A Service Provider Model for Demand Response Management

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***Abstract*—A demand response management model that is characterized by the use of a service provider as the middleman between the customers and their respective utility is presented. The task of the service provider is to continually find an optimum solution where energy consumption is favorable to the utility and customer. The service provider solves for an optimal solution based on two objectives, a better demand curve for the utility to meet and satisfaction of the customer with some degree of acceptable comfort level while maximizing the monetary savings for both parties. This solution involves a two-stage two-algorithm (TSTA) based method. The first stage and algorithm involves using discrete particle swarm optimization to find a reasonable intermediate solution via global search. The second stage involves using a shift-left-shift-right time scheduling algorithm to drive the first stage solution to a near optimum solution, via local search. Customer satisfaction and the utility expected demand are mathematically modeled with the service provider earning a percentage of the savings of both utility and customer. TSTA simulation studies were based on data from the Real-Time Power and Intelligent Systems Laboratory's smart neighborhood research platform. The potential of customer participation in demand response was also categorized based on their profiles.**

Keywords—demand response management; global search; local search; particle swarm optimization; service provider

I. INTRODUCTION

Traditionally, power management, generation and distribution has been the sole responsibility of the utility. As long as the customer is willing to pay, the utility must generate the necessary power whenever the demand dictates. Since the customers' demand change drastically over the course of a day, week, seasons and years, the customer behavior is reflected on the side of the utility as a huge peak at some instances of time and virtually no demand at other times. Consequently, the utility must maintain costly generation capacity plus some reserve to manage these fluctuations in use, which are neither economically efficient nor environmentally friendly.

One solution for managing these uncertainties entails changing the consumer behaviors rather than trying to adapt power generation to meet constantly varying consumer demands. This change in consumer behavior is known as 'demand response' (DR) or 'demand-side management'. These methods have been implemented, tested and responses are analyzed all over the world [1], [2]. Integrating demand response into practice is studied in [3] and [4].

The literature has but a few DR approaches described therein, which fall into either one of two categories: incentive based DR [5] or price based DR [6]. In incentive based DR, the customer, motivated by an incentive offered by the utility, agrees to limit the energy usage or change the usage patterns in such a way that favors the utility. Direct load control, curtailable rates and DR in emergencies are but a few such DR types [7], [8]. It is also possible to reduce the electric load by changing the price rates of the electricity through time-of-use pricing schemes. In these schemes, the utility offers a pricing curve to the consumer that changes with time instead of flat rates. The pricing depends on the estimated cost of generation at that time of the day. The economically-concerned consumer then adjusts his/her power consumption patterns according to this price signal.

Various studies and comparisons of real-time pricing schemes have been undertaken and documented [9, 10]. The most notable of which have been Howlett et al. who introduced an algorithm for direct load control, Gatsis et al. who created a demand response program in an attempt to minimize the cost of electricity when prices are known ahead of time [11, 12]. Other similar studies include that of Gudi et al., who introduced a residential demand response simulation tool which implements particle swarm optimization (PSO) algorithm to manage multiple energy sources [13]. A method for controlled water heater use for optimum power use and a direct load control method for residential energy users have also been created in [14] and [15]. Surveys of demand response studies have also been undertaken [16, 17].

The contributions described in this paper are presented as follows. First, a demand response management model is introduced in which a service provider is involved to ensure fairness between the consumer and the utility. The service provider solves for an optimal solution based on two objectives, a better demand curve for the utility to meet and satisfaction of the customer with some degree of acceptable comfort level while maximizing the monetary savings for both parties. This solution involves a two-stage two-algorithm (TSTA) based method. The first stage and algorithm involves using discrete particle swarm optimization to find a reasonable intermediate solution via global search. The second stage involves using a shift-left-shift-right time scheduling algorithm to drive the first stage solution to a near optimum solution, via local search.

The rest of the paper is organized as follows. In Section II, the roles of each of the party involved in the proposed demand

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response management (DRM) model are described. In Section III, the problem formulation for DRM is presented. Section IV explains the two stage two algorithm based methodology for DRM. Section V describes the Real-Time Power and Intelligent Systems (RTPIS) Laboratory's smart neighborhood research platform and the dataset used in the case studies described. Section VI presents typical results from the DRM and finally, the conclusions are provided in Section VII.

