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Investigating the Impact of Discomfort in Load Scheduling Using Genetic Algorithm

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Abstract— Energy consumers oftentimes suffer some element of discomfort associated with the implementation of demand response programs as they aim to follow a suggested energy consumption profile generated from scheduling algorithms for the purpose of optimizing grid performance. This is because people naturally do not like to be told what to do or when to use their appliances. Although advances in renewable energy have made the consumer to also become energy supplier, who can actively cash in at times of the day when energy cost is high to either sell excess energy generated or consume it internally if required, thereby nullifying the adverse effect of this discomfort. But a majority of consumers still rely wholly on the supply from the grid. This impact on users' comfort who are active participants in demand response programs was investigated and ways to minimizing load scheduling discomfort was sought in order to encourage user participation.

Keywords—Demand response, Discomfort, Genetic algorithm, Load profiles, Scheduling.

I. INTRODUCTION

Discomfort can be described as an unpleasant feeling of being disturbed which can result to a state of physical unease, pain and constraint. It can also be associated with a burden which a customer that has accepted to participate in demand response (DR) program is expected to bear while agreeing to follow a load scheduling program. This burden is one of the leading causes as to why several consumers of electricity supply end up withdrawing from an earlier signed-up intention to participate in DR programs as indicated by [1]. Discomfort is usually occasioned by a request from the utility or localized scheduling algorithm to the consumers to adjust and modify their energy consumption pattern in order to aid grid performance which incidentally, may not be so desirable to the consumers. This may imply having to move significant amount of energy consumed at any instant, from certain times of the day to other times and as a result, could cause a significant impact on the level of discomfort associated with DR participation.

A positive response to a request to implement a change in consumption behavior gives rise to user discomfort. A typical example could be how uncomfortable a customer could feel if requested to ignore making a cup of tea at any given time and perhaps delay the activity to another futuristic time. In this scenario, if the customer had wanted the drink due to thirst, they might be required to fetch another type of drink. Or if they wanted to feel warmer inside, they might have to put up with the cold for much longer. But certain customers who feel slightly discomforted may heed to the advice and respond positively, while some other customers who might not be able to accept such prescribed change due to high impact discomfort caused, could ignore the schedule. Hence, scheduling algorithms should have user comfort considerations to ensure active user participation [2]. Nevertheless, several new algorithms are being proposed and increased DR participation is encouraged to facilitate peak load reduction in order to ensure grid sustenance [3]. This is usually enhanced by the means of offering financial incentives to consumers in order to increase their engagements in DR programs, or could include the inclusion of a penalty term in the cost function in order to discourage having large changes in scheduling programs [4]. Also the use of dynamic pricing is becoming a common practice in several countries whereby avoiding energy use during high energy cost oftentimes translates to reduced cost of energy use on the user's energy bill [5].

The work presented in this paper is an improvement from a previous work done by the same authors whereby discomfort function was considered as one of the input variables of the genetic algorithm (GA) fitness function [6]. The primary aim of the paper was to understand how GA can be used to optimize domestic load scheduling using certain defined inputs variables at the fitness function. Whereas here, we are able to expand on the analysis of the effect of discomfort on energy users and then simulate different scenarios that can arise. Therefore we will demonstrate how GA can be used to identify the impact of discomfort on load optimization on users, while also looking at a broader scenario about how a measure of discomfort is important in attempting to implement DR programs on households. There will also be a suggestion on possible ways to reducing discomfort, while also taking into consideration its reversed impact on cost reduction.

II. RELATED WORK

Related literature involved in this area of research are based on the observed failure to successfully engage consumers to participate in DR programs and the effect this lack of active participation has on the grid [7]. One of the reasons for inadequate participation in DR programs was identified to be due to the difficulty experienced by the consumer in having to follow price changes which occurs on a daily basis as indicated by [8]. The authors listed certain factors such as having to manually check online on a daily basis, to ascertain times of the day when prices are high in order to avoid using appliances at those times. A study carried out in Chicago showed that several consumers who initially signed up to dynamic pricing scheme ended up withdrawing from it as a result of a further increase in electricity bill, rather than having a reduction when compared to the original fixed flat rate [1]. The solution they proposed was to introduce an effective home automation systems which should help in making those decisions, thereby improving user participation.

