Distributed Intelligent Load Management and Control System

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***Abstract*—Demand response (DR) is becoming a key component of future smart grid that can reduce peak load and adapt elastic demand to fluctuating generations. While reducing energy bills for the participant, DR usually decreases its utility, which is different for distributed occupants inside a participating entity. A two-level distributed intelligent load management and control system is proposed in this paper to minimize the cost of the participant, where the cost is a measurement of disutility, considering differences across plug loads, with the load reduction constraint of a DR event.**

The control system contains a smart DR controller and distributed intelligent gateways. In the system, the cost function of a load is modeled to reflect the dissatisfaction of the occupant for switching off or dimming the load, and a two-level optimization method is deployed to minimize the participant's aggregated cost. Each intelligent gateway collects the cost functions of loads in the neighborhood of an occupant, generates its optimal cost function and sends to the smart DR controller. The smart DR controller utilizes those cost functions to allocate the load reduction among the gateways, which can then optimize the load reduction among loads for the distributed optimum. While the cost function of the loads can be modeled as either continuous or discrete functions based on the type of the load, Lagrange multipliers and particle swarm optimization (PSO) are utilized for optimization, respectively. This innovative method is implemented in a DR system of a building, and tests results show that the proposed distributed DR method is practical and promising.

***Index Terms*—Demand response, Distributed Control, Two-level Optimization, Lagrange Multipliers, Particle Swarm Optimization, Disutility.**

I. Introduction

Demand side management is becoming a key component of future smart grid that can help reduce peak load and adapt elastic demand to fluctuating generations. In 2009, Federal Energy Regulatory Commission reported in [1] that the peak demand without any demand response is estimated to grow at an annual average growth rate of 1.7%, reaching 810 GW in 2009 and approximately 950 GW by 2019. The report also projected that existing DR programs could offset 4% of U.S. peak demand by year of 2019. Furthermore, if these programs were expanded to cover the entire country and a small number of price-responsive programs were added to mix, the impact would rise to 9%. The benefits from demand response with peak reduction and load shifting will defer new infrastructure investment and improve generator operation efficiency [2].

DR is becoming an integral part of the power system and market operational practice [3], because not only the volume of DR is quickly growing, but these resources are treated as dispatchable capacity resources so that they are being called on much more frequently and in larger amount than in previous DR programs. [4] presented and analyzed case studies of different electric utility programs. Implementation of advance metering infrastructure and other smart grid technologies further increase the utilization of DR resources in planning and operation [5].

DR control strategies regarding different commercial centralized systems are discussed in [6], [7] and [8]. In a project initiated by Southern California Edison's Design and Engineering Services (D&ES) group, control strategies and technologies that would allow commercial customers to participate in DR programs by shedding load from ice machines were evaluated in [6]. [7] discussed the control strategies regarding Heating Ventilation and Air Conditioning (HVAC) system to optimize electricity cost and users' comfort. [8] investigated use of DR control strategies in commercial buildings and provided specific details on DR control strategy design concepts for a new building in New York by utilizing EnergyPlus simulations.

However, there are two limitations with state of the art building demand response control strategy. Firstly, distributed loads were never contributing. As plug loads become a major driver of building energy growth, to include distributed load into DR can improve DR capacity tremendously. Secondly, many aspects of the interaction between DR server and DR clients are regulated by static long-term contract and strategies that define the available load-shedding capacity and the distribution of it among different energy end consumer, without taking into account the current energy usage state. As a main consequence, the DR performance is strongly constrained since the possibility to dynamically accommodate building space utilization and weather change on building energy usage during DR event is very limited or even not possible. This generates inefficiency of the loads' shedding capacity utilization while degrading the productivity of some of the building occupants.

The concerns discussed above motivate us to study the dynamic building DR including distributed loads. A two-level DR system for distributed DR is proposed in this paper, where the decision making is distributed to local gateways which serves as the aggregator of distributed loads around it. The top-tier DR manager only passes DR signals or generate goals to

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the second tier DR gateways. The local gateways, for example, could react to DR events using market mechanisms like in [9], [10] and [11] by bidding either for energy service or load shedding if economic incentive is given. The gateways can also sense, derive, plan and execute autonomously. For enable analysis on realistic appliances, we will introduce load-level cost function for each load, either continuous or discrete. We will also present optimization algorithms for both continuous and discrete cost functions.