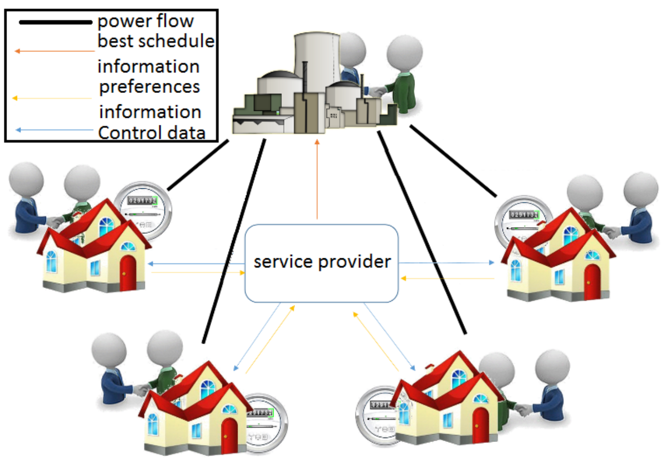

Fig. 1. Role of the Service Provider

II. Demand Response Management

The demand response management model involves three parties: customer, utility and service provider. A description of each party is given below.

A. Customer

As the end user of electricity, the customer enters into an agreement with the service provider and responds to the demand response, which benefits all involved. Upon entering into this agreement with the service provider, the customer saves money by using appliances according to the schedule and pays the provider a fraction of the savings as agreed in the agreement.

B. Utility

The utility is the electricity generator. Upon entering into an agreement with the service provider for demand response, the utility also pays the service provider a fraction of savings realized in this agreement.

C. Service Provider

The service provider is the facilitator of this demand response scheme (i.e. the middleman). The service provider collects information from both parties and carries out the optimization which is of benefit to both parties. The service provider receives a percentage of savings from both the customers and the utility (see Fig. 1 illustrating the role of the service provider in this business model).

III. Problem Formulation

To provide the service provider with the necessary values for the calculation of the demand response schedule, *'S'*, the customer initially creates a schedule for each electric appliance as if he/she uses them freely without any restriction. The time is sectioned into time intervals for the schedule. For instance, in this case, the day is divided into 48 half hour time intervals. The demand response scheduling is carried out with respect to these divisions. Function v as established by the customer is then used to define the importance of each electric appliance of the house with respect to the time interval. For example, consider a dish washer, an appliance that should be used somewhere between the end of one meal and the beginning of the other. The time interval just after a meal may have a low importance for the dishwasher. Therefore, the importance value, v_{ij}, might be very low at that time, which can expressed as:

$$v_{ij}(t_a) = 0.01 \tag{1}$$

where t_a is the time interval just after the meal and j is number assigned for the dishwasher of the i^{th} house and v_{ij} is the importance function. Immediately prior to the next meal, however, the use of the dishwasher is most important. Therefore the customer might may assign a higher value expressed as

$$v_{ij}(t_b) = 0.9 \tag{2}$$

where t_b represents the time interval just before the next meal. These values are provided by the customer according to their comfort preferences. In addition, the customer provides information about flexibility for each device, which is defined as a range of intervals for scheduling of a particular appliance. Afore mentioned function v is defined in these flexible regions. Outside the flexible regions the value of v is zero.

A new parameter, known as the comfort penalty, which is expressed as

$$p_{ij} = \left(startTime_{ij} - intendedTime_{ij}\right) \times \{v_{ij}\left(startTime_{ij}\right) - v_{ij}\left(intendedTime_{ij}\right)\} (3).$$

is then used to facilitate the calculation. Here, p_{ij} is the comfort penalty for device j of house i; $startTime_{ij}$ is the actual starting time of the appliance; and $intendedTime_{ij}$ is the time that customer intends to start the appliance in the original schedule. A vector $\theta(t)$ which has a number of entries equal to the number of time intervals in the time horizon is then defined. These entries, each of which are, represent a single time interval of the DR cycle. For each time interval in which a particular appliance is activated, its' $\theta(t)$ contains a member with a value of 1 with the remainder zero. For instance the appliance j of the house i remained in use from the 2^{nd} to the 5^{th} time interval, $\theta(t)$, which is expressed as follows:

$$\theta_{ij} = [0\ 1\ 1\ 1\ 1\ 1\ 0\ 0\ 0\ 0\ 0] \quad (4)$$

As the customer interest involves minimizing the discomfort, the following objective is used for that purpose, and expressed as:

$$O_{customer} = \lambda_1 \sum p_{ijk} \quad (5)$$

where λ_1 is a scaling factor. The total power usage of the customer is not considered a factor in the objective function as it remains constant. That is, the power usage expectation during the time period under consideration without the demand response in effect is the same as the power usage with demand response. A consideration solely based on customer's acceptable degree of comfort would result in a schedule that does not result in customer savings regarding real-time pricing. Therefore another constraint is added to the objective function as follows:

$$cost_{new} \leq cost_{in} \quad (6)$$

Where $cost_{new}$ is the cost for the customer after the optimization and $cost_{in}$ is the estimated cost calculated without demand response. An equation for the residential cost can be formed as follows:

$$cost_i = l \times \sum_{k=1}^{N} \sum_{j=1}^{M} \theta_{ijk}\, d_{ij}\, price_k \quad (7)$$

Here $cost_i$ is the cost for i^{th} home, l is the length of a time interval in hours, N is the number of time interval in the total time under the DR scheme, θ_{ijk} is the member value of the vector in (4) corresponding to k^{th} time interval for the j^{th} appliance of the i^{th} customer, d_{ij} is the power rating of the j^{th} appliance of the i^{th} customer, and $price_k$ is the unit price offered to the customers in dollars per Watt hour.

On the other hand, the total power usage of all the customers for a single time interval can be calculated as:

$$u_n = l \times \sum_i \sum_j \theta_{ijn}\, d_{ij} \quad (8)$$

Here d_{ij} is the power usage of the j^{th} device of the i^{th} house and n is the time interval under consideration. Traditionally, the utility might expect an unvarying constant demand throughout the day. However, with the integration of renewables, this situation might change. The objective of the utility can then be defined as minimizing the difference between this ideal power demand and the actual demand. If the expected power usage curve is *e(i)*, the objective function for the utility involves minimizing that difference, expressed as:

$$O_{utility} = \frac{\lambda_2}{n} \sum_{i=1}^{n} \left| 1 - \frac{u_i}{e(i)} \right| \quad (9)$$

where λ_2 is the scaling factor and u_i the actual power consumption at i^{th} time interval. This is the objective function for the utility. For scenarios where the utility buys the power, the following constraint is added order to avoid the utility making less profit than before:

$$profit_{in} \leq Profit_{new} \quad (10)$$

where $profit_{new}$ is the profit of the utility after optimization and $profit_{in}$ is the initial estimated profit of the utility. The profit of the utility can be calculated as follows:

$$profit = l \times \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k}^{P} \theta_{ijk} u_{ij} (sp_k - bp_k) \quad (11)$$

where sp_k is the electricity selling price by the utility and bp_k is the buying price (in dollars per Watt hour). Parameters α_c and α_u are used to combine these two objective functions, through which the following objective function to be minimized by the service provider can be devised:

$$O = \alpha_c O_{customer} + \alpha_u O_{utility} \quad (12)$$

And subjected to the following inequality constraints,

$$\sum_{k=1}^{N} \sum_{j=1}^{M} \theta_{ijk}^{a}\, u_{ij}\, price_k - \sum_{k=1}^{N} \sum_{j=1}^{M} \theta_{ijk}^{b}\, u_{ij}\, price_k \geq 0 \quad (13)$$

and,

$$\sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k}^{P} \theta_{ijk}^{a}\, u_{ij} (sp_k - bp_k) - \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k}^{P} \theta_{ijk}^{b}\, u_{ij} (sp_k - bp_k) \geq 0 \quad (14)$$

where α_c and α_u are weighting factors, θ_{ijk}^{a} the θ vector values after DR and $\theta_{ijk}^{b}$the θ vector values before DR. The vector θ is defined in (4). These constraints ensure that the customers pay lesser before the DR and the utility will make a larger profit larger than is possible before the DR.

IV. DRM Optimization Methodology

The DRM optimization methodology involves a two-stage two-algorithm based method. The first stage and algorithm involves using discrete particle swarm optimization to find a reasonable intermediate solution via global search. The second stage involves using a shift-left-shift-right time scheduling algorithm to drive the first stage solution to a near optimum solution, via local search. The two algorithms are described below.

