Scalable Residential Demand Response Management

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ABSTRACT In this paper, a scalable framework based on a hierarchical architecture for residential demand response (DR) is introduced. The architecture, which overlays the physical architecture of the power system, allows to decompose the problem into several parts and solve it in a distributed manner. The computational time required to solve the DR optimization problem by this framework is shown to be only dependent on the number of levels in the hierarchical architecture. Hence, when the demand response computation is carried out entirely in parallel, adding more homes to the optimization does not add to the optimization time, thus making the computation scalable. Moreover, since the architecture overlays on the hierarchy of the physical power system, each node’s physical constraints can also be integrated into the optimization problem. Additionally, metrics are introduced to quantify the DR program’s success, balancing between the performance, the number of participants in the DR program as well as the stress on the consumer due to the optimization. For DR management, the consumer comfort as well as the demand response target is considered. The generated schedule can be carried out as a direct load control by the demand response aggregator or through a home energy management system. To demonstrate the scalability of the proposed method a one million home demand response program is successfully simulated and typical results are presented.

INDEX TERMS Demand response, energy management, hierarchy, smart residential homes

Nomenclature

- $\epsilon_{\text{calc}, s.f.n.h}$: calculated possible minimum $\epsilon$ value for $n$th home of the $f$th feeder of the $s$th substation
- $\epsilon_{\text{init}, s.f.n.h}$: initial agreed $\epsilon$ value for $n$th home of the $f$th feeder of the $s$th substation
- $\epsilon_{s.f.n.h}$: $\epsilon$ value selected for the final optimization of the $h$th home of the $f$th feeder of the $s$th substation
- $\alpha_h, \beta_h$: thermal characteristics of home $h$
- $C^{\text{co}}_h$: controllable comfort objective of home $h$
- $C^{\text{sh}}_h$: shiftable comfort objective of home $h$
- capacity: the capacity of the subtransmission
- $c_{s.f.n.h}$: the capacity of the subfeeder $n$ of the feeder $f$ of the substation $s$
- $c_{s.f}$: the capacity of the feeder $f$ of the substation $s$
- $d_{s.f.n.h}$: the binary decision variable denoting the participation status of the home $h$ of the subfeeder $n$ of the feeder $f$ of the substation $s$
- $F$: number of feeders per substation
- $H$: number of homes per subfeeder
- $p^t$: total power usage of the subtransmission for the time interval $t$
- $P^t_{\text{new}}$: optimized power usage at time interval $t$
- $p^t_{s.f.n.h}$: total power usage of the home $h$ in subfeeder $n$, feeder $f$ and substation $s$ for the time interval $t$
- $p^t_{s.f.n}$: total power usage of the subfeeder $n$ in feeder $f$ and substation $s$ for the time interval $t$
- $p^t_{s.f}$: total power usage of the feeder $f$ in substation $s$ for the time interval $t$
- $p^t_s$: total power usage of the substation $s$ for the time interval $t$
- $SF$: number of subfeeders per feeder
- $SS$: number of substations for the subtransmission

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**I. INTRODUCTION**

The future smart grid is expected to incorporate independent entities both generating and consuming power. These ‘prosumers’ are envisioned to plug in their generation or consumption devices at their own discretion and carry out their transactions as they see fit. Additionally, the penetration of variable renewable energy resources in the power grid is expected to increase steadily. These future changes in power generation and consumption are expected to introduce challenges to the stability of the power system. One tool to cope with these challenges is demand response. Instead of generating enough power for the load at all times, DR attempts to shape the load according to the power generation profile.

DR implementations have numerous operational benefits. First, DR could control the peaks induced by general habits and the comfort requirements of the general public. For instance, the New York Independent System Operator Inc. reports that the peak power demand for New York was 31,861 MW in 2018, while the average power demand was merely 18,392 MW: a difference of almost a double [1]. DR could be used to mitigate this disparity between peaks and valleys of power demand. A second use-case for DR would be the maximum utilization of renewable energy. For instance, if the solar generation is at the peak at the time the power demand is minimum, the excess energy generation has to be either discarded or stored. But storage technologies come with its own set of problems ranging from inefficiency to expense, size, environmental effects and safety issues. The less technically complicated solution would be using DR to encourage the end-user to move most of the energy uses to the time interval most renewable generation is available [2].

