A Distributed Energy Management Approach for Residential Demand Response

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***Abstract*—The implementation of large-scale optimization and control of residential appliances to support demand response (DR) programs comes with the challenges of coordinated communication, privacy, and consideration of customer preferences. Solving this complexity is best suited through a distributed optimization and control approach at the residential level by leveraging the availability and intelligence of a home energy management systems (HEMS). In this paper, a hierarchical control scheme to coordinate large-scale residential demand response through coordination of HEMs is proposed. This scheme is based on the exchange of a reward price and aggregated load information between utility system and HEMS. Numerical results on a one hundred-house model demonstrate the computational efficiency of the proposed approach.**

Keywords- distributed computation; home energy management system (HEMS); HVAC; load aggregator; residential demand response; water heater.

I. INTRODUCTION

As the electrical grid continues to expand and become more complex, there is a need to examine opportunities of shifting electrical enegy consumption to improve uitility load factor or the peak-to-average ratio (PAR). According to the U.S. Energy Information Administration, the PAR of electricity consumed in the United States has been increasing for the past few decades [1]. A growing PAR leads to network congestion and traditionally higher cost for upgrading and maintaining electrical system infrastructure [2]-[4].

One method to improve the utility PAR is to utilize some means of storing energy. While electro-chemical systems provide an option for storing electricity, building loads such as heating, ventilation, and air conditioner (HVAC) and water heaters can also provide support through thermal energy storage via the building envelope and water tank. The use of residential appliances could potentially be a lower cost solution compared to the utilization of large energy storage systems [5].

Existing demand response (DR) research has primarily focused on deployments for industrial customers [6]-[7]. These customers tend to have large loads that are more easily targetable with energy management systems. However, residential load accounts for 37% of the total electricity consumption in the United States (2013) and suggest a significant missed opportunity [8]-[9]. Still, challenges to energy shifting for residential loads do exist. Unlike industrial load, the residential load is composed of numerous low-power home appliances. In addition, the electricity consumption habits of residential customers are highly varied and dynamic.

Many efforts have been dedicated to investigate the load controls and optimizations in residential networks. In [10], an open-source home energy management platform is developed to enable the secure communication between the control center and multiple responsive loads in residential buildings. Various DR control schemes are demonstrated to reduce the PAR and the system operation costs. In [11], a centralized energy management system is proposed to reduce the electricity consumption and costs of residential buildings. The approach requires collecting the parameter settings of devices, external environment information, and users' preferences, followed by calculation of the optimal operating decision of each component over the operating horizon. In [12], a game theoretic-based algorithm is discussed that targets to lower the PAR and energy costs in distribution systems. The approach assumes that electrical energy consumers are charged proportionally to the total daily electricity demand. Consumers broadcast aggregated load information to other consumers and iterate until Nash Equilibrium is obtained.

In review, most studies considered the total electricity consumption as a fixed property and assumed that responsive load demand could be shifted without considering comfort factors such as indoor or water temperatures. Furthermore, these approaches require significant information exchange which is not scalable for large-scale applications. In this paper, a new approach is proposed that addresses these challenges. The main contributions of this paper are:

1) a distributed control scheme is presented with a centralized aggregator to reduce the computational complexity and ensure feasibility for large-scale applications,

2) data exchange is limited to aggregated load and incentive pricing to reduce communication bandwidth and maintain customer privacy,

3) the centralized optimization complexity is reduced through management of incentive variables instead of models of the entire population.

4) users' discomfort index and the temperature constraints for HVAC and water heater are included into consideration.

In the following sections of this paper, classifications of residential DR programs are reviewd, mathematical formulations for the residential appliance models are provided

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as well as optimization objectives and constraints, and a modeled case study is presented.

II. Classifications of Residential Demand Response Programs

A. Classification by Control Architectures

There are two types of architectures for communication and control of residential loads to support DR programs: centralized control and distributed control [13]-[14].

In a centralized scheme, the main objective is to maximize the overall social welfare. For this approach to work, operational data and constraints within the residential buildings are needed to form the optimization problem at the centralized location. This limits the centralized control approach to small networks as the computational and communication needs can grow significantly with each additional entity.