A. Discrete Particle Swarm Optimization

Kennedy and Eberhart [18] first proposed particle swarm optimization as a heuristic optimization method inspired by nature. Here, a number of 'particles' that fly through a solution space are used. These particles are actually agents that calculate the value for the objective function at the current location of the solution space. A particle has a certain 'velocity' with which it flies. The particle calculates the value of the objective function at the current point at every iteration. A global best for all the particles and a personal best for each of the particle is then calculated. The velocity of each particle for $k+1^{st}$ iteration is calculated according to the equation:

$$V_{id,k+1} = wV_{id,k} + c_1\, rand_1 \left(X_{pbestid,k} - X_{id,k}\right) + c_2\, rand_2 \left(X_{gbestd,k} - X_{id,k}\right) \tag{15}$$

where, w is the inertia weight, $V_{id,n}$ is the velocity in the d^{th} dimension of i^{th} particle at iteration n, c_1 and c_2 are cognitive and social acceleration constants, respectively, $rand_1$ and $rand_2$ are random numbers between 0 and 1, $X_{pbestid,k}$ is the personal best in d^{th} dimension of i^{th} particle at iteration k. $X_{id,k}$ is the current position of the i^{th} particle in the d^{th} dimension and $X_{gbestd,k}$ is the global best position so far found by the system in the d^{th} dimension at iteration k. This problem is of a discrete nature, therefore the result above is rounded.

$$V_{id,k+1} = round(wV_{id,k} + c_1\, rand_1\, (X_{pbestid,k} - X_{id,k})\; c_2\, rand_2\, (X_{bestd,k} - X_{id,k})) \tag{16}$$

The feasible region for each appliance represents one dimension in the solution space. Each time interval in the feasible region is given a number, starting from 1. The new position of the particle is calculated by adding the velocity to the current position. At each position update, the time point at which the machine is activated is delayed (if X_{id} is positive) or advanced (if X_{id} is negative) X_{id} times. However, this might result in particle falling off the restricted region (flexible area) imposed by the customer. Therefore, a special function is used to add the new velocity to the particle position. Here, should the activation time of the appliance extend beyond the restricted region, the particle moves backwards until all the steps are taken. With this special adding function, the position update is then represented as follows:

$$X_{id,k+1} = add(X_{id,k}, V_{id,k}) \tag{17}$$

The pseudocode for adding is shown in Algorithm 1.

B. Shift-Left -Shift-Right Time Scheduling Algorithm

A shift-left-shift-right (SLSR) time scheduling search method is applied to the best schedule, S, (global best solution from PSO) obtained from stage 1 to attain an improved new schedule, S_{new}. The pseudocode for the SLSR method is described in Algorithm 2. The algorithm starts with S, iterates through the list of appliances in all the houses and attempts to produce a better schedule by scheduling the appliance a time interval later or earlier. In case this newly created schedule (S_{temp} in Algorithm 2) is better (evaluates to a lower objective value when (12) is calculated) than the current S_{new}, S_{temp} becomes the new S_{new}. The algorithm repeats this until no further improvement could be obtained. This algorithm guarantees reaching the closest local minimum since it accepts solutions that only improve the value of the objective function.

Fig. 2. RTPIS Lab Demand Response Research Platform

Algorithm 1: Position Modification by Velocity

```
procedure ADD(X,V,regions)
  left ← abs(V)
  if V > 0 then
    increment ← 1
  else
    increment ← (-1)
  endif
  while left != 0 do
    if X+ left is beyond region then
      increment ← (-1) * increment
    endif
    X ← X + increment
    left ← left – 1
  endwhile
return x
```

V. DRM Laboratory Platform

A. Smart Neighborhood Research Platform

The dataset used was from RTPIS Laboratory smart neighborhood research platform customer profiles. The platform comprises of a miniature village complete with ten model houses, one model village center and two circuits of model street lights [19]. While the usage load is symbolized as an LED in the house, a set of resistors off the show-case village system is use to simulate the real power consumption equivalent that is equivalent to the loads.

A real-time price list for one day was obtained from PJM interconnection and the peaks were adjusted for the current usage data set [20]. Since the actual utility costs are not available, a 2% profit at the high cost interval, a 10% profit at the medium cost interval, and 2% loss at the low cost interval were used. The buying and selling prices are shown in Fig. 6.