Even with these benefits, DR is mostly underutilized in the home energy sector. Although many DR mechanisms are explored in research, the only available option for most residential consumers is simple pricing mechanisms. However, almost 38% of the total energy consumption in the US is from the residential sector [3]. This means that copious amounts of DR resources are going unutilized. One of the primary reasons is that the individual residential consumer consumes a minimal amount of energy compared to the total grid demand. That is, the residential loads to be controlled are highly distributed. Controlling such distributed resources

| Symbol | Definition |
|--------|------------|
| $T_h$  | number of time intervals per day |
| $T_{h,i}$ | comfortable temperature of home $h$ |
| target\(_{s,f,n}$ | target set for the subtransmission at time $t$ |
| target$\,_{s,f,n,h}$ | target set for the home $h$ of subfeeder $n$ of feeder $f$ of substation $s$ by the subfeeder |
| target$\,_{s,f,n,h}$ | target set for the subfeeder $n$ of feeder $f$ of substation $s$ by the subfeeder |
| target$\,_{s,f,n,h}$ | target set for the subtransmission for time period $t$ |
| $U^t$ | potential of the subtransmission at time $t$ |
| $U^t_s$ | potential of $s$th subtransmission at time $t$ |
| $U^t_{s,f,n,h}$ | potential of $h$th home of $n$th subfeeder of $f$th feeder of $s$th substation at time $t$ |
| $U^t_{s,f,n}$ | potential of $n$th subfeeder $f$th feeder of $s$th substation at time $t$ |
| $U^t_{s,f}$ | potential of $f$th feeder of $s$th substation at time $t$ |
| $k^t$ | variable associated with the shiftable appliance of the $h$th home at $t$th time interval for the $k$th time interval since the appliance is turned-on |
| $h_{c,i}$ | the power consumed by the $i$th shiftable appliance of the $h$th home at $k$th time interval after it is turned on |
| $h_{a,i}$ | number of interruptible appliances in home $h$ |
| $h_{B,i}$ | baseload of home $h$ at time $t$ |
| $h_{k,c,i}$ | comfort cost associated with the $i$th appliance of the $h$th home at time $t$ |
| $h_{f,i}$ | ending charging time for $i$th interruptible appliance of the $h$th home |
| $h_{L,i}$ | needed power of the $i$th interruptible appliance of the $h$th home |
| $h_{l,i}$ | lower power rating of the $i$th interruptible appliance of the $h$th home |
| $h_{s,i}$ | the number of time intervals the $i$th shiftable appliance of home $h$ runs |
| $h_{s,i}$ | starting charging time for $i$th interruptible appliance of the $h$th home |
| $h_{temp,i}$ | indoor temperature of home $h$ at time $t$ |
| $h_{w,i}$ | variable associated with the $i$th interruptible appliance of the $h$th home at $t$th time interval |
| $h_{u,i}$ | higher power rating of the $i$th interruptible appliance of the $h$th home |
| $h_{u,i}$ | decision variable associated with the controllable appliance of the $h$th home at $t$th time interval |
| $h_{Y,i}$ | capacity of the $i$th interruptible appliance of the $h$th home |
| $o_{temp}$ | outside temperature at time $t$ |
| $\Delta^k E_{g}$ | the deviation from the target when only $k\%$ of the population is participating and if only $g\%$ of the consumers existed out of the total population in consideration |
| $k_{final}E_{100}$ | the total power of all the consumers at time $t$ after $k\%$ of the consumers participated in optimization |
| $k_{final}E_{k}$ | the total power of $k\%$ of participating consumers at time $t$ after optimization if they optimized only the power of the participating $k\%$ of the consumers |
| $k_{initial}E_{k}$ | the total power of the participating $k\%$ of the consumers at time $t$ |
| $k_{initial}E_{100}$ | the total power of all the consumers at time $t$ before optimization |
| $k_{new}P_{s,f,n,h}$ | power of home $h$ of subfeeder $n$ of feeder $f$ of subfeeder $s$ after $k\%$ of consumers have optimized the power usage of only participating $k\%$ of users |
| $k_{new}P_{s,f,n,h}$ | power of home $h$ of subfeeder $n$ of feeder $f$ of subfeeder $s$ after $k\%$ of consumers have optimized all the consumer’s power usage |
would require many control devices and a highly complex optimization process. However, few pilot projects have been carried out worldwide that analyse the ability to employ different DR mechanisms in practice. Examples for these work include [4], [5].

Not only such a process would be challenging to implement but it would also raise privacy concerns. Additionally, this would require installing relatively more expensive ‘smart’ electronic measurement and control devices. However, with the recent exponential expansion of the electronic market, this situation is slowly changing. The availability of cheap computational power means that, instead of a central computer carrying out the optimization on behalf of the homes, the homes can now carry out the optimization by themselves. The concept of home energy management system (HEMS) attempts precisely this.

Home energy management and demand response research has been a very active field of research [6], [7]. Since privacy issues are an essential consideration in residential DR, most residential DR researches concentrate on distributed optimization techniques that allow the home to carry out its own partial optimization. For instance [8] introduces a game-theoretic method of distributed optimization by incentivizing the consumers through pricing. The consumer model in this paper does not consider more complex appliances such as shiftable appliances. More distributed methods are introduced in [9] and [10]. However, in these papers, the scalability to order of millions is not considered. In [11] and [12] real-time pricing schemes are introduced for DR optimization. More recently, the focus has been turned to demand response and home energy management systems with network and/or demand uncertainty [13]–[15]. Research has also been carried out on coordination of DR for communities with integrated energy systems with EV charging stations [16].