In a distributed scheme, optimization and control is distributed to each residential building. Information exchange between a centralized system and the residential buildings is limited to economic signals and expected load responses. Hence, most of computational complexity is distributed leading to a reduced burden on the centralized system and a more scalable architecture.

B. Classification by Reward Mechanisms

Depending on the approach for driving the economic signal, residential DR can also be categorized into incentive-based or price-based [15]-[16].

In the incentive-based approach, the centralized system (often a load aggregator) make payments to the residential building owners (RBO) when the grid reliability is jeopardized or the market price is high. During the load reduction, the control center can either remotely control the residential load or penalize the RBO who do not curtail their appliances. Examples of the incentive-based approaches include direct load control (DLC), curtailable service, and capacity market program [17]-[18].

In the price-based approach, the load aggregator offers Time of Use (ToU) rates to encourage customers to shift consumption. Price-based DR usually includes critical peak pricing, peak load pricing, and real-time pricing concepts. Generally, RBO can make their own choices on whether to change the load consumption for the 24-hour horizon or not [17].

III. Mathematical Formulations for Responsvie Loads

Since the objective is to develop a residential DR control scheme that is scalable and protects the RBOs' safety and privacy, a distributed control and a price-based reward approach has been chosen.

In this work, the HVAC and water heater are the distributed energy resources (DERs) which are available to participate in the optimization and control formulation. The HVAC and water heater loads represent 45% of residential electricity use and support storage through the building and water heater envelopes [19]. HVAC and water heater models are applied and the details of the simulated parameters are discussed.

A. HVAC Model

The input parameters for the HVAC models are the forecasted day-ahead outdoor temperature. The HVAC model is represented as:

$$T_{i,t}^{in} = T_{i,t-1}^{in} + \left[\left(T_{i,t}^{out} - T_{i,t-1}^{in} \right) / R_i^{house} - S_{i,t}^{hvac} \cdot P_i^{hvac} \right] / C_i^{house} \tag{1}$$

where $T_{i,t}^{in}$ is the indoor temperature of house i at time t, $T_{i,t}^{out}$ is the outdoor temperature of house i at time t, R_i^{house} is the thermal resistance of house i, $S_{i,t}^{hvac}$ is a binary variable that represents the operating status of the HVAC in house i at time t, P_i^{hvac} is the power rating of the HVAC in house i, and C_i^{house} is the thermal capacitance of house i. The values of R_i^{house} and C_i^{house} at each house are assumed to be uniformly distributed and the parameters are provided in TABLE I.

TABLE I. HVAC Parameters Used In Models

Parameter	Quantity
C_i^{house}	U[4.25, 5.75] J/K
R_i^{house}	U[6.80, 9.20] K/W
P_i^{hvac}	3.50 kW

B. Water Heater Model

Similar to the HVAC model, the water heater model is represented as:

$$T_{i,t}^{wh} = T_{i,t-1}^{wh} + \left[\left(T_{i,t}^{in} - T_{i,t-1}^{wh} \right) / R_i^{wh} + S_{i,t}^{wh} \cdot P_i^{wh} \right] / C_i^{wh} \tag{2}$$

where $T_{i,t}^{wh}$ is the hot water temperature in house i at time t, R_i^{wh} is the thermal resistance of the water heater in house i, $S_{i,t}^{wh}$ is a binary variable that represents the operating status of the water heater in house i at time t, P_i^{wh} is the power rating of the water heater in house i, and C_i^{wh} is the thermal capacitance of the water heater in house i. The values utilized in the water heater model are provided in TABLE II.

TABLE II. Water Heater Parameters Used In Models

Parameter	Quantity
C_i^{wh}	U[4.25, 5.75] J/K
R_i^{wh}	U[18.70, 25.30] K/W
P_i^{wh}	2.50 kW

C. Discomfort Index

The discomfort index is developed to provide a metric for the range of operation for temperature control. The discomfort index of each house is calculated based on the distance between the actual temperature and desired temperature range. This is represented as the sum of discomfort indices for indoor temperature and water temperature, as calculated by (3):

$$\begin{aligned} Dis_{i,t} &= max\left\{0, T_{i,t}^{in} - T_{i,t}^{in,max}, T_{i,t}^{in,min} - T_{i,t}^{in}\right\} \\ &+ max\left\{0, T_{i,t}^{wh} - T_{i,t}^{wh,max}, T_{i,t}^{wh,min} - T_{i,t}^{wh}\right\} \end{aligned} \tag{3}$$

where $Dis_{i,t}$ is the discomfort index of customer i at time t, $T_{i,t}^{in,max}$ is the maximum indoor temperature of house i at time t, $T_{i,t}^{in,min}$ is the minimum indoor temperature of house i at time t, $T_{i,t}^{wh,max}$ is the maximum hot water temperature in house i at time t, $T_{i,t}^{wh,min}$ is the minimum hot water temperature in house i at time t.