The authors in [9] brought to the fore, the capabilities of demand response program implementations in individual households in creating a disruption on the aggregate demand profile of a community if the schedules are not properly coordinated. The authors envisaged that a random distribution of energy requests could disrupt energy balance within the neighborhood, which also goes to show the prevalence of discomfort while implementing load scheduling programs. The paper proposed the formulation of coordinated home energy management system in order to minimize grid discomfort.

Transformers as well, are not spared from encountering some operational stress occasioned by application of demand response programs. The authors in [10] acknowledged the importance of DR in supporting the integration of renewables into the grid, and the impact of such integration on the transformer lifetime. The investigation on the effect of ageing was carried out using two models:

1. By ascertaining the ageing based on the load of certain customers who operated without DR application,
2. By ascertaining the ageing based on the load of those customers if they operated with DR application.

Result showed that operating the transformer at the rated load is critical in preserving the life of the transformer. This goes to suggest that DR applications can cause the transformer to operate outside the rated load. But if it was ensured that the transformer were to operate within the rated load, up to 75% reductions in ageing was achieved.

Finally, in each of the instances discussed on the related work, it is obvious that there is an effect of disturbance experienced while applying DR programs which can affect any section of the grid. In the next section, we shall be introducing the proposed method used in modelling the discomfort which can be encountered by users who engage in DR programs and how to manage it effectively using GA optimization.

III. PROPOSED METHOD

It is proposed in this paper that a measure of discomfort can be obtained by the relationship between the standard deviation of the historical load profiles and the change in energy consumption. The historical data of the household is assumed to be available, possibly stored in the smart meters. Based on this data, it is possible to forecast what the load profile of the customer would be, and segregated according to what day of the week, month and season when each reading is taken. This forecast would be expected to represent the preferred behaviour or most comfortable behaviour of the consumer without involving load optimization.

With the introduction of load optimization, a new optimized load profile can be obtained and in this work, GA was used to achieve this purpose. The fitness function derived was as a result of the need to either maximize or minimize certain characteristics. The input variables are reflections of all the observable characteristics that could affect the function within certain constraints as modelled in GA. Optimization of load profile assumes that appliances will be scheduled to meet the new optimized load profile.

Given that the forecast load profile is estimated from historical energy data, the consumer may be advised to apply a prescribed load consumption pattern at the beginning of a new day, given as the optimized load profile. But the choice to adhere to such suggestion depends on the consumer who may or may not follow strictly, the optimized load profile suggested. The actual load profile is therefore, only obtainable at the end of the day.

A. *Impact of Energy Change in Discomfort Measure*

The change in energy consumption is the absolute difference between the forecasted load profile and the optimized load profile for a day. Change in energy usage due to load scheduling, contains an element of discomfort. Being responsive to forgo a desire to use energy at any given time is a sacrifice to make, and the component of discomfort inherent in responding to change requests resides in the absolute magnitude of this change. The optimized load profile is expected to generate the best energy-use after considering other factors of load scheduling such as forecasted real-time-price.

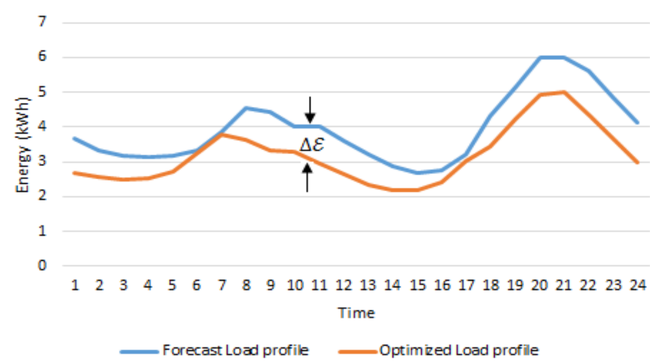

Figure 1. Standard deviation of 2 samples of Load profiles.