In home energy optimization research, attention is being shifted towards intelligent home energy management systems to co-operate with DR signals. The applied technologies include fuzzy logic and neural networks as well as modern meta-heuristic optimization methodologies such as particle swarm optimization (PSO) [17], [18], reinforcement learning [19], and agent-based systems [20]. More detailed descriptions of DR methodologies can be found in literature reviews such as [21], [22].

However, a HEMS alone cannot carry out DR. A HEMS can only consider the objectives of the home itself. To insert the objective of DR into consideration, an incentive has to be offered as an external signal. When considering a million homes, this calculation could be a bottleneck. Making DR as scalable as possible is a well-researched topic. However, these studies do not consider a very large-scale optimization scenario that extends up to million homes. For instance, the distributed solutions found in the literature are usually iterative [23]. The number of iterations needed for convergence start to grow as the number of parties involved increases. The research work [24] clusters similar appliances to decrease the system’s complexity, but this cannot be extended to a million users with privacy concerns distributed all over the grid.

This paper addresses these challenges by introducing a DR framework scalable to a millions of participants. The contributions of this paper are as follows:

- A scalable DR framework based on a hierarchical architecture is introduced. The framework allows practical considerations such as non-contributing consumers and power flow limitations at various points of the power grid. The framework consists of the hierarchical architecture and the accompanied optimization model.
- New metrics are introduced to evaluate the success of a DR program and the corresponding stress on the DR participants.
- To demonstrate the scalability of the proposed method a one million home demand response program is successfully simulated and typical results are presented. The insights from the metrics are discussed.

The rest of the paper is organized as follows. Section II introduces the hierarchical architecture on which the framework is based on. Section III describes the optimization model. Section IV discusses the proposed metrics. Section V discusses case study and the results. Finally, Section VI provides the conclusion and future work.

II. HIERARCHICAL ARCHITECTURE

The hierarchy of power flow from subtransmission to homes is shown in Fig. 1. It can be summarized as follows. A subtransmission supplies power for several substations. One substation supplies power to several feeders. One feeder delivers power to several subfeeders. One subfeeder powers several homes. The group of homes on the same subfeeder is referred to as a ‘Smart Neighborhood’ in this study. A Smart Neighborhood is a collection of homes in close proximity with appropriate contracts in place with the DR aggregator [25]. The optimization executed at the neighborhood level and is a day-ahead optimization. To enable this, either the aggregator can carry out a direct load control over the appliances in homes (as permitted by the contracts), or home energy management systems can carry out their own optimizations coordinated by the aggregator. The aggregator will impose penalties as agreed in the contracts for not following the agreed power schedule. For the optimization, both the DR target and the comfort of the consumer are considered.

The optimization is carried out throughout the hierarchical architecture as follows. First, to establish a baseline, each home in the system optimizes only for its own comfort. The optimization is a day ahead optimization planning for the next day. The tentative power schedule will then be communicated to the subtransmission level through the hierarchy. As discussed earlier, the subtransmission controls a number of substations. At this point, the subtransmission would observe the aggregated power requirements for the next day at each substation. The subtransmission will then dispatch a target power usage for each substation considering the amount of power requested by each substation and considering physical...
FIGURE 1. The hierarchical architecture of power delivery from subtransmission to home. The arrows show the information flow directions. The power demand flows upwards and the targets flow downwards. Each level computes independently in parallel and the other levels would wait for the lower (or the upper) level to finish power flow limitations of the substation. To set the target, the objective of the subtransmission has to be considered. In most cases, the objective of a DR program is to minimize the disparity between the peak and the average power demand. In this case, the average power demand would be a candidate target. However, other objectives could also be considered, such as the effective incorporation of renewable energy generation. In that case, the target could follow the energy generation forecast of the renewable power plants.

Upon receiving the dispatched target from the subtransmission, each of the substations will dispatch a target (calculated by a similar logic as the subtransmission) to each feeder controlled under them. By recursively repeating the above process, a target dispatch would flow down to each home, using which, the each individual home would optimize their own power usage. This optimization is further discussed in the next section.

As mentioned earlier, at each entity, possible power flow capacity limits have to be applied. The capacity of an entity at a certain level is the sum of capacity values of the levels under that entity. That is,

\[ \text{capacity} = \sum_{s=1}^{SS} \text{capacity}_s \]  

\[ \text{capacity}_s = \sum_{f=1}^{F} \text{capacity}_{s,f} \]  

\[ \text{capacity}_{s,f} = \sum_{n=1}^{SF} \text{capacity}_{s,f,n} \]  

Analysing the hierarchy presented in Fig. 1, it can be seen that if the optimization is carried out in a fully distributed manner, that is, if every home carries out its own optimization in parallel to all other homes, then the optimization time will depend on the number of levels in the system. That is, the
optimization time would be in order of $O(n)$, where $n$ is the number of levels. The reason for this is that all the homes carry out their optimization in parallel. This fact implies that adding more homes to the system does not change the optimization time largely proving the system to be scalable.