In Eq. (3), the maximum/minimum indoor and water temperatures in each house are preset by the customers. If the indoor/water temperature is within the range formulated by the minimum and maximum values, the discomfort index is zero. Otherwise, the discomfort index will be a positive value and added to the objective function that is minimized during the optimization.

IV. The Proposed Algorithm for Residential Demand Response

The proposed approach has two layers, a load aggregator and RBOs, as illustrated in Figure 1. A RBO home energy management system (HEM) is assumed to be available to provide communications with the aggregator and local DERs and the house-level optimization. The aggregator provides a reward price to drive electrical consumption adjustments. The mathematical formulations, as well as the flowcharts of the proposed distributed algorithm are discussed.

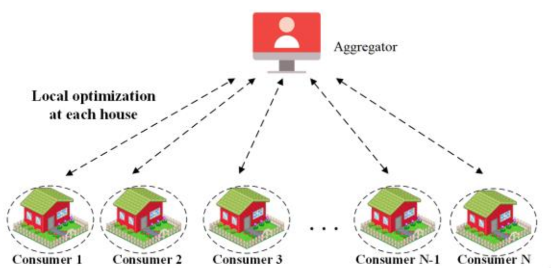

Figure 1. Architecture of proposed distributed algorithm.

A. RBO Optimization

At the house level, the HEMS is expected to receive a DR reward price from the aggregator, run a local optimization to generate a load forecast, and respond to the aggregator with a load profile. This optimization is formulated as a mixed integer linear programming problem with operating schedule of home appliances determined by local HEMS input. The goal is to minimize the electricity bill and customer's discomfort, as given by (4):

$$min\sum_{t}\left[\alpha\cdot Dis_i^t+\beta\cdot\left(c_t-r_t\right)\cdot D_i^t\right],\forall i \tag{4}$$

where α is the weight factor associated with user's discomfort index, β is the weight factor associated with user's electricity purchasing cost, c_t is the unit electricity price at time t, r_t is the unit DR reward price at time t, D_i^t is the aggregated load of customer i at time t.

The constraints for the RBO optimization problem include indoor temperature constraint, water temperature constraint, discomfort constraint, and load summation of each house, as shown by (1), (2), (3), and (5).

$$D_{i,t}=S_{i,t}^{hvac}\cdot P_i^{hvac}+S_{i,t}^{wh}\cdot P_i^{wh} \tag{5}$$

B. Aggregator Calculation

The initial reward price at different time is set as zero and sent from the load aggregator to the participating RBOs. Each RBO responds with load information which is collected and aggregated. The DR reward price is recalculated based on the difference between the aggregated load and desired load. Also, the DR compensation cost should be less than the expected limit that set by the aggregator. Consequently, the upper-level control can be described:

$$r^0=\left[0,0,\ldots,0\right] \tag{6}$$

$$D_t^{agg}=\sum_i D_{i,t} \tag{7}$$

$$D_t^{margin}=max\left(D_t^{max}-D_t^{agg},0\right) \tag{8}$$

$$r_t^{iter}=r_t^{iter-1}+\varepsilon\cdot D_t^{margin} \tag{9}$$

$$\sum_{t=1}^{T}\left(r_t^{iter}\cdot D_t^{agg}\right)\le\theta\cdot\sum_{t=1}^{T}\left(c_t\cdot D_t^{agg}\right) \tag{10}$$

where r^0 is the initial DR reward price, D_t^{agg} is the aggregated load at time t, D_t^{margin} is the load margin at time t, D_t^{max} is the maximum allowable load at time t (which is usually a known parameter that assigned by the aggregator), r_t^{iter} is the DR reward price at the *iter*th iteration, ε is the step size coefficient, and θ is a coefficient that between 0 and 1.