Fig.1 shows sample forecasted and optimized load profiles as well as the magnitude of change in energy $\Delta\mathcal{E}$, obtainable at any given instant [11].

B. *Standard Deviation Application in Discomfort Measure*

Standard deviation as used in this paper for load scheduling is used to understand the likelihood of load usage for any specified time interval considered. Consider a household inhabited by a certain number of residents, and the fact that their day to day schedule varies from individual to individual, and from time to time. Information about the overall energy consumption behavior can be found on the load profile of the household. The intervals of low standard deviation implies that there is an increased difficulty to schedule at those times, while intervals with high standard deviation produces a reduced difficulty to apply load scheduling at those intervals. Mathematically, a population standard deviation is calculated from the expression:

$$\sigma = \sqrt{\frac{\Sigma f\ (x - \mu)^2}{\Sigma f}} \qquad (1)$$

Where:

σ = Standard Deviation

μ = mean

f = Frequency of samples taken

x = Energy samples

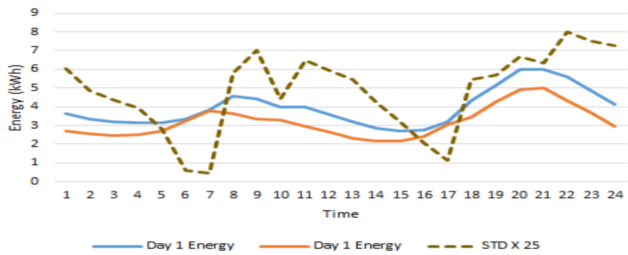

Figure 2. Standard deviation of 2 samples of Load profiles.

Fig.2 shows a 2-day sample of historical load profiles of energy consumed by all the appliances in a household. The calculated standard deviation as obtained from [11].

C. Computing Discomfort in Load Scheduling using GA

In the method proposed here, the difference between the optimized and forecasted load profiles will indicate discomfort, but when it is related to the standard deviation, gives a better understanding about the realistic discomfort the customer could experience. Table I shows the truth table used to investigate this relationship.

Table I: Truth table of cost and comfort relationship

Standard Deviation	Energy Change	Output State
Low	Low	Fairly Comfortable
Low	High	Very Uncomfortable
High	Low	Very Comfortable
High	High	Fairly Uncomfortable

It could be observed that a high standard deviation of energy use and a low change in energy consumption is desirable to achieve an optimum comfort state. This is because a high standard deviation means that load usage at those time intervals are not very routine to the customer, hence load scheduling is encouraged. On the other hand, a low energy change is desirable for the consumer who may not be very happy to move a lot of their loads if requested by the scheduling algorithm. However, there may not be much gain in not being able to shift loads. A combination of both variables' states produces an output that represents "Very Comfortable" state.

On the other hand, an opposite relationship which encourages a minimal standard deviation and a maximum change in energy produces a "Very Uncomfortable" state, otherwise referred to as the Discomfort.

The "Fairly Comfortable" state indicates that although it is comforting to have a low change in energy, a low standard deviation will make it difficult to apply scheduling, just as the state of "Fairly Uncomfortable" indicates that a high standard deviation is desirable but a high energy change is not desired. Effectively, both states are considered equivalent to each other.

The relationship as derivable from Table I can be presented mathematically in Eqn.2 which gives the discomfort, D as a dimensionless quantity as shown:

$$D = \frac{\Delta\mathcal{E}}{\sigma} \qquad (2)$$

Where:

σ = Standard deviation of load profile

$\Delta\mathcal{E}$ = Abs (Forecast load profile – Optimized load profile)

D = Discomfort measure

D. GA Optimization Involving Discomfort

The discomfort experienced during load scheduling can be computed for every iteration during the optimization process using genetic algorithm. Table II shows the formulated fitness function, with various weightings attached to the input variables. Eqn.3 shows that the fitness function is a minimization function. Variables with positive signs implies minimization while those with negative signs are maximized.