### III. DEMAND RESPONSE OPTIMIZATION

The DR optimization is a day-ahead optimization. The day is divided into several time intervals, and for each time interval, an amount of power is dedicated by the optimization. The DR aggregator initially has to come to an agreement and sign a contract with the participants to regulate the power usage. In addition, the participant agrees to a certain ‘flexibility’ offered for the purpose of DR. The agreed upon flexibility is denoted by $\epsilon_{init,s.f.n,h}$ in this study. More details on this flexibility parameter is discussed in the next subsections. The remainder of the Section describes each optimization step in detail. A flowchart summarizing the optimization process is shown in Fig. 2.

#### A. BASELINE CALCULATION

The homes that contribute to optimization are assumed to be ‘smart homes’. That is, each home is equipped with smart devices that could execute optimization algorithms and control home appliances. Given the growth of electronic devices in the market, this is not an unrealistic assumption. The smart device can optimize power usage in one of two modes: with DR signal or without DR signal. The first step is to optimize without the DR signal. This optimization is carried out to establish the baseline power usage. For this optimization, the home electric appliances are categorized into the four categories of uncontrollable appliances, shiftable appliances, interruptible appliances and controllable appliances.

Uncontrollable appliances are the appliances that are not under the control of DR. Although these appliances cannot be controlled, the power usage of these appliances have to be considered in the optimization. To do this, the uncontrollable appliance power usage has to be accurately predicted. In this study it is assumed that this prediction can be done accurately. The sum of the power usage by all uncontrollable appliances is called ‘baseload’ in this study.

Shiftable appliances are devices that cannot change their power consumption behavior. Once turned on, they should not be turned off before completion. The power consumption pattern, once turned on, is not under control of the user. Examples of this kind of appliances would be the washing machine and clothes dryer. These appliances would have a power consumption pattern spanning a number of time intervals. The power usage profile of the appliance can be represented with a vector, $\{e_1, e_2, e_3, ..., e_n\}$. Each element of this vector represents the power demand of the appliance at each time interval. For the ease of modeling, each of these elements in the profile will be treated as a separate appliance but with the restriction that if the first one is turned on at one time interval, the second one must be turned on in the next time interval and so on and so forth. Since these appliances are just turn-on or turn-off, the decision variable would be a binary vector with the size of number of intervals in the day. For a shiftable appliance that runs $h_{n_i}$ number of time intervals when turned-on, $h_{n_i}$ such size $T$ vectors will represent the decision on that appliance.

To make sure each part of the power usage profile follows the previous part, the necessary constraint is,

$$h_{b_i}^k = \frac{k-1}{h} b_{i-1}^{k-1} \forall h \in 1, ..., H, \forall k \in 2, ..., h_{n_i}, \forall i \in 1, ..., h_{a_s}, \forall t \in 2, ..., T$$

To make sure that one appliance turns-on only one time
during the day the following constraint should be held:

\[
\sum_{t=1}^{T-h_n} b_t^i \leq 1 \quad \forall h = 1, \ldots, H, \forall k \geq 2, \ldots, h_n, \forall i \in 1, \ldots, h_a
\]  

(5)

This makes sure that the appliance turns-on with sufficient time for the completion of the cycle and it turns-on only once in the day. The comfort of using these appliances depends on the time of the day that it is turned-on on. For instance, it could be rather uncomfortable if the washing machine is turned on at 2 a.m. in the morning. To capture this, a ‘discomfort’ value is defined for each time interval the appliance is turned-on. This discomfort value has to be defined by the consumer and should be based on their experiences and daily schedule. The total discomfort value for a given schedule for all shiftable appliances of a given home would be:

\[
C_{sh}^h = \sum_{t=1}^{T} \sum_{i=1}^{h_n} (b_t^i \times c_i^h)
\]  

(6)

Notice that only \( b_t^i \) is considered here since the discomfort is defined for turn-on time intervals.

The interruptible appliances on the other hand, include appliances that can have variable power supply but a deadline to meet. For instance, the electric vehicle battery can be charged during the day. And the comfort target is to maintain the current temperature of water/air between the right values. For this research, HVAC is chosen to be modeled. The general model used for the HVAC system is:

\[
h_{temp}^t = h_{temp}^{t-1} + (1 - h\alpha) \times (h_{temp}^t + h_\beta\times h_{wind}^t)
\]  

(11)

The discomfort of the HVAC is measured by the deviation of inside temperature from a given comfortable temperature set by the consumer.

\[
C_{co}^h = \sum_{t=1}^{T} (h_{temp}^t - T_h)^2
\]  

(12)

Using the above discomfort measurements the following objective to be minimized can be established. Minimize,

\[
C_{init}^h = C_{sh}^h + C_{co}^h
\]  

(13)

With this scheduling the total power usage for a given time interval \( t \) for one home can be calculated as follows:

\[
p_{s, f, n, h}^t = n B^t + \sum_{i=1}^{h_n} b_t^i + \sum_{i=1}^{h_n} u_t^i + h_{wind}^t
\]  

\[\forall t \in 1, \ldots, T, \forall h \in 1, \ldots, H\]

(14)

B. DEMAND RESPONSE OPTIMIZATION

Once the baseline is established, DR process could be started. The DR process includes the upward flow of information on the baseline power usage, downward flow of the targets calculated considering the baseline, and the optimization considering the target set for each home. Each of these steps are explained in detail below.