II. Problem formation and system design

A. System description

In this paper, we consider a demand response system with a central manager. The central manager receives DR event from utility and controls centralized appliances, e.g. HVAC, central lighting, as well as the overall electricity usage in the building. In addition to the centralized appliances, we consider distributed plug loads are also controllable. Gateways, are introduced as distributed controllers, which is the intermediate level between plug appliances and the central controller. Each gateway is connected to distributed sensors and actuators of appliances, and deployed as an appliance aggregator who creates its portfolio with the summation of all appliances around it. Therefore, the central manager considers each gateway as a load instead of every plug appliance in a DR event, distributes power at the gateway level, and the gateways distribute power at the plug appliance level. The system is illustrated in Figure 1.

In each level, the power distribution is a mathematic optimization problem, where the objective is to minimize the cost of shedding loads, with the constraint of load reduction requirement of a DR event and the appliances. The cost model at appliance level and the optimization problem with the model will be described in the following sections.

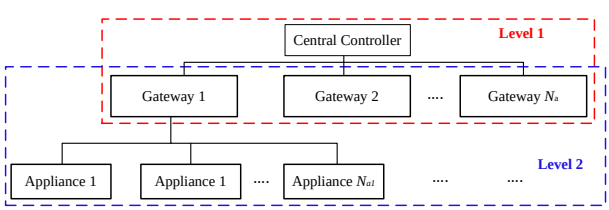

Fig. 1. Two-level Control System

B. Cost function model

The idea of cost function derives from the utility function in economics [12], where utility is a measure of relative satisfaction. To quantify utility, Samuelson stated the 'revealed preferences' in his classical publication [13] that they cannot be measured directly, but only indirectly by the price which a person is willing to pay for the fulfillment or satisfaction of his desire.

Consumers have different preferences on different appliances related to their activities. For example, if the consumer is reading, he usually prefers the light to be brighter, and other appliances less important; if he is working on the laptop, the task light is less important. In this paper, we propose an appliance-level cost function, where each controllable appliance has a cost function related to consumer's preference so that the gateway can allocation optimal power to each load. The cost function of an appliance is modeled to be a function of the appliance's disutility according to the change of the power reduction of the appliance. For instance, when the consumer has no need to save any electricity, he is assumed to be fully satisfied when the appliances can be used without constraint, thus the cost is zero when the power reduction is zero. However, during a DR event, if the consumer decides to reduce power by shutting down an appliance, his corresponding disutility is quantified as a positive cost of the appliance when the power reduction is positive. Therefore, the cost is a non-decreasing function of power reduction.

Similarly, when multiple appliances are considered as a group, the overall cost function is an weighted summation of cost functions of each and every individual appliance.

1) Continuous cost function: Previously the cost functions are often assumed to be continuous, differentiable, and convex like in [10] and [11]. In this paper, quadratic function is chosen as in [10] for continuous analysis in (1).

$$f(r) = a_1 r + a_2 r^2, \quad \forall r \in [0, r_m] \tag{1}$$

where $a_1 \geq 0$ and $a_2 \geq 0$ are parameters based on consumer's preference and $r_m > 0$ is the maximum power reduction of the appliance.

2) Discrete cost function: The continuous models are suitable for the scenarios where loads can be controlled continuously, or the cost function of an aggregator where large number of loads are aggregated. However, a discrete model is necessary if we consider a model for realistic appliances, e.g. task lights, laptops and printers, which only have discrete control levels. While defining the cost function of an appliance, the comfortable level that it brings to the consumer as its output, e.g. light or temperature change, varying with its power input is quantified. In addition, when there are more than one appliance used by a consumer, he usually considers each appliance with different importance. Therefore, the relative importance is modeled as a part of the cost function.