Table II: Fitness Function Application

<u>Input/output Variables used</u>

Min Function $F_{j,i} = w_a*\sum A_{j,i} + w_b*\sum B_{j,i} + w_c*\sum C_{j,i} - w_d*\sum D_{j,i}$ (3)

<u>Constraints used and Applications</u>

1. $E_{min} \leq x \leq E_{max}$ (4)
2. $\sum_{j=1}^{24} E_j = \sum_{j=1}^{24} x_j$ (5)

Where:

A = $\Delta\mathcal{E}$ * Occupancy = Change in Energy on occupants

B = Optimized Load * Price = Cost

C = $\Delta\mathcal{E}$ / Standard deviation of Load Profiles = Discomfort

D = Optimized Load / Forecast Load = Optimization Factor

E = Forecasted load profile.

E_{max} = Maximum value of forecasted load profile

E_{min} = Minimum value of forecasted load profile

i = Iteration number

j = hourly time interval in a day.

w = Weighting factor

x = randomly generated load profile.

All input variables are obtained from:

i. The forecasted load profile.
ii. Randomly-generated load profile which serves as the initial population.
iii. Occupancy to show times when residents are at home.
iv. Standard deviation of load profile.
v. Dynamic pricing of energy supply.

A represents the effect of absolute change in energy use on all occupants. However, at any instant when nobody is in house, then the change has no effect on the residents. This is why it is proposed that $\Delta\mathcal{E}$ is multiplied by the occupancy to give A, which offers a better measure than $\Delta\mathcal{E}$. A low impact of such change is favorable to the consumer.

B represents change that effects energy cost reduction. Cost is a major incentive to the adoption of demand response programs, hence its inclusion on the fitness function equation.

C represents the discomfort experienced due to scheduling which expected to be minimized in order to reduce drastic reassignments of loads from the original forecasted load profile to other times for the new day whereby the impact could be so high that the user might end up rejecting majority of the load assignments in the suggested optimized load profile.

D represents the optimization factor which attempts to scale the optimized load to the magnitude of the forecasted load at every iteration. This is where the support of C is expected to play an important role by ensuring that the optimized load profile created does not deviate so much from the forecasted load profile. D is therefore used to determine how effectively a forecasted load profile should be used to create an optimized load profile with minimal discomfort. A high effect of this application is considered favorable to the consumer.

Table III: Pseudo codes for Genetic Algorithm Procedure

```
// Initialization;
for i = 1000 (initial population of samples)
  for j = 24 (hourly load profile interval)
     Randomly generate x_{j,i} in the range ( E_min, E_max);
     Scale the sum of x_{j,i} to the sum of E ;
    end for;
  end for;
for iteration = 3000 (enough for convergence)
    Evaluate fitness F_{j,i} ;
    Evaluate sum of fitness G = ∑ F_j for all i ;
    Swap G_{i min} for G_{i max} ;
    Randomly set chromosomes in pairs for mating ;
    Randomly select crossover site ;
    Apply mutation ;
    Update results after iteration
End for ;
```

Finally, Table III shows the pseudo codes for the genetic algorithm applied to simulate a convergence of all the variables used after 3000 iterations. 1000 samples were chosen to ensure that the accuracy of the convergence is high even if the algorithm is run over and over again. Although similar results were obtainable if fewer number of samples in their hundreds were chosen, but anything less than a hundred initial samples are discouraged because the optimized load profiles changes significantly if the initial population is too low. Furthermore, hourly load profile was chosen because the pricing data from [12] and energy data from [11] are both from the same country, which happens to be hourly based. More accurate results are expected if data with shorter time intervals are available.

