Demand Response for Residential Appliances via Customer Reward Scheme

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***Abstract*—This paper proposes a reward based demand response algorithm for residential customers to shave network peaks. Customer survey information is used to calculate various criteria indices reflecting their priority and flexibility. Criteria indices and sensitivity based house ranking is used for appropriate load selection in the feeder for demand response. Customer Rewards (CR) are paid based on load shift and voltage improvement due to load adjustment. The proposed algorithm can be deployed in residential distribution networks using a two-level hierarchical control scheme. Realistic residential load model consisting of non-controllable and controllable appliances is considered in this study. The effectiveness of the proposed demand response scheme on the annual load growth of the feeder is also investigated. Simulation results show that reduced peak demand, improved network voltage performance, and customer satisfaction can be achieved.**

***Index Terms*—Customer rewards, demand response, direct load control (DLC), hierarchical controller, voltage improvement.**

I. Introduction

CONCERNS regarding the stability and reliability of an electricity network arise due to the adverse effect of peak power demand. Demand response is one way to deal with peak events and prevent network overloading because it provides the flexibility required to time shift loads [1], [2]. It is a cost effective technique and can be achieved by either price based (indirect load control) or incentive based (direct load control) demand response programs.

Indirect load control or price based demand response can be achieved through electricity price changes which encourage customers to regulate their consumption patterns [3]. Real time pricing, Time Of Use (TOU) tariffs, and critical peak pricing can be categorized under price based demand response where the fluctuations and risks in wholesale electricity prices are imposed on the end consumers [4]. The non-residential critical peak pricing scheme is shown to reduce peak demand [5]. The real time pricing scheme has equity problems due to highly varying day-time and night-time prices [6]. Moreover, it was also found that consumers are less likely to make active decisions about their load on an hourly basis under the real time pricing scheme [7].

Direct Load Control (DLC) or incentive based demand response can be used by utilities to adjust and time shift customer load directly during network peak events [8]–[10]. Although incentives are provided to consumers for their participation in the DLC program, recent field experiences showed some resentment due to mandatory interruption of electricity services [11]. Few pilot studies involving peak time rebates were conducted in the past where a priory fixed rebate structure is used which neglects the actual supply-demand status [12]. A variable rebate based demand response was proposed recently in [13], which took into account the variability of customer participation and offered coupons and incentives to achieve peak shaving.

All the models considered above did not investigate detailed appliance modeling and customer satisfaction, which is necessary for residential demand response. Air conditioners (ACs) were modeled and proposed to adjust the temperature for demand response in [14]. Similarly, the charging profile of electric vehicles as a load in distribution networks was considered in [15]–[17]. A real-time appliance scheduling scheme using time sensitivities and duty cycles of appliances was considered in [18]. These previous studies considered only a few selected appliances in the network. However, a holistic study, incorporating all major appliances has yet to be investigated.

Moreover, approaches in the literature aimed at network peak shaving via overload reduction completely neglected feeder voltage issues. In another study, Peças Lopes proposed a strategy for load shedding with coordinated voltage support using an optimization program [19], which was limited to a small system with few appliances. Optimizing the decision vector handling multi-layers of the demand response using customer priority criteria and satisfying both utility and consumer was proposed in [20]. ACs, water heaters and cloth dryers were the only controllable appliances considered in this study. Another attempt to bring the actual load consumption curve closer to the desired load consumption curve through an optimization process was proposed in [21], but it neglected the effect on customer satisfaction.

This paper proposes a new incentive based residential demand response using a Customer Rewards (CR) scheme, which not only achieves peak shaving but also improves the feeder voltage profile under different spatial distributions of residential loads. The proposed load control strategy does not depend on the

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TABLE I
SAMPLE CUSTOMER SURVEY QUESTIONNAIRE

Appliance	Availability/ Priority order		Desired Operation Region A	B	C
Water Heater (WH) Desired Tank Temperature	✓ 62 °C	1	×	✓	✓
Pool Pump (PP) Average Total operating time	✓ 8 hrs	7	✓	✓	×
AC- hysteresis (ACH) set point of AC	×	0			
AC- inverter (ACI) set point of AC	✓ 24 °C	2	×	✓	✓
Electric Vehicle (PEV) battery capacity	✓ 2 kW	4	✓	×	✓
Dish Washer (DW) Average total operating time	✓ 60 min	3	×	✓	✓
Cloth Washer (WA) Average total operating time	✓ 55 min	5	×	✓	✓
Dryer (DR) Average total operating time	✓ 70 min	6	×	✓	✓
A= off peak (2200hrs:0700hrs) , B=shoulder peak (0700hrs:1600hrs, 2000hrs:2200hrs); C=peak hours(1600hrs:2000hrs)					

TABLE II
REQUIRED DATA FROM CUSTOMERS.