Algorithm 2: Shift-Left -Shift-Right Time Scheduling Search

procedure Minimize_objective(S)
$S_{\text{new}} = S$
// Evaluate the objective function in (12)
O_{new} = evaluate(S_{new})
while there is improvement in S_{new} **do**
  for each appliance '*a*' in the system **do**
    S_{tmp} = appliance '*a*' scheduled half an interval than in
    S_{new}
    O_{tmp} = evaluate(S_{tmp})
    if $O_{tmp} < O_{new}$ **then**
      $S_{new} = S_{tmp}$
      $O_{new} = O_{tmp}$
    endif
    S_{tmp} = appliance 'a' scheduled half an interval later
    than in S_{new}
    O_{tmp} = evaluate(S_{tmp})
    if $O_{tmp} < O_{new}$ **then**
      $S_{new} = S_{tmp}$
      $O_{new} = O_{tmp}$
    endif
  endfor
endwhile
return S_{new}

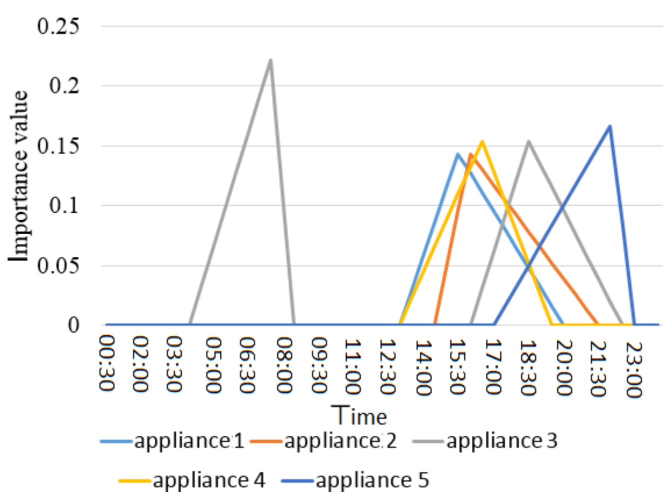

Fig. 3. User data

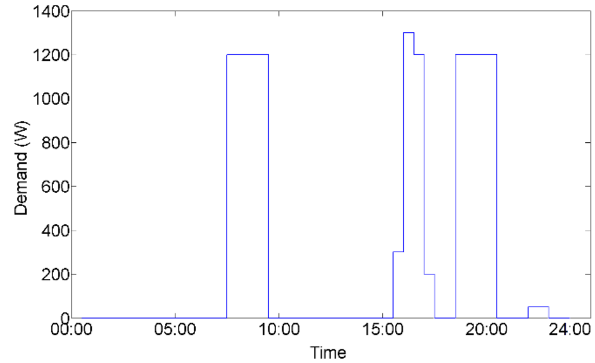

Fig. 4. Demand without DR of a customer

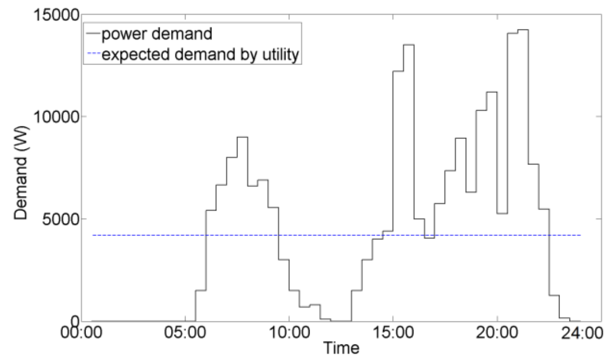

Fig. 5. Overall power demand of the initial system

Fig. 6. Buying and selling prices of electricity by the utility

B. Impementation parameters

At the initial stage, the parameters were set to the standard, tested values, which were then further refined by trial-and-error until the convergence (discussed below, under results) was achieved. The inertia weight of PSO was initially set at 0.9 and reduced to 0.4 with iterations. Acceleration constants c_1 and c_2 were set to 0.5 and 2 respectively. A total of 1,000 iterations with 20 particles were used for the entire calculation. The normalization factor of the customer objective, λ_1 was set to 1/15 and λ_2 was set to 1 depending on the possible values for them. These are the constants used in

(5) and (9), respectively, to scale the two objective values for the addition. The values α_c and α_u are biasing constants that largely depend on the preferences of the customer and the utility. The higher the value for α_u in comparison to α_c, the more both parties save while lower α_u values increase the comfort level, which results in less savings.