E. *Limiting Discomfort in Load Scheduling*

In as much as we have been able to minimize discomfort experienced by users who participates in DR programs, we can also limit how much discomfort that is permissible at any given time interval during optimization. Therefore a threshold can be chosen in order to limit the differential between the optimized and forecasted load profiles thereby limiting the discomfort level experienced by the user.

The expression for the discomfort threshold activation function $f(D_t)$ is given as:

$$f(D_t) = \begin{cases} D_{th}, & D_t > D_{th} \\ D_t, & D_t < D_{th} \end{cases} \tag{6}$$

Where:

t = 1 to 24 (Time intervals).

D_t = Discomfort D, at time t.

D_{th}= Discomfort threshold.

In comparison with the implementation of the previous work by the same authors as cited in [6], the discomfort factor was defined as a product of change in energy and the variance of the load profile. If we reflect this on Table I, it represents "Fairly Uncomfortable" state unlike as defined in Eqn.2 which is the preferred definition as "Very Uncomfortable" state. The mathematical definition of what causes maximum discomfort as derived from Table I presents a superior definition. Hence the discomfort function presented herein is a massive improvement from the previous work and the function was effectively used to simulate real life impact of how uncomfortable it could be to request users to move around large proportion of their peak load.

Finally, the discomfort threshold is expected to be set by the user depending on their load consumption behavior. It is suggested that such behavior can be modelled by obtaining how much change the user is willing to accept while implementing the optimized load profile. This data can only be made available at the end of the day, from where the actual discomfort can be calculated. We can therefore refer to the discomfort presented in this paper as the forecasted discomfort, while the actual discomfort becomes the discomfort threshold to be used in computation which indicates the user's acceptable tolerance while applying algorithm of the load scheduling optimizer.

IV. RESULTS AND DISCUSSION

Day ahead real time pricing scheme is not used in the UK at the moment [13]. However it is used in some states in the US and a sample of such pricing scheme as published by Ameren, Illinois is used in the simulation [12]. It is assumed that such a pricing scheme would be used to engage the public consumer in a more responsive way to shifting load. Fig.3 shows the profiles of the basic input data applied.

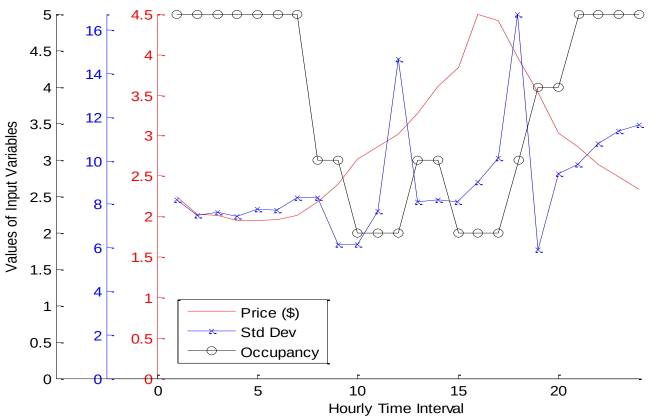

Figure 3. Basic Input variables used.

The weightings of the optimization function are all maintained at the same value of one, which means they all have the same impact. Varying the weightings is expected to generate more diverse results, but the scope of this paper does not include weighting variations. This experiment is conducted in three categories which includes: a case of no discomfort considerations, a case of discomfort considerations without clipping and a case of discomfort considerations with clipping. The convergence of the fitness function after 3000 iterations as shown in Fig.4. It is also worth noting that the convergence shown here is for case 2 only, although this convergence is very similar for all cases presented herein, despite the discomfort axis not being available for case 1.