The load aggregator updates the DR reward price to attempt to meet the objective load profile. The key flexible parameter ε, the step size coefficient, must be chosen appropriately: 1) too large a value and the reward price steps can be large overshooting the expected maximum DR compensation cost set by the aggregator and 2) too small a value requiring significant number of iterations for convergence. This is further discussed.

C. Overall Process

To conclude, the flowchart of the overall process is plotted in Figure 2. , and the detailed steps are summarized as follows:

Step 1: aggregator announces the initial reward price to the customers within the service region.

Step 2: end-use customers input the desired indoor and water temperature ranges to HEMS, and HEMS automatically pulls the day-ahead outdoor temperature forecast from the local weather service center.

Step 3: HEMS determines the operation schedule for responsive loads based on the outdoor temperature, preset temperature intervals, and optimized economics and reports the initial total load information to the aggregator.

Step 4: aggregator waits until all the customers' load information is collected.

Step 5: aggregator calculates the amount of aggregated load and decides if the total load is less than or equal to the desired maximum load. If yes, then aggregator send a message to all the HEMS to stop, otherwise go to the next step.

Step 6: aggregator updates the reward price based on the load margin and broadcasts the new DR reward price to all the HEMS.

Step 7: HEMS receives the updated reward price and recalculates the operating schedule and reports the total load information to the aggregator.

Step 8: go back to Step 4.

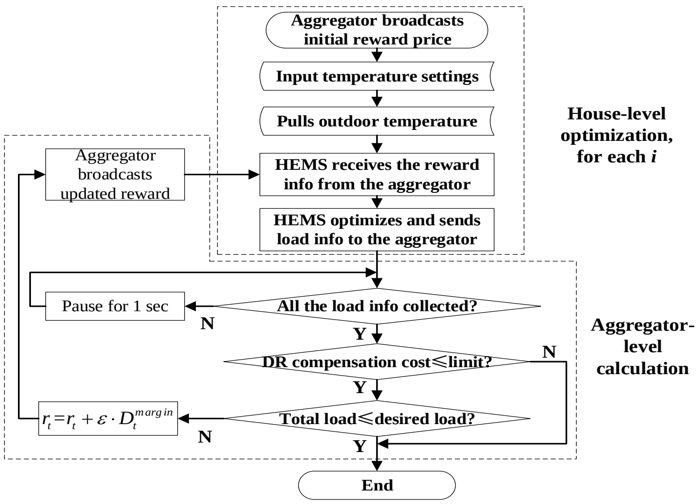

Figure 2. Flowchart of proposed distributed approach.

V. Case Study

The proposed distributed algorithm is tested on a hybrid platform, MATLAB 2018a and GAMS 24.7, where MATLAB is used for creating input data profiles and storing computation results. The hardware environment is a laptop with Intel® Core™ i7-8650U@1.90GHz and 16GB RAM.

A. Performance on a 100-house Test System

The simulation test system is composed of one aggregator and 100 houses. The required time interval is set to 15 minutes, and the day-ahead forecasted output temperature is given in Figure 3. A distribution of weight factors, responsive load parameters, and temperature settings were provided to each house model to provide variation, as given in TABLE III.

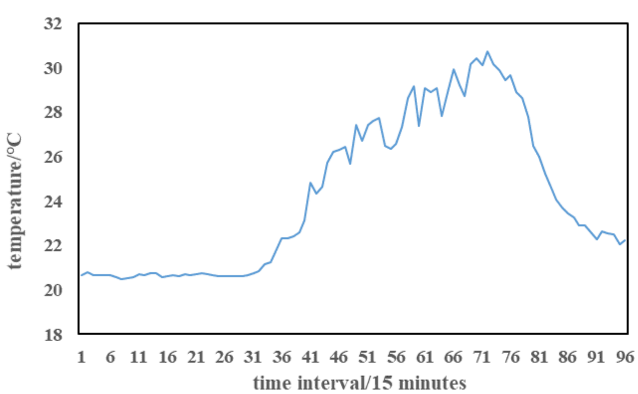

Figure 3. Day-ahead forecasted outdoor temperature.