The cost function of the appliance is defined in (2).

$$f(r) = \bar{I} g(r, T), \tag{2}$$

where $\bar{I}$ is the relative importance configured by the consumer of the appliance comparing with other appliances, and $g(r, T)$ is the comfortable level which evaluates the satisfaction of the consumer by using the appliance alone given the power reduction r and the appliance type T. Both parts will be explained later. In (2), when T is fixed and $\bar{I}$ is configured for each appliance, $f(r)$ is a function of r.

When a consumer is using multiple appliances, given I_{th} as the threshold importance for an appliance to participate in the load shedding or not, he can decide the importance I of each appliance. Therefore, the relative importance of an appliance is defined as $\bar{I} = I/I_{th}$, where for the appliances that the customer considered to participate load shedding in a

Comfortness	Power consumption control	
	continuous	discrete
continuous	A: Task light with incandescent bulb, heater, humidifier, fan	N/A
discrete	B: Refrigerator	C: Laptop, printer, desktop monitor, task light with fluorescent bulb

TABLE I
TYPES OF APPLIANCES

DR event,I is chosen in the range of $[1, \cdots, I_{th}]$. However, if the appliance is considered to be too important to bear any load shedding during a DR event, the importance should be set as $I > I_{th}$. In the optimization algorithm, the status of the appliance with importance $I > I_{th}$ should never be changed during the DR event.

To model the comfortable level $g(r, T)$ of different appliances, in this paper, we define three types of appliances based on how their power consumption can be controlled and how the output relates to consumer's comfort as in Table I.

The power consumption control of an appliance is considered as continuous when its power consumption can be controlled continuously, e.g. the mean power to an incandescent light can be decreased or increased continuously by a dimmer, and the mean power of a refrigerator can be controlled by increasing or decreasing the frequency of its cooling cycle. On the contrary, the appliances can only be controlled between several discrete levels, like a fluorescent light with On or Off level, and a laptop working on either AC supply or battery, their power consumption control is defined to be discrete.

When the power input of the appliance is continuous, and consumer's comfort in relation to its output can also be continuous. For instance, for a sensitive consumer, the brightness of an incandescent light is varying continuously with its power input. For other appliances, when the power input is continuous, their output can also be discrete. Like a refrigerator, although the average temperature inside is changing continuously with the power consumption, any temperature within the range of the optimal temperature for the food has no difference, however, any temperature outside the range is not acceptable. On the other hand, all appliances with discrete power input must have an discrete output.

The majority of the appliances fall into the three categories in table I. Therefore, $g(r, T)$ can be defined for each type $T \in [A, B, C]$.

- For type A,
$$g(r, A) = \frac{r}{r^M} \tag{3}$$
where r^M is the maximum load reduction.
- For type B, assume there are N_l levels of output of the appliance,
$$g(r, B) = \begin{cases} \frac{r_1}{r^M} & r \in [r_1, r_2) \\ \vdots & \\ \frac{r_{n-1}}{r_m} & r \in [r_{N_l - 1}, r_{N_l} = r^M] \end{cases} \tag{4}$$
- For type C, where r is discrete, assume there are N_l levels of power consumption of the appliance,
$$g(r, C) = \begin{cases} \frac{r_1}{r^M} & r = r_1 \\ \vdots & \\ \frac{r_{N_l}}{r^M} = 1 & r = r_{N_l} = r^M \end{cases} \tag{5}$$

The category of an appliance may change according to consumer's preference. Take the incandescent light as an example. Although the brightness as lumens is varying with the mean power, the sensitivity of a consumer may have several levels instead of continuous reaction. In this case, this light changes from category A to B.

C. Optimization model for demand response

Assume a demand response control problem with n participants and the total load reduction demand R given by the DR controller. The cost function of participant i is denoted by $f_i(r_i)$ which can be either continuous in (1) or discrete in (2), where r_i is the load reduction of participant i. The demand response system should minimize the dissatisfaction of the occupants while still meeting the specified set-points of the DR controller. The system should also consider the constraints of each device/load such as minimum load reduction and maximum load reduction. Thus, this problem is an optimization issue, which can be expressed in (6), where r_i^L and r_i^U are the minimum and maximum load reduction of participant i, respectively.