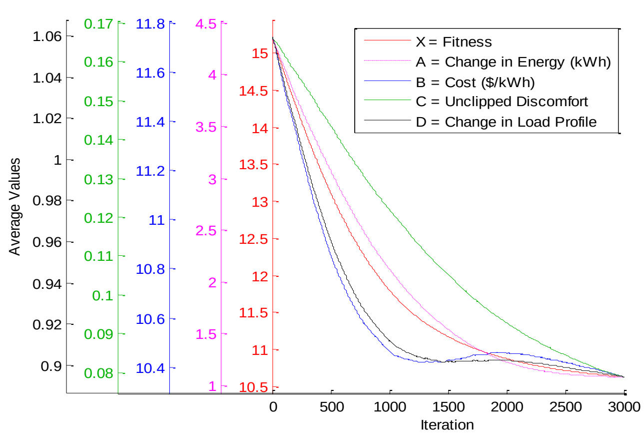

Figure 4. Graph of Convergence of variables with iteration

Case 1. No Discomfort Considerations

Fig.5 shows load profile optimization using GA, without implementing the discomfort function as an input variable. It could be observed that at several time intervals on the graph, there exists huge differentials between the optimized and forecast load profiles. Notable among these times is at 01:00 when the difference is over 2kWh despite having a low standard deviation (see Fig.3) which should have naturally minimized scheduling at intervals when standard deviation is low. This is because the discomfort function which contains the standard deviation factor was not implemented thereby allowing the very low price of energy at that time to be a decisive factor for the scheduler to shift a significant amount of energy to 01:00 hours.

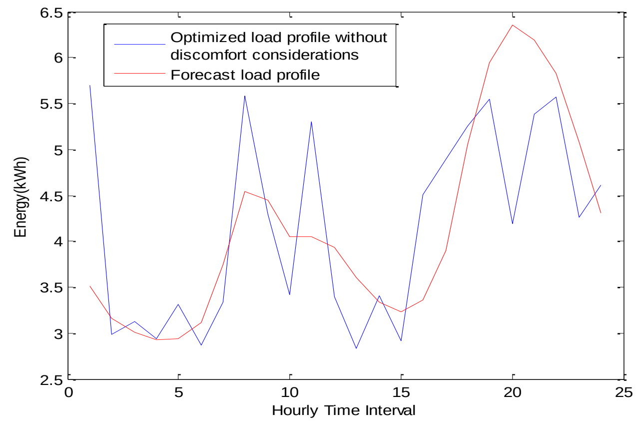

Figure 5. Load profiles with no discomfort consideration

Case 2. Discomfort Considerations Without Clipping

Fig.6 shows unclipped optimized and forecast load profiles with discomfort reduction considerations. Here, there is a significant improvement from the differentials observable between the two load profiles, than in case 1. We can also observe that the large energy gap at 01:00 from case 1 has been narrowed, although there still exists significant energy variations at 10:00 and 18:00 which the user may or may not consider to be too excessive depending on their choices.

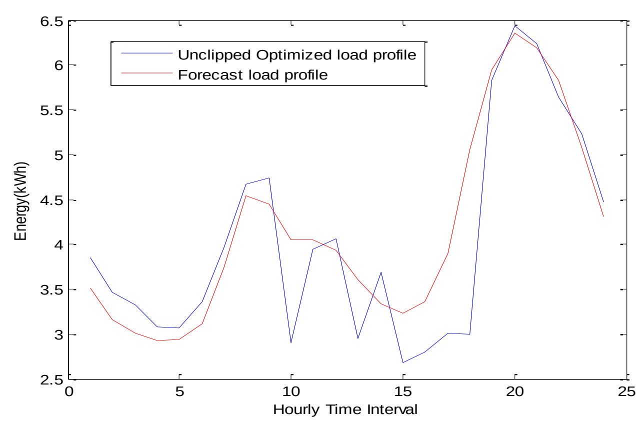

Figure 6. Load profiles with no limited discomfort

Case 3. Discomfort Considerations With Clipping

Fig.7 shows a significant narrowing of the gap between 10:00 till about 19:00 hours which is due to the limitation imposed concerning how much energy variation that is allowed due to the discomfort threshold value applied. Therefore, the very wide margins after optimization can be reduced depending on the extent of discomfort limiting imposed. Therefore the customer can effectively manage their scheduling algorithms to their specific requiements.

