteed peak load reduction algorithm to re-schedule individual WHs. The algorithm is partly implemented on the aggregator and on consumer sides, showing the distributed character of the suggested coordination scheme.

Simulation results demonstrate the potential of the proposed mechanism to achieve the guaranteed load reduction by balancing between the interests of the utility and consumers.

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