VI. RESULTS

A. *Convergence test*

The algorithm was tested to determine its strength in finding the minimum value of the objective function. Consider the comfort penalty defined in (3). If the appliance started at the intended time, the value is zero. As a result, if all the appliances started at the intended times, the customer objective given in (5) must be zero. Therefore, the minimum value of this objective function is zero. If the utility side of the final objective function (8) is ignored (i.e. α_u equals to zero), then the algorithm should produce a zero upon reaching the minimum value of the solution space. At this point, all the appliances are scheduled per customer preference (i.e. for the maximum comfort of the customer). These scheduling results are given in Fig. 7.

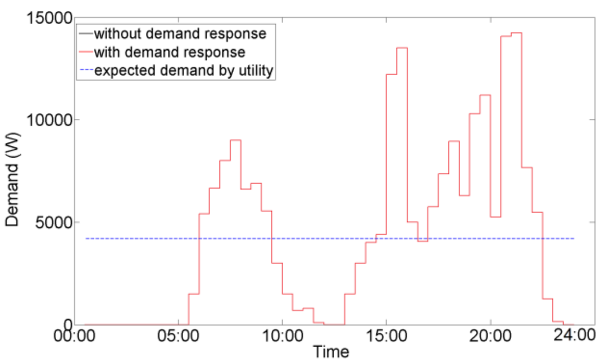

Fig. 7. Result of the convergence test

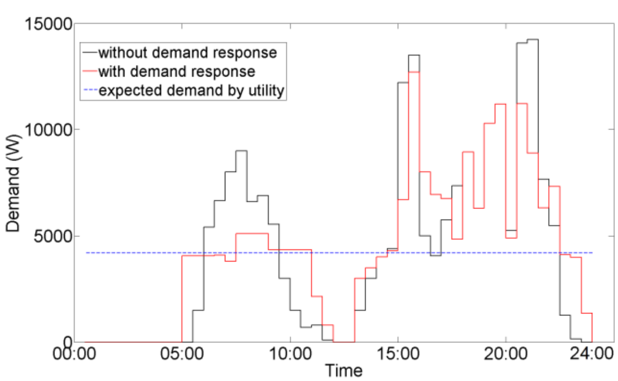

Fig. 8. Overall power demand for scenario 1

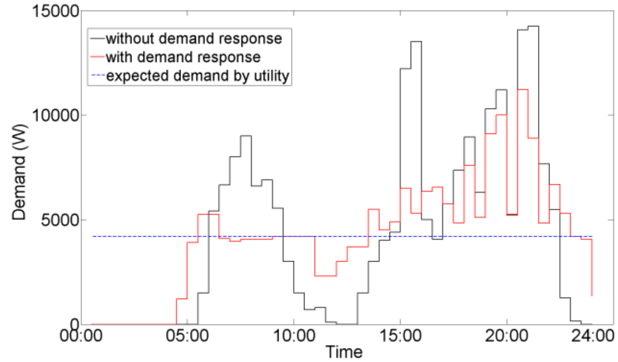

Fig. 9. Overall power demand for scenario 2

B. *Sample Scenarios*

The algorithm was implemented for several scenarios with varying priorities for the customer and utility, the results of which are next described. Three of the scenarios are presented below.

1) Scenario 1

In scenario 1, customer comfort was prioritized. For this test, α_c was given a value of 0.7 and α_u given a value of 0.3. The result of this optimization is shown in Fig. 8. Note the closeness to the estimated schedule without demand response, which is due to the bias towards more comfort than towards more demand

2) Scenario 2

In scenario 2 the utility objective was prioritized. For this test α_c was given a value of 0.3 and α_u is given a value of 0.7. The result of this optimization is shown in Fig. 9. Note here a closer adherence towards the utility's goal and the significant departure from the original demand curve. Since there are restrictions by the user and the conditions imposed by (6) and (10) the algorithm cannot match the utilities goal exactly.

3) Scenario 3

In this scenario both utility and customer are given equal priority. For this test, α_c was given a value of 0.5 and α_u is given a value of 0.5. The result of this optimization is shown in Fig. 10. Note the clear intermediate level between the comfort of the user and the optimal demand curve for the utility. The cost savings for all three scenarios are shown in Table I.

C. *Analysis*

It can be seen from the results that different customers have gained different levels of savings. An analysis of the results reveals that customer flexibility and the wattage of the appliances used by the customer determine how much the customer and utility save with demand response.

An indicator for guiding the service provider on the potential of the customers and DR availability can be estimated using the formula below.