Data in Customer Survey	Required Instance
Total operating time of pool pump Set point of AC and water heater Battery capacity of electric vehicle Average total operating time of dishwasher, cloth washer and dryer	For appliance satisfactioncalculations
Ordered list of appliances thatthe customer likesto connectbetween 16:00-22:00 hrs (peak and shoulder peak time)	For appliance prioritycalculations
Adjustable range of time for each appliance within a day	For flexibility calculations

cost of electricity consumption. Various indices reflecting customer priority, satisfaction, and flexibility are included in this research. Houses are ranked with a factor reflecting their impact on voltage due to their load. A LV distribution network, subject to real time load adjustment, is considered in this paper. Rewards for each customer are based on their willingness to participate in the scheme and are calculated dynamically every day.

The paper is organized as follows. The detailed description of demand response for residential appliances is proposed in Section II. Specifically, the concept of a customer reward (CR) scheme is explained in Section II.D. A critical assessment on the CR scheme is discussed in Section III. The realistic residential load model including the distribution feeder and the corresponding results are presented in Sections IV and V concludes the paper.

II. CUSTOMER REWARD BASED DEMAND RESPONSE FOR RESIDENTIAL APPLIANCES

Customer participation is usually encouraged through a detailed survey at the beginning of the demand response program. The information obtained is then used to calculate various indices to incorporate customer preferences and hence satisfaction during load adjustment. These indices, including network topology, are used to define an appropriate load adjustment. Customer rewards are calculated every 24 hours based on their participation. The details are discussed below.

A. Seeking Customer Preferences for Demand Response

A customer survey is given to all residential customers for their inputs and preferences regarding their participation in the demand response programs. A sample survey or questionnaire is shown in Table I. Utilities are interested to know appliance preferences of various customers and their time of operation. For simplicity, the survey may divide a day into three separate operation regions namely A, B, and C representing off peak, shoulder peak, and peak hours respectively.

The survey should be designed to collect important information such as the items listed in Table II. In order to verify the collected data from customers, past and current appliance usage patterns can be carefully studied for each house. Customer priority and the flexible range of usage time for appliances can be extracted from the above data. Details in the customer questionnaire can be verified with the extracted values. Moreover, these extracted values can be used when the information provided is inconsistent and/or ambiguous.

Customer preferences are taken into account before designing the load control algorithm. It is assumed in this study that each house has ten non-controllable loads (lighting, fridge, freezer, cooker, electric oven, microwave, television, computer, stand-by appliance, and miscellaneous appliance) and seven controllable loads (swimming pool pump, PEV, electric water heater, dish washer, clothes washer, dryer, and AC). They are modeled according to residential load modeling data provided in [22], [23].

B. Calculation of Various Criteria Indices Using Information From Customer Survey

Information from customers is used to define various indices for appropriate load selection. Therefore, five criteria indices ($C(i,j,k)$ for the k^{th} criteria index of the i^{th} house and the j^{th} controllable load, $C(i,j,k) \in [0,1]$) are proposed in this paper to reflect the customer's satisfaction, flexibility, and willingness to participate in demand response. They are explained next.

1) Appliance Priority Index (API): API is a user-defined value where the user (i.e., the customer) has the authority to order/arrange loads that should be operated per the priority of the duties. This is also obtained from the customer survey considering the 8-hour time span from 16:00 to 00:00. API_{ij} for the i^{th} house and for the j^{th} appliance can be calculated using the priority value (Pr_{ij}) in the ordered list. This is shown in (1). The maximum of Pr_{ij} represents the total available controllable appliances within that house

$$API_{ij} = \begin{cases} 1 & override = 1 \\ \frac{\mathrm{Pr}_{ij}}{\max(\mathrm{Pr}_{ij})} & override = 0 \end{cases}. \quad (1)$$

Table III gives the order of appliances in house 1 which has 7 controllable appliances. It is obtained from the customer survey as in the 2nd column of Table I. It shows that lower priority appliances, like the swimming pool have higher possibility for load adjustment. Further, Fig. 1 shows the priority of selected appliances such as the washing machine, swimming pool, and water heater for houses in phase-A of a selected feeder. If the customer chooses to turn on the appliance more than once, it can

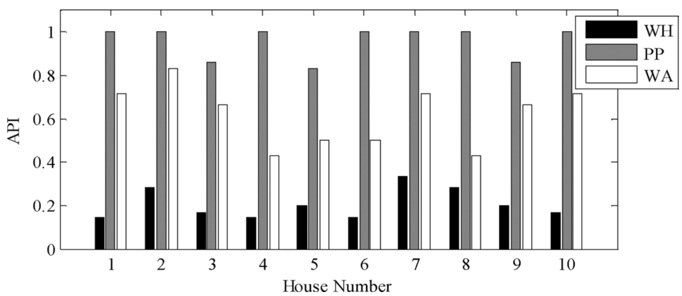

Fig. 1. API of houses in phase-A of feeder 1.