1) Upward Flow of Information

By considering the results of the basic optimization, at the subfeeder, these values will be summed together to get the total power usage.

\[
p_{s, f, n}^t = \sum_{h=1}^{H} p_{s, f, n, h}^t \quad \forall t \in 1, \ldots, T
\]  

(15)

The feeder, substation as well as the subtransmission use a similar equation to calculate their total power demand levels.

\[
p_{s, f}^t = \sum_{n=1}^{SF} p_{s, f, n}^t \quad \forall t \in 1, \ldots, T
\]  

(16)

\[
p_{s}^t = \sum_{f=1}^{F} p_{s, f}^t \quad \forall t \in 1, \ldots, T
\]  

(17)

\[
p^t = \sum_{s=1}^{SS} p_s^t \quad \forall t \in 1, \ldots, T
\]  

(18)

Both of these cases depend on the power supplied throughout the day. And the comfort target is to maintain the current temperature of water/air between the right values. For this research, HVAC is chosen to be modeled. The general model used for the HVAC system is:

\[
h_{temp}^t = h_{temp}^{t-1} + (1 - h\alpha) \times (h_{temp}^t + h_\beta\times h_{wind}^t)
\]  

(11)

The discomfort of the HVAC is measured by the deviation of inside temperature from a given comfortable temperature set by the consumer.
2) Downward Flow of the Target

The subtransmission will have a target to accomplish. This target could either depend on the total energy usage of the system or it can be independent of it. For example, the target at the subtransmission can be set to the average power consumption at subtransmission.

\[
\text{target}^t = \frac{\sum_{s=1}^{SS} \sum_{t=1}^{T} p_s^t}{T}
\]  

(19)

Or if there’s a specific solar PV profile to be followed, a different target value can be calculated. The subtransmission level then spreads out the target among the lower substations with consideration to their ‘DR potential’. The DR potential is the ability to meet DR targets. DR potential can be defined in several ways. One such analysis has been carried out in [26].

When distributing the targets among the substations, the following points should be taken into consideration. The target should be set in proportion to the potential of each substation. If the target exceeds the power limit of the substation, the target for that specific substation has to be capped at that limit. The excess power after capping has to be distributed among the rest of the substations, again in proportion to their potential. Once the target for a substation is set, the substation, in-turn, distributes the target among the feeders under its control using a similar logic. A similar logic is also carried out by the subfeeder to assign targets to homes, except that the power demand of the opting out homes has to be deducted from the target and then the target has to be assigned to the homes that contribute to DR. A common algorithm for all entities (subtransmission, substation, feeder and subfeeder) to calculate the target is given in Algorithm 1.

3) Final Optimization

The DR optimization is a multi objective problem that aims to strike a balance between accomplishing the power consumption target and maintaining the comfort of the consumer. This balance is set by the constant \( \epsilon_{s.f.n.h} \) defined for each home separately. This constant (unique to each home) defines a constraint which a consumer should obey in power usage.

This new constraint is:

\[
(p_{s.f.n.h}^t - \text{target}_{s.f.n.h}^t)^2 \leq (\epsilon_{s.f.n.h} \times \text{target}_{s.f.n.h}^t)^2
\]  

(20)

That is, the power usage of the home at a time interval cannot deviate more than a \( \epsilon_{s.f.n.h} \) fraction from the given target. (how this \( \epsilon_{s.f.n.h} \) fraction is set will be explained in the following paragraphs). While maintaining this constraint, the consumer is allowed to optimize the power usage for the maximum comfort. That is, the optimization in (13) will be carried out again but with the constraint given by (20) as the final optimization step.

The constant \( \epsilon_{s.f.n.h} \) can be interpreted as the constant deciding the point in the pareto front of the multi-objective optimization at which the optimization balances at. This method (called \( \epsilon \) optimization method) was first proposed by Haimes et. al. in 1971 [27]. In this case, deviation from the target at each time interval for each home is considered a separate objective and is converted into a constraint. Instead of generating a separate value for each of these objectives, a single \( \epsilon_{s.f.n.h} \) value is employed to limit all of them. This framework has the advantage of having a strong mathematical base while having an easy-to-understand physical interpretation.