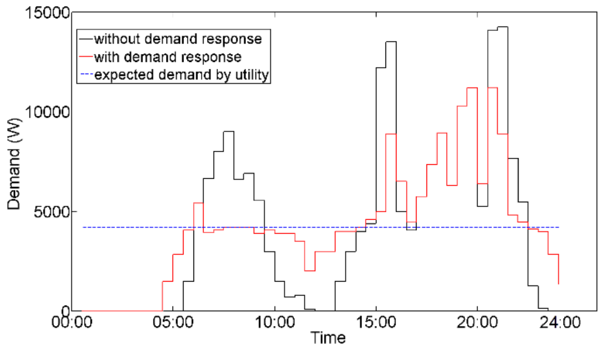

Fig. 10. Overall power demand for scenario 3

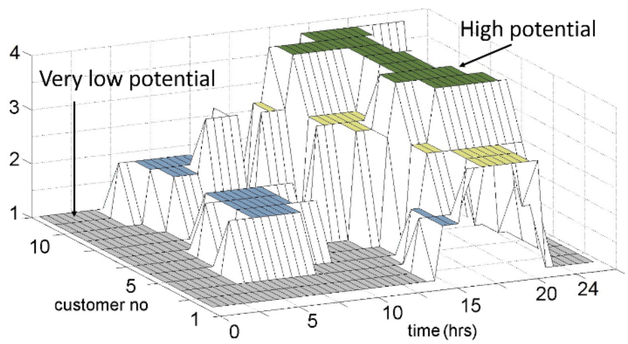

Fig. 11. DR Potentials of the customer

$$P_{customer} = \sum_{j} f_{ij}\ wattage_j \qquad (18)$$

where i denotes the interval and j denotes the appliance of the customer. $wattage_j$ is the power wattage of appliance. f_{ij} is defined as follows for ith appliance in jth interval according to flexibility of the customer at that interval:

$$f_{ij} = \begin{cases} 1, & appliance\ is\ allowed\ to\ schedule \\ 0, & appliance\ is\ not\ allowed\ to\ shedule \end{cases}$$

The customers were categorized into four groups by calculating their quartiles. Each customer is given one of the following categories at each time interval:

- 4 – High potential
- 3 – Medium potential
- 2 – Low potential
- 1 – Very low potential

The DR potentials of the customers are depicted in Fig. 11.

TABLE I. SAVINGS FOR THE CUSTOMER AND UTILITY

Customer	Scenario	Cost Before DR	Cost After DR	% Savings By Customer	% Savings By Utility
1	1	1.29	1.28	0.77	0.17
	2		1.28	0.77	0.14
	3		1.28	0.77	0.02
2	1	1.29	1.28	0.77	0.17
	2		1.28	0.77	0.14
	3		1.28	0.77	0.02
3	1	1.45	1.44	0.68	0.21
	2		1.43	1.37	0.21
	3		1.44	0.68	0.21
4	1	1.81	1.75	3.31	0.25
	2		1.65	8.83	0.65
	3		1.72	4.97	0.26
5	1	1.85	1.82	1.62	0.26
	2		1.78	3.78	0.28
	3		1.85	0.00	0.00
6	1	1.77	1.75	1.12	0.01
	2		1.77	0.00	0.00
	3		1.69	4.51	0.32
7	1	1.83	1.82	0.54	0.44
	2		1.68	8.19	0.67
	3		1.64	10.38	0.64
8	1	1.28	1.28	0.00	0.00
	2		1.19	7.03	0.02
	3		1.28	0.00	0.00
9	1	2.86	2.79	2.44	0.20
	2		2.78	2.79	0.20
	3		2.77	3.14	0.22
10	1	2.89	2.67	7.61	0.60
	2		2.72	5.88	0.62
	3		2.69	6.92	0.61
11	1	2.28	2.12	7.01	0.08
	2		2.21	3.07	0.05
	3		2.21	3.07	0.05

VII. CONCLUSION

A service provider model for demand response management has been presented. The service provider solves for an optimal solution that provides a better demand curve for the utility to meet and satisfaction for the customers with some degree of acceptable comfort level while maximizing the monetary savings for both parties. A hybrid computational intelligence algorithm for effective global and local search has been applied to solve for the optimal solution. Typical results show that it is possible for the utility and customers who participate in demand response to optimize energy generation and consumption yielding in cost savings. Future work involves treating the service provider problem formulation as a multi-objective optimization problem.

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