$$\begin{aligned} \min \quad & \sum_{i=1}^{n} f_i(r_i) \\ s.t. \quad & \sum_{i=1}^{n} r_i = R \\ & r_i^L \le r_i \le r_i^U, \quad i = 1, 2, \cdots, n \end{aligned} \tag{6}$$

III. ALGORITHMS FOR OPTIMAL DEMAND RESPONSE

According to section II-B, the cost function $f_i(r_i)$ in (6) can be modeled as either continuous or discrete functions based on the type of load, thus different optimization methods for different models are more than necessary. In this section, the optimization methods for both continuous and discrete function are introduced first. Furthermore, the two optimization methods can be deployed in different DR control systems. The centralized system is introduced first as the traditional solution and the two-level DR control system will be proposed later.

A. Optimization method

1) With continuous cost function: Without loss of generality, we assume that cost functions in (6) are continuous and convex. Thus, there exists $r_i^\star$ such that the total cost of loads is minimized while still satisfying all constraints.

Problem (6) with only the equality constraint can be solved using Lagrange multiplier by introducing another variable λ [11]. The inequality constraints will be added later in solving the problem iteratively.

The Lagrange function with equality constraint is defined as

$$\min \sum_{i=1}^{n} f_i(r_i) - \lambda \left(\sum_{i=1}^{n} r_i - R \right). \tag{7}$$

Generally, the optimization results satisfy the equations

$$\frac{\partial f_i(r_i)}{\partial r_i} - \lambda = 0, \tag{8a}$$

$$\sum_{i=0}^{n} r_i - R = 0. \tag{8b}$$

Obviously, if an optimal allocation is achieved, the derivatives of $f_i(r_i)$ for all the participants equal to λ. Therefore, (8) can be addressed in an iterative way as follows.

1) Initialize λ with $\lambda = \lambda_0$.
2) Solve (8a) for r_i . Usually, (8a) is a nonlinear equation, thus we can use Newton-Raphson method to solve it. The iteration formulas are shown in (9) as

$$\Delta r_i^k = \frac{\frac{\partial f_i(r_i)}{\partial r_i} - \lambda}{\frac{\partial^2 f_i(r_i)}{\partial r_i^2}}\Big|_{r_i = r_i^k}, \tag{9a}$$

$$r_i^{k+1} = r_i^k + \Delta r_i^k, \tag{9b}$$

where k is the number of iterations. Adding the inequality constraints in (6) into consideration where each r_i is constrained with low bound and upper bound, (9) should be modified as

$$\begin{cases} r_i^{k+1} = r_i^U & \max\left(\frac{\partial f_i(r_i)}{\partial r_i}\right) \le \lambda \\ r_i^{k+1} = r_i^k + \Delta r_i^k & \min\left(\frac{\partial f_i(r_i)}{\partial r_i}\right) \le \lambda \\ & \le \max\left(\frac{\partial f_i(r_i)}{\partial r_i}\right) \\ r_i^{k+1} = r_i^L & \lambda \le \min\left(\frac{\partial f_i(r_i)}{\partial r_i}\right) \end{cases}. \tag{10}$$

3) If $\left|\sum_{i=1}^{n} r_i^{k+1} - R\right| < \varepsilon$, set r_i as the optimal results. Otherwise, update λ as

$$\lambda^{k+1} = \lambda^k - \alpha^k \left(\sum_{i=1}^{n} r_i^{k+1} - R \right) \tag{11}$$

and continue to step 2.

In this way, we can obtain the optimal load reduction when all the loads have continuous cost functions. However, when cost functions are discrete, the previous method is not applicable. Therefore, we introduce a discrete optimization method in the following section to address the corresponding problem.

2) With discrete cost function : In this section, particle swarm optimization (PSO) method in [14] is deployed to solve the problem addressed in (6), where the cost function $f_i(r_i)$ can be discrete.

Let $x = [r_1, r_2, \cdots, r_n]$, then the inequalities constraints in (6) can be written as

$$g_i(x) \le 0 \quad i = 1, 2, \cdots, J, \tag{12}$$

where J is the number of inequalities.

The equalities constrains in (6) can be written as

$$h_j(x) = 0 \quad j = 1, 2, \cdots, K, \tag{13}$$

where K is the number of equalities constraints.