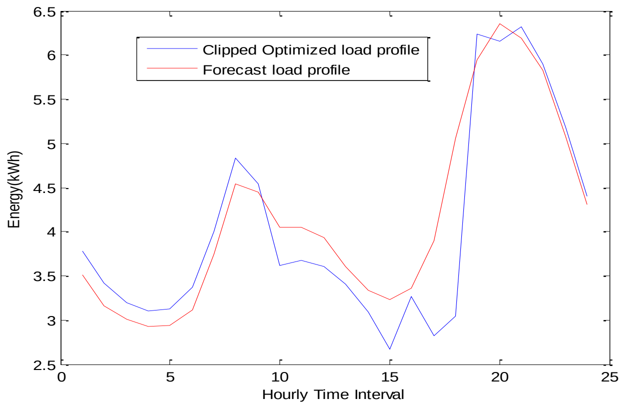

Figure 7. Load profiles with limited discomfort

Furthermore, Fig. 8 shows the graph of the clipped and unclipped discomfort levels whereby the magnitude of the clipped discomfort is at a threshold at 0.2 which represents about 40% of the maximum unclipped discomfort. By observation, it is clear which time intervals are prevented from generating excessive energy differentials as shown in Fig.6 but modified in Fig.7 based on the user's choice of discomfort threshold level.

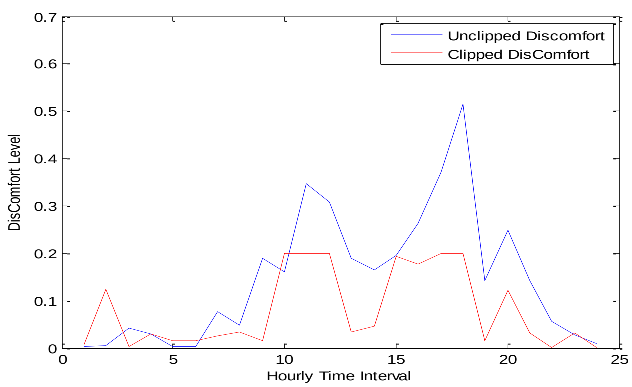

Figure 8. Comparison of discomfort between clipped and unclipped strategies

Cases 1 and 2 were used as a control in order to compare them with when the discomfort is clipped. The discomfort measure as used here is a novel approach towards improving customer satisfaction while implementing load scheduling. Although GA takes a considerable amount of time depending on the computational speed of the processor (in this case, up to 3 minutes), it did not affect the system significantly as the results are required to be computed at the end of each day.

Results obtained shows that where a maximum differential of about 60% exists at various time intervals between the optimized and non-optimized load when optimization is considered without discomfort factor, this differential could be lowered by half with the introduction of discomfort function. Further results showed that the differential can be lowered much further depending on the user's choice. In as much as one can lower the discomfort threshold line as desired, it is also important to note that lowering this threshold reduces the savings in energy cost accruable to customers who participate actively in DR programs.

V. CONCLUSION

In this paper, we have proposed a discomfort factor to demonstrate the role of the discomfort function in order to improve the quality of load scheduling. The introduction of discomfort clipping helps in stabilizing the optimization process. This can be viewed as a feedback system which is a novel idea that can be implemented in order to encourage more user participation in demand response programs as well as improving their confidence to engage more actively.

Future work will be aimed at investigating the effect of weightings to see how savings could be improved by minimizing cost. Although some savings were made here, they remained very minimal. Also to be considered are ways to improving the speed of convergence in order to accommodate applications on real time scenarios. Finally, the use of actual discomfort would be investigated to see how it could be used to determine the discomfort threshold, thereby equipping this technique to a system with some level of artificial intelligence.

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