TABLE III. Parameter Settings In the Case Studies

Parameter	Quantity
β/α	U[2.25 2.75]
c_t	\$0.15/kWh
$T_{i,t}^{in,min}$	19℃~20℃
$T_{i,t}^{in,max}$	21.5℃~23℃
$T_{i,t}^{wh,min}$	45.5℃~46.5℃
$T_{i,t}^{wh,max}$	48℃~48.5℃

In the demonstrated case, the proposed algorithm required 6 iterations to converge when the value of ε is set to 1e-6. Within each iteration, the highest level of the hierarchy requires 0.025 seconds at maximum to perform the calculation while the lower level takes 0.82 seconds at maximum to complete one iteration. Since the proposed approach is a distributed algorithm and each house is able to operate in parallel, the total computational time to converge is 5.07 seconds. However, due to the communication delays, the time consumption in practical applications should be longer than 5.07 *sec*. Since the communication delay varies in different communication channels which deserves another full-fledged paper, only the computational time is considered in this work.

Figure 4. compares the aggregated load with and without implementing the DR. On the load aggregator level, the peak load without DR is 284.0 kW, which is larger than the 260.0 kW maximum desired load. After implementing the proposed DR algorithm, the peak load is reduced to 253.0 kW, which is only about 89.1% of the initial load. Notice that load aggregators may encounter peak demand charges if the aggregated load is too large. Peak demand charge is the product of the peak load and a higher electricity rate. The cost for peak demand charge can be as much as \$18.64/kWh [20]. In this case study, the peak load is reduced from 284.0 kW to 253.0 kW, which is only about 89.1% of the original load. Therefore, the customers' electricity bills are significantly saved by reducing the pass-through cost from the load aggregator.

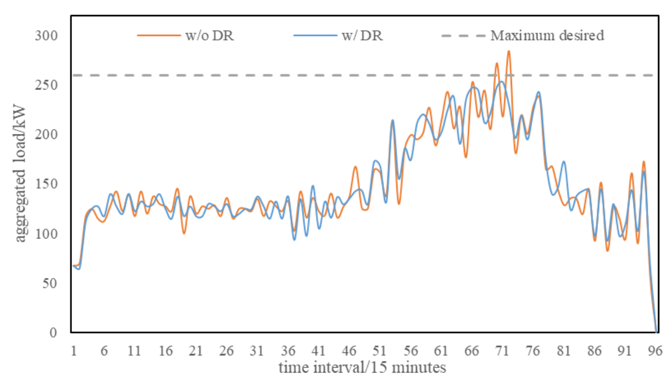

Figure 4. Aggregated load with/without implementing DR.

Moreover, the DR participants can also benefit from a lower retail electricity price. The unit DR reward price and total reward saving at each time interval is presented in Figure 5. Despite the slight increase in average aggregated load level from 148.2 kW to 148.5 kW after implementing the DR, the electricity cost of all the customers is decreased from \$533.6 to

\$533.0. It is also observed that the reward at peak period is usually smaller than that at off-peak period, which verifies the fact that the peak load reduction is realized by providing DR reward price at off-peak hours to incentivize load shifting to off-peak periods.

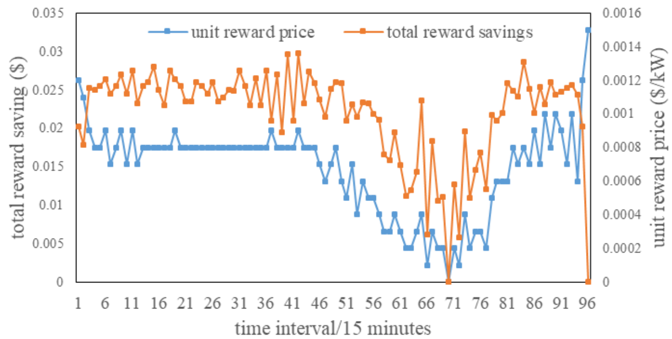

Figure 5. DR reward price at each time interval.