In order to implement PSO, (13) is reformed to

$$\begin{cases} -h_j(x) - \varepsilon \le 0 \\ h_j(x) - \varepsilon \le 0 \end{cases} \quad j = 1, 2, \cdots, K, \tag{14}$$

where ε is an infinitesimal arbitrary constant.

Notice that (14) has the same form of inequalities constraints as (12), then the constraints can be written as

$$g_i(x) \le 0 \quad i = 1, 2, \cdots, J, J+1, \cdots, J+2K. \tag{15}$$

A penalty function $P(x)$ is introduced to handle the constraints, which is defined as

$$P(x) = y(k)H(x). \tag{16}$$

where k is the algorithm's current iteration number and $y(k)$ is dynamically modified penalty value defined as

$$y(k) = \sqrt{k} \quad \text{or} \quad k\sqrt{k}, \tag{17}$$

and $H(k)$ is the penalty factor as

$$H(x) = \sum_{i=1}^{J+2K} \theta\left(q_i(x)\right) q_i^{\gamma(q_i(x))}, \tag{18}$$

where $q_i(x) = \max\{0, g_i(x)\}, i = 1, 2, \cdots, J + 2K$is a relative violated function of constraints, $\theta\left(q_i(x)\right)$ and $\gamma\left(q_i(x)\right)$ can be determined according to [15].

The objective of PSO is defined as

$$F(x) = f(x) + P(x), \tag{19}$$

where $f(x) = \sum_{i=1}^{n} f_i(x)$ and $P(x)$ is defined in (16).

When N_P particles are utilized for implementation, the search space for each particle is n-dimensional, which can be represented by the vector $\mathbf{x}_i = (r_{i1}, r_{i2}, \cdots, r_{in})$. The best particle of the swarm is denoted by $\mathbf{p}_g = (p_{g1}, p_{g2}, \cdots, p_{gn})$, the best previous position of the ith particle is represented as $\mathbf{p}_i = (p_{i1}, p_{i2}, \cdots, p_{in})$ and the position change (velocity) of the ith particle is $\mathbf{v}_i = (v_{i1}, v_{i2}, \cdots, v_{in})$. The process of iteration of PSO is represented in [14] as

$$\begin{cases} \mathbf{v}_i^{k+1} & = \beta\left(w\mathbf{v}_i^k + c_1 r_{i1}^k(\mathbf{p}_i^k - \mathbf{x}_i^k)\right) + c_2 r_{i2}^k(\mathbf{p}_g^k - \mathbf{x}_i^k) \\ \mathbf{x}_i^{k+1} & = \mathbf{x}_i^k + \mathbf{v}_i^{k+1} \quad i = 1, 2, \cdots, N_P \end{cases}, \tag{20}$$

where β is a constriction factor used to control velocities, w is the inertia weight, c_1 and c_2 are two positive constants, named the cognitive and social parameter, respectively, and r_{i1} and r_{i2} are random numbers uniformly distributed within the range $[0 \quad 1]$.

B. Optimization in different Control System Structure

1) Centralized Control System: One way to implement the optimization of DR system is the centralized method. In this case, the gateways is used to forward information between the DR controller and the loads. The central controller is able to have all the cost functions information of loads and control each load directly. The centralized DR control system can be

found in [16] and [17] where the procedure can be described as follows.

1) All the loads send their cost functions to the central DR controller.
2) The DR controller calculates the optimal load reduction of each load using the optimization methods (continuous cost function or discrete cost function) introduced before, and sends the results to each load.
3) Once each load receives the load reduction command, the load controller implements the load reduction.

In the centralized case, the central DR controller needs to communicate to all the loads in order to obtain the cost functions of them. For a DR system in a building, the number of distributed loads becomes so large that it can cause a huge communication payload. In addition, it requires the central controller to have more powerful processor with larger memory to implement the optimization without too much delay. To overcome the listed disadvantage, we propose a two-level control system for the DR system in the following subsection.