The value for \( \epsilon_{s.f.n.h} \) is decided in the following manner. First, minimum possible \( \epsilon_{calc,s.f.n.h} \) value for the home is calculated using the following minimization:

\[
\epsilon_{calc,s.f.n.h} = \min_{t} \frac{(p_{s.f.n.h}^t - \text{target}_{s.f.n.h}^t)^2}{(\text{target}_{s.f.n.h}^t)^2}
\]  

(21)

Then the initially agreed upon \( \epsilon_{init,s.f.n.h} \) value is compared...
with the $\epsilon_{\text{calc},s.f.n.h}$ value and the smaller value is chosen to be $\epsilon_{s.f.n.h}$ for the optimization. The reasoning behind this choice is that, although the consumer initially agrees to an $\epsilon_{s.f.n.h}$ value, given the target, it might not be feasible. In this case, smallest possible $\epsilon$ (calculated by (21)) is used for the optimization.

$$\epsilon_{s.f.n.h} = \min(\epsilon_{\text{calc},s.f.n.h}, \epsilon_{\text{init},s.f.n.h})$$ (22)

### IV. DEMAND RESPONSE METRICS

In this Section, analysis methods for DR effectiveness are presented. In this study, three indices are introduced to measure the various aspects of DR program. These are explained in the following subsections.

#### A. PERFORMANCE INDICATOR

The success of the DR method can be measured as the adherence to the target at each time interval. More specifically, the new optimized values can be compared with the baseline case values for a better measurement of the success of DR.

To quantify the success of DR, the current adherence to the target is taken as a fraction of the adherence to the target by the baseline case. The averaged sum of all these values are considered as a performance indicator (PI). That is,

$$PI = \frac{1}{T} \sum_{t=0}^{T} \frac{|\text{target}^t - p_t| - |\text{target}^t - p_{\text{new}^t}|}{|\text{target}^t - p_t|}$$ (23)

where $p_{\text{new}^t}$ is the optimized power usage at time interval $t$. Similar PI values imply similar DR effectiveness.

#### B. EFFECTIVENESS INDICATOR

Although higher PI values mean better DR, a better DR generally requires a larger participation of consumers. However, as discussed before, if a certain consumer does not participate in DR, the remaining consumers attempt to balance out the impact by changing their own power consumption within their limits. In some cases, the DR participants are able to remove the impact of the non-participants completely. In this scenario the contribution of the non-participating consumer is unnecessary in the first place. In these scenarios, similar PI values occur. Since convincing consumers to participate in DR programs is difficult, utilities may find it more useful to get the maximum out of less number of participants.

To measure this an ‘effectiveness indicator’ ($EI$) is introduced. To emphasise on the necessity of DR performance, $PI$ is squared in this measurement, and to encourage the less participation, it is divided by the participation percentage. $EI$ is thus defined as:

$$EI = \frac{\text{sgn}(PI) \times PI^2}{\text{participation}\%}$$ (24)

where $\text{sgn}(\cdot)$ function represents the sign function which is defined as:

$$\text{sgn}(x) = \begin{cases} -1, & x < 0 \\ 1, & \text{otherwise} \end{cases}$$

### C. STRESS FACTOR OF DEMAND RESPONSE PARTICIPANT

Even if less number of consumers can fulfill the requirements of the utility, the ‘stress’ of the consumer increases as more deviation of power usage is demanded by the DR program.

That is, when lesser number of members participate, the available members have to shift the power that those who do not shift. To measure this additional ‘burden’ on the participating consumers a new $stress$ measurement is introduced. This measurement is defined by the difference between the power shift of the consumers when they shift power for the whole community and the power shift of the same consumers if only that population existed in the DR community. To mathematically represent this, first, initial and final power of the system is defined as follows:

$$\text{initial}E_{t}^{100} = \sum_{s=1}^{SS} \sum_{f=1}^{F} \sum_{SF}^{SF} \sum_{H}^{H} p_{s.f.n.h}^t$$

$$k_{\text{final}}E_{k}^{t} = \sum_{s=1}^{SS} \sum_{f=1}^{F} \sum_{SF}^{SF} \sum_{H}^{H} p_{s.f.n.h}^t d_{s.f.n.h}$$

$$k_{\text{initial}}E_{k}^{t} = \sum_{s=1}^{SS} \sum_{f=1}^{F} \sum_{SF}^{SF} \sum_{H}^{H} p_{s.f.n.h}^t d_{s.f.n.h}$$