Figure 6. and Figure 7. show the indoor and water temperature of house 1 with and without implementing the proposed DR algorithm. The preferred indoor temperature range for house 1 is between 19 ℃ and 22 ℃, and the preferred water temperature range is between 45.5 ℃ and 48 ℃. After implementing DR, the indoor temperature range is between 19.2 ℃ and 22.0 ℃, and the water temperature range is between 45.5 ℃ and 46.9 ℃. From the graphs, it is observed that both the indoor temperature and water temperature with DR are within the range of preset temperature intervals. Therefore, the comfort level of customers is not significantly affected after implementing the proposed DR algorithm.

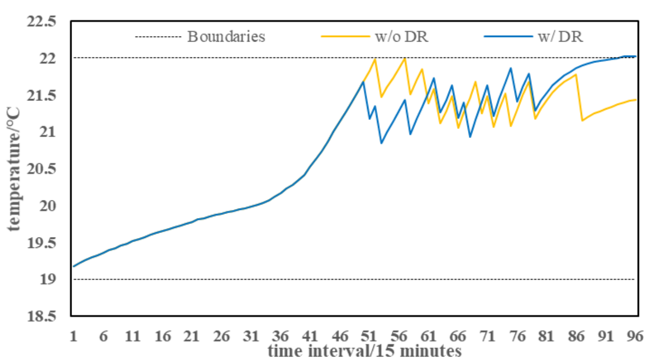

Figure 6. Indoor temperature of house 1 with/without implementing DR.

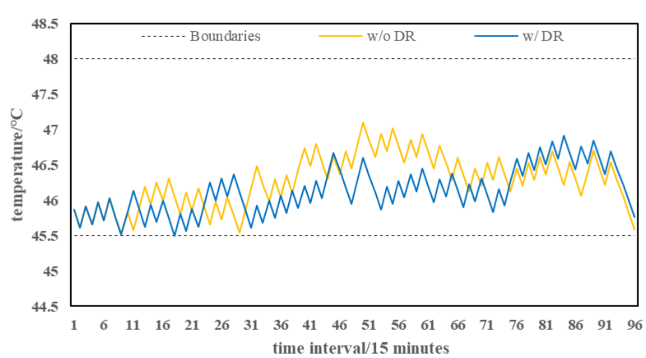

Figure 7. Water temperature of house 1 with/without implementing DR.

To conclude, the end-use customers can save money by participating the DR programs and the system peak demand is reduced to the prescribed value.

B. Impact of Peak Load Limit and Step Size on Computational Time and Optimization Results

The impact of peak load limit and step size on computational time and optimization results are also investigated by respectively changing the values of D_t^{max} and ε, respectively. The results are given in TABLE IV. and TABLE V. The step size in TABLE IV. is set to 1e-6, and the maximum desired load in TABLE V. is set to 265 kW. Other parameter settings are the same as Section V.I.

TABLE IV. IMPACT OF PEAK LOAD LIMIT ON OPTIMIZATION RESULTS

peak limit (kW)	270	265	260
achieved peak (kW)	257.5	261	255
iteration	9	13	26
average customer’s saving (\$/month)	5.0	4.4	5.7

TABLE V. IMPACT OF STEP SIZE ON OPTIMIZATION RESULTS

ε	1e-4	1e-5	1e-6	1e-7	1e-8
iteration	n/a	n/a	5	13	34
customer’s electricity cost (\$/day)	n/a	n/a	5.3	5.4	5.3

From TABLE IV. it is observed that when the peak load limit decreases, the number of iterations increases. While the simulation studies in TABLE V. suggest that the value of the step size has to be sufficiently small. When ε equals to 1e-4 or 1e-5, the distributed algorithm fails to converge. Then if the step size is further reduced, the computational time can be increased. Therefore, the peak load limit and step size should be adjusted based on practical applications.

VI. CONCLUSIONS

This paper proposes a hierarchical distributed algorithm for residential demand response. The proposed approach takes the indoor temperature and water temperature into consideration and introduces the discomfort index. Moreover, end-user customers do not have to release the operating status of their home appliances to the load aggregator or their neighbors, which considerably protect their privacy. Further, customers may only need to input the desired temperature settings for HVAC and water heaters, and HEMS will automatically calculate the optimal operating schedule and controls for responsive loads. Finally, the distributed algorithm reduces the computational burden of the load aggregator and ensures the feasibility of the proposed algorithm for large-scale residential DR applications.

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