2) Two-level Optimization Control System: In the two-level control strategy, the central DR controller has no knowledge of the cost functions information of each load. The gateways aggregates the information of loads and generate one cost function per gateway, and the central controller collects information from the gateways and allocate load reduction to each gateway. Since gateway knows the cost function of loads in its area, it can further allocate the load reduction to the responding loads. In the sense of control architecture, the control system is hierarchical distributed control system (not decentralized system). In order to determine the optimal allocation among gateways, each gateway should generate its cost function according to cost functions of the corresponding loads. Meanwhile, for an arbitrary load reduction assigned to a gateway, it should minimize the total cost in its area in order to allocate the load reduction to each load. This means that the cost function of the gateway is actually the optimal load reduction trajectory of the loads of its area.

Assume a distributed DR system is consisted of N_a gateways. The total load reduction L_i of gateway i is denoted as

$$L_i = \sum_{j=1}^{N_{ai}} r_{ij}, \tag{21}$$

where $i \in [1, 2, \cdots, N_a]$, r_{ij} is the load reduction of load j at gateway i, where $j \in [1, 2, \cdots, N_{ai}]$, and N_{ai} is the number of loads at gateway i.

From the above analysis, $f_i(L_i)$ should be generated. And a numerical way is utilized to achieve that, the procedure is introduced as follows:

1) Initialize L_i^k with the minimum load reduction, L_i^0, which can be obtained by setting each load of this gateway as the minimum value, and set $k = 0$.
2) Solve the optimization problem in (22), we can obtain one optimal cost value $f_i(L_i^k)$ with the load reduction of L_i^k.

$$\begin{cases} \min \left(\sum_{j=1}^{N_{ai}} f_j(r_{ij}) \right) \\ s.t. \sum_{j=1}^{N_{ai}} r_{ij} = L_i^k \end{cases} \tag{22}$$

3) Update L_i with

$$L_i^{k+1} = L_i^k + \Delta L_i \tag{23}$$

until it reaches the maximum value which can be obtained by setting each load of the gateway as the maximum value, then set $k = k + 1$.
4) Continue to Step 2 to obtain next cost value $f_i(L_i^k)$.

Through the process described above, a series of values of $f_i(L_i^k)$ with specified load reduction allocation of L_i^k is obtained, and we denote it with

$$f_i(L_i) =< L_i^k, f_i(L_i^k) > . \tag{24}$$

(24) can be used as the cost function of the gateway. After the cost functions of all the gateways are obtained, the optimization methods in III-A can be utilized to obtain the optimal allocation among gateways. Though the cost function generated in the previous section using (23) is a discrete cost function, cost function of the gateway can also be approximated to be continuous when the cost functions of load are continuous as in [18]. Therefore, both the continuous and the discrete method in III-A can be used to address the optimization problem among gateways. In practice, the progress is described as follows:

1) All the load sets send their cost functions to the corresponding gateways.
2) The gateways obtain their cost functions as (24).
3) The gateways send their cost functions to the DR controller.
4) The DR controller determines the load reduction allocation by solving the optimization problem as (6) with gateways' cost functions and sends the optimal results to each gateway.
5) Since each gateway has received the allocation, it determines the optimal load reduction of the load sets by solving the optimization problem as (6) with appliances' cost functions and sends the results to them.
6) After the each load receives the load reduction command, the load controller implements the load reduction.

In the subsequent section, we present both simulations and demonstration for the proposed two-level optimization algorithm.

IV. Test results

In this part, we provide two test scenarios with either continuous or discrete cost functions to illustrate the performance of the proposed two-level DR control system. In both cases, we compare the results to the centralized DR control system to evaluate the performance of the two-level system.

A. Continuous cost function scenario

In the first test scenario, the cost functions of the devices (loads) are modeled to be quadratic as (6). The test case includes 4 gateways, 9 loads in total, cost functions are provided in Tab. II, and total load reduction requirement is $500W$.

The optimization results of the two-level system are presented in Tab. III. In the system, we approximate the cost function of the gateways using quadratic functions as in [18] with the cost functions of loads. The centralized controller is allocating load reductions among gateways, and each gateway allocate load reductions to corresponding loads. To compare the performance, The results of a centralized system when the DR controller can collect the cost functions of each device directly are also shown in Tab. IV. In both Tab. IV. and Tab. III, the cost values are normalized with base 100.