Here $\text{initial}E_{t}^{100}$ denotes the total power of all 100% of the consumers at time interval $t$ before optimization and $k_{\text{final}}E_{k}^{t}$ represents the total power after $k$% of the consumers have optimized the system at time $t$. The variable $k_{\text{initial}}E_{k}^{t}$ represents the initial demand of only the $k$% of the consumers that participate in the DR program. Notice that, each term of power is multiplied by $d_{s.f.n.h}$ which is a binary decision variable denoting whether the consumer contributes to DR or not. When the consumer contributes to DR, this variable gets the value of 1 and it gets a 0 otherwise. Variable $k_{\text{final}}E_{k}^{t}$ is the same calculation after optimization. Notice that $k_{\text{new}}p_{s.f.n.h}^t$ is different from $k_{\text{new}}p_{s.f.n.h}^t$. This is because the optimal demand when 100% of the load is considered is different from the optimal demand when only $k$% of the demand is considered. The deviation from the target could be then defined as:

$$\Delta^k E_{100} = \sum_{t=0}^{T} \left| \frac{\sum_{t=0}^{T} k_{\text{initial}}E_{t}^{t}}{T} - k_{\text{final}}E_{t}^{t} \right|$$ (29)

The deviation from the average when $k$% of the consumers would participate in the optimization can be calculated as:

$$\Delta^k E_{k} = \sum_{t=0}^{T} \left| \frac{\sum_{t=0}^{T} k_{\text{initial}}E_{k}^{t}}{T} - k_{\text{final}}E_{k}^{t} \right|$$ (30)
Finally, the stress experienced by \( k \)% consumer participation by the participating consumers can be calculated as a percentage of the ratio between \( \Delta^k E_{100} \) and \( \Delta^k E_k \):

\[
stress_k = \frac{\Delta^k E_{100}}{\Delta^k E_k} \times 100\%.
\]

**V. CASE STUDIES, RESULTS AND ANALYSIS**

The simulation studies was carried out for a million homes with the following structure. Fifty substations for the subtransmission. Twenty feeders per substation. Fifty subfeeders per feeder. Twenty homes per subfeeder. Simulation studies were carried out to explore the effects of optimization on individual homes and the power system. Specifically, the case studies were designed to observe the effects of \( \epsilon \) and the percentage of participation on the system. These case studies were implemented on RTPIS Lab high performance computing cluster of Clemson University [28].

**A. DATA SET**

The data set is mostly based on Pecan Street Inc. Dataport data. However, the HVAC data was generated with a selected outside temperature using the HVAC model in use. Since the data set is far small for a one million user base, a random normal noise was added to the initial data template to get the one million home power demand. The HVAC model requires the thermal characteristic parameters to be set. These were set by adding a normal random value to common parameters of a home. The power demand for HVAC was generated for particularly cold day in the winter causing the power demand for the early morning and later afternoon to shoot up. The mid day power demand is quite low since the most appliances are turned off in the mid day. The huge disparity between the mid day and the rest of the day is caused by the lack of industrial and commercial power demands.

**B. DEMAND RESPONSE POTENTIAL QUANTIFICATION**

As described in Section III, a DR potential quantification is needed to run Algorithm 1. In this study DR potential is assumed to be proportional to the total power usage. Since the target is calculated in proportion to the potential, the DR potential could just be assumed as the total power usage. Therefore:

\[
U_{s}^t = p_s^t
\]
\[
U_{s,f}^t = p_{s,f}^t
\]
\[
U_{s,f,n}^t = p_{s,f,n}^t
\]
\[
U_{s,f,n,h}^t = p_{s,f,n,h}^t
\]

**C. EXPERIMENTS**

The optimization framework was simulated with several different \( \epsilon \) values and participation percentages. \( \epsilon \) values were generated in a normal distribution with a specific mean value. Several such mean \( \epsilon \) values were tested with several different participation percentages. The effect of each \( \epsilon \) value and participation percentage is shown in Figs. 3 - 7. Furthermore, the community might not be as easy to characterize with a mean \( \epsilon \) value as a Gaussian distribution. The electricity consumers are usually categorized in categories which have similar behaviors. Therefore, another possible model would be a mixture model which is a combination of multiple Gaussian distributions with different \( \epsilon \) values. Mixture models are used extensively in data-driven technologies [29]. Fig. 8 shows the result of the optimization of a population where 50% of the population contributes to with a mean \( \epsilon \) value of 0.1 and 25% of the population contributes with 0.2 mean \( \epsilon \) value.

**D. EFFECTS AT DIFFERENT LEVELS OF THE HIERARCHICAL ARCHITECTURE**

The optimization is carried out from bottom up, starting at homes. At various levels of the hierarchical architecture, the changes in power usage add up and the effects of DR start to appear more and more as the levels go up. In Figs. 9-12 this fact is demonstrated. These figures illustrate effects of DR carried out with 0.1 \( \epsilon \) and 75% participation at selected entities of the hierarchy and at each figure, it is easily noticed that the valleys are being filled and peaks are being shaved more and more, which is the target of the DR program.

**E. EFFECTS ON AN INDIVIDUAL HOME**

The effects of the optimization on individual home was explored by changing the \( \epsilon \) value over a range of values and measuring the discomfort values. For the shiftable devices, the average deviation of the appliance from the most comfortable scheduling time was measured. As seen in Fig. 13, the results show that the shiftable appliances remain mostly at the desired scheduling intervals. This is because DR on HVAC unit and interruptible appliances dominates over shiftable appliances. The thermal discomfort was measured by the average deviation of temperature from the desired temperature. Fig. 13 also shows the thermal comfort changes as the \( \epsilon \) increases.