Gateway	Device	Parameters of cost function		r^L (W)	r^H (W)
		a_1	a_2		
1	1	0.0002	0.02	0	70
	2	0.3	0	0	80
	3	0.1	0.0015	0	100
2	1	0.2	0.008	0	100
	2	0.07	0.005	0	150
3	1	0.01	0.01	0	150
	2	0.04	0.008	0	100
4	1	0.25	0.006	0	120
	2	0.07	0.007	0	130

TABLE II
THE DETAILED INFORMATION OF DEVICES AND GATEWAYS

From Tab. III and Tab. IV , it can be seen that the proposed two-level optimization system achieves almost the same results by the centralized system. As we generate the cost function of the gateway along the optimal trajectory, which, in turn, ensures the global optimization results.

B. Discrete cost function scenario

The second test scenario is the discrete cost function scenario. In this case, we implemented the optimization algorithm into an actual building DR control system. In this DR system, we have three gateways controlled by the central DR controller, and each gateway has the same appliances: a task light, a simulated appliance, a laptop and a printer. The appliances are categorized according to I. The task light is a category A appliance with incandescent bulb, the simulated appliance is a one category B appliance, the laptop and the printer are two category C appliances. We define $I_{th} = 4$. Based on (3),(4) and (5), we calculate the cost function for each appliance as follows.

- For the task light with incandescent bulb, $r^M = 60w$ and $I = 1$. Therefore,

$$f(r) = \frac{I}{I_{th}} \times \frac{r}{r^M} = \frac{r}{240} \tag{25}$$

.

- For simulated appliance, $r^M = 500w$, $I = 2$, $N_l = 3$, $r_1 = 0$, $r_2 = 150w$ and $r_3 = r^M = 500w$. Therefore,

$$f(r) = \begin{cases} 0 & 0 \le r < 150w \\ \frac{1}{2} \times \frac{150}{500} = \frac{3}{20} & 150w \le r < 500w \\ \frac{1}{2} \times \frac{500}{500} = \frac{1}{2} & r = 500w \end{cases} \tag{26}$$

- For the laptop , it could work either on AC supply, which consumes about $73w$, or on battery, which consumes $0w$. Thus $N_l = 2$, $r^M = r_2 = 73w$, $r_1 = 0w$ and $I = 3$. Therefore,

$$f(r) = \begin{cases} 0 & r = 0w \quad \text{on AC} \\ \frac{3}{4} & r = 73w \quad \text{on battery} \end{cases} \tag{27}$$

- For the printer, it could be printing, which consumes about $400w$, or standby, which consumes $1w$. Thus $N_l = 2$, $r^M = r_2 = 400w$,$r_1 = 1w$ and $I = 4$. Therefore,

$$f(r) = \begin{cases} 0 & r = 0w \quad \text{printing} \\ 1 & r = 400w \quad \text{standby} \end{cases} \tag{28}$$

Assume the total load reduction R from the central DR controller is $800W$. The optimization results using two-level system are shown in Tab. V. In addition, the load reduction results using centralized system are shown in Tab. VI. In each method, we perform the optimization 5 times.

From Tab. V and Tab. VI, it can be seen that the results obtained using two-level control satisfy the DR controller constraints, which can enable the DR system to operate properly. In this system, the DR system does not require fast DR controller or communication network between load controller and the central controller. However, we have the following remarks regarding the discrete optimization results.

- In this simulation tests, the two-level strategy optimization obtain the similar optimization results to the centralized method.
- Although the PSO method can achieve the local optima in some extent, it is a stochastic method by nature and cannot ensure to achieve the global optima.
- The cost functions are discrete, the cost functions of devices 2, 3 and 4 are having maximum three level. The properties of these kinds of cost functions cannot ensure the existence of an optimal solution, thus we target to discovery the satisfactory solution which can meet the requirements of the DR controller.
- Only 4 devices are aggregated in a gateway, and the search space of optimization method is relatively small. On the other hand, the discrete properties of the cost functions will also degrade the performance of the optimization methods.

V. CONCLUSION

In this paper, a two-level Demand response control system, with a smart DR controller and multiple gateways is introduced to control plug loads. An appliance-level discrete cost functions is proposed, and optimization using continuous and discrete cost functions are presented. The cost model and optimization are deployed in the proposed two-level DR system with corresponding simulation results. From the results, the

Num.	Lagrange Multiplier	Gateway Reduction									Total Reduction	Cost Value
		Gateway 1			Gateway 2		Gateway 3		Gateway 4			
0	0.0000	23.03			0.00		10.71		0.00		33.74	0.04
1	0.4663	111.71			57.47		55.99		47.62		272.79	0.66
2	0.6935	154.93			94.26		78.06		82.65		409.89	1.46
3	0.7836	172.07			108.85		86.81		96.54		464.89	1.86
4	0.8193	178.86			114.63		90.28		102.05		464.27	2.03
5	0.8335	181.56			116.93		91.66		104.24		485.83	2.10
6	0.8391	182.63			117.84		92.20		105.10		494.38	2.13
7	0.8413	183.31			118.42		92.55		105.66		499.94	2.15
Device Reduction		70.00	69.48	47.99	40.42	77.68	41.87	50.46	49.81	55.55	499.94	2.21

TABLE III
OPTIMIZATION USING TOW-LEVEL STRATEGY

Num.	Lagrange Multiplier	Device Reduction									Total Reduction	Cost Value
		Gateway1			Gateway2		Gateway3		Gateway4			
0	0.0000	0	0	0	0	0	0	0	0	0	0	0
1	0.5000	70.00	25.00	26.67	18.75	43.00	24.50	28.75	20.83	30.71	288.21	0.74
2	0.7118	70.00	51.47	40.79	31.99	64.18	35.09	41.99	38.48	45.84	419.82	1.57
3	0.7920	70.00	61.50	46.13	37.00	72.20	39.10	47.00	45.16	51.57	469.65	1.94
4	0.8223	70.00	65.29	48.15	38.89	75.23	40.62	48.89	47.69	53.74	488.51	2.10
5	0.8338	70.00	66.73	48.92	39.61	76.38	41.19	49.61	48.65	54.56	495.65	2.16
6	0.8382	70.00	67.27	49.21	39.88	76.82	41.41	49.88	49.01	54.87	498.35	2.18
7	0.8398	70.00	67.48	49.32	39.99	76.98	41.49	49.99	49.15	54.99	499.38	2.19
Geatway Reduction		186.8			116.97		91.48		104.14		499.38	2.19

TABLE IV
OPTIMIZATION USING CENTRALIZED METHOD

Num.	Gateway 1				Gateway 2				Gateway 3				Total Reduction	Total Cost
	1	2	3	4	1	2	3	4	1	2	3	4		
1	20	500	0	0	0	150	0	0	0	150	0	0	820	3.54
2	11	150	0	0	48	500	0	0	13	150	0	0	872	4.40
3	11	150	0	0	28	500	0	0	49	0	73	0	811	6.31
4	41	0	0	0	41	150	73	0	7	500	0	0	812	6.33
5	0	500	0	0	0	150	0	0	20	150	73	0	893	5.79

TABLE V
OPTIMIZATION USING TWO-LEVEL STRATEGY

Num.	Gateway 1				Gateway 2				Gateway 3				Total Reduction	Total Cost
	1	2	3	4	1	2	3	4	1	2	3	4		
1	0	500	0	0	0	150	0	0	0	150	0	0	800	3.20
2	50	150	0	0	23	150	0	0	30	0	0	400	802	6.90
3	11	500	0	0	51	150	73	0	17	0	0	0	801	6.15
4	0	500	0	0	0	150	0	0	20	150	73	0	893	5.79
5	38	500	0	0	28	150	0	0	12	0	73	0	801	6.15

TABLE VI
OPTIMIZATION USING CENTRALIZED METHOD

two-level DR system is proved to achieve similar performance with the centralized system using either continuous or discrete cost functions and optimization methods, with less communication payload and processing power at the central controller, while at the same time provides more flexibility at the gateway level.

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