**F. PERFORMANCE AND EFFECTIVENESS INDICATORS**

The performance indicator calculated for the current data set is shown in Fig. 14 and it reveals several facts about the optimization. At high contribution percentages and low \( \epsilon \) values, more contribution increases \( PI \) as generally expected. However, it can also be noticed that for large mean \( \epsilon \) values, the optimization could get worse as participation increases. This is because as the participation increases, less flexible contributions increase in the DR program.

The \( EI \) graph is shown in Fig. 15. Notice that in \( \epsilon = 0.1 \) graph 75% participation has a better \( EI \) value than 100% participation. Since 75% can achieve the same effect as 100% participation, this indicator shows a better value for 75% case than 100% case. The effectiveness of DR at the 75% case over other cases can be seen in the overall power usage graph (See Fig. 3). In this graph the 75% and 100% graphs look quite similar and yield the same amount of DR while the rest progressively worsen as the participation percentage.
FIGURE 3. Different total power demands for different participation percentages at $\epsilon = 0.1$

FIGURE 4. Different total power demands for different participation percentages at $\epsilon = 0.2$

FIGURE 5. Different total power demands for different participation percentages at $\epsilon = 0.3$

FIGURE 6. Different total power demands for different participation percentages at $\epsilon = 0.4$

FIGURE 7. Different total power demands for different participation percentages at $\epsilon = 0.5$

FIGURE 8. Total power demand for a population of 50% of $\epsilon = 0.1$ and 25% of $\epsilon = 0.2$ and rest non-contributing.
FIGURE 9. Results for the substation 34 for $\epsilon = 0.1$ and 75% participation. This specific substation had 70.52% participation.

FIGURE 10. Results for 3rd feeder of the 29th substation for $\epsilon = 0.1$ and 75% participation. This specific feeder had 72.0% participation.

FIGURE 11. Results for subfeeder 1 of the 9th feeder of the 20th substation for $\epsilon = 0.1$ and 75% participation. This specific subfeeder has 85% participation.

FIGURE 12. Results for home no 1 of the 29th subfeeder of the 41st feeder of the 15th substation for $\epsilon = 0.1$ and 75% participation. 17 out of 20 homes in the specific subfeeder where this home is located contributed towards DR (85%).

FIGURE 13. Average deviation of temperature and comfort from the preferred values of a home.

go down. The stress calculation is shown in Fig. 16. The graph shows that the stress for programs with very low participation is very high, but as participation grows, the stress on the consumer goes down. It can be noted that at 75% participation, the stress values almost converge and at 87%, they converge entirely. And the performance indicator graph (Fig. 14) shows that the performance indicator (i.e., the contribution towards DR) is similar in 75% and 87.5% cases. (For further comparison, The total demand for the 75% and 87.5% case is shown in Fig. 17) That is, in both cases, both the utility target of flattening the demand and the consumer target of maintaining more comfort (less stress) are achieved at 75% of participation of the community. The remaining 12.5% participants do not add much to the optimization. This is because the target is divided to the consumers, and the consumers carry out their own optimizations without knowing the amount of optimization the others are carrying out. This analysis reveals that, careful analysis on the participant has to be carried out in order to not to let the DR program performance degrade. The utility has to carry out the effectiveness calculation and the stress calculation on
VI. CONCLUSION AND FUTURE WORK

A scalable framework for demand response optimization is introduced in this paper. The hierarchical architecture is central to this framework and allows the addition of participants to the DR program without slowing down the optimization. Furthermore, it allows the optimization to take power flow limits in the power system into consideration, which is necessary for the practical implementation of a large-scale DR program. The presented case study and results obtained illustrate the success of the framework. The proposed framework has been successfully illustrated in a one million home case study. This framework could be applied to other power systems with different numbers of homes, subfeeders, feeders, and substations.

Additionally, new metrics to measure the success of the demand response program as well as the stress of the demand response participant have been presented. These measurements not only allow the utility to decide on the number of participants to incorporate in the DR program but also allows the participants to judge the stress they undergo in participating in DR. The application of these metrics in the explored case study shows that incorporating all possible participants might not be the best case for the utility. This result illustrates the fact that the DR aggregator needs to know the behavior of the electricity consumers in the population before involving the consumers in the DR program.

The proposed scalable DR framework can be expanded by the inclusion of distributed energy resources including generation and storage. The quality of DR program depends on the accuracy of the base load prediction. To have a maximum leverage of the demand response capability, the time between the demand response scheduling and execution needs to be reduced. To achieve this, a near real-time scheduling can be implemented such as an hour-ahead or even a smaller time-horizon.
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