TABLE III
PRIORITY OF APPLIANCES IN HOUSE 1

Appliance	WH	PP	ACI	PEV	DW	WA	DR
Priority(Pr_l)	1	7	2	4	3	5	6
API_l	0.143	1	0.286	0.571	0.429	0.714	0.857

TABLE IV
FLEXIBILITY OF APPLIANCES

Appliances	WH	PP	ACI	PEV	DW	WA	DR
Adjustable time range (hrs)	13	18	6	11	2	2	2
AFI	0.542	0.75	0.25	0.458	0.083	0.083	0.083

be considered as an "Override". This "Override" will change the API for that appliance to 1.

2) Appliance Flexibility Index (AFI): AFI is a measure of the adjustable range of time of appliances and it depends totally on their characteristics and necessity. For example, a swimming pool pump can be operated at any time during a day and therefore has the maximum flexibility. Washer and dryer have the lowest flexibility because they can only be operated in-between 6 p.m. to 11 p.m. This desired appliance operation time range is obtained from customer survey data. Each customer will specify the flexible range of time of his appliances in advance, according to the TOU tariff of that particular season [24]. Off peak (9 hrs), shoulder peak (11 hrs), or peak region (4 hrs) is selected by a customer for a desired operation as shown in Table I. Hence, he/she determines his/her appliance usage pattern within a day according to a time schedule to reduce the cost. Here, the total available time is one day or 24 hours.

Finally, the utility calculates the appliance flexibility index for load adjustment using (2). Here, the user defined data (adjustable range of time) is divided by the total available time within 24 hours. Table IV provides the sample values of flexibility for each controllable appliance when customers are at home

$$AFI_{ij} = \frac{\text{adjustable range of time}}{\text{total available time (24 hrs)}} = C(i,j,2). \quad (2)$$

3) Appliance Satisfaction Index (ASI): ASI is calculated every four minutes and indicates how close the appliance operating state is to its limiting state of operation. ASIs of different appliances are calculated as shown in Table V and used as the criteria index $C(i,j,3)$. The current power level and time of operation state of each controllable appliance is used to calculate this index. The desired values and the set points are randomly defined within the program. For example, a mean value of 67°C and 25°C are chosen for set point of the water heater and AC, respectively, for random data generation. ASI is maintained close to unity. Here, T_{tank} is the water heater tank temperature and $\Delta\mathrm{T}$ is the temperature difference (i.e., Actual Room Temperature – Set Point) of AC. For dish washer, clothes washer, and dryer the cycle has to be completed once started by the customer. If this load is delayed by utility, then it will reset and start again at a later time. These loads are given low AFIs and hence the least priority for adjustment. ASI will help to maintain a high probability that the dish washer, clothes washer, and dryer will not be interrupted in the middle of a cycle via decision matrix values as (9).

TABLE V
CALCULATION OF ASI FOR DIFFERENT APPLIANCES.

Appliances		Satisfaction
Water Heater	Actual T_{tank}<desired T_{tank}	$\frac{(\text{actual } T_{tank} \text{ - set point})}{(\text{desired } T_{tank} \text{ - set point})}$
	Actual T_{tank}>desired T_{tank}	1
AC	$\Delta T<\Delta T_{min}$	0
	$\Delta T_{min}<\Delta T<\Delta T_{max}$	$\frac{(\Delta T_{maximum} - \Delta T_{actual})}{(\Delta T_{maximum} - \Delta T_{minimum})}$
	$\Delta T>\Delta T_{max}$	1
Swimming Pool		$\frac{\text{time taken for the operation}}{\text{desired total operating time}}$
PEVs		$\frac{\text{available charge of PEV}}{\text{capacity of the battery of PEV}}$
DishWasher, Cloth Washer and Dryer		$\frac{\text{time remaining to complete that cycle}}{\text{Appliance operating cycle time}}$

4) Power Similarity Index (PSI): PSI represents how close a load is to the required amount of total load adjustment and it is used as the criteria index $C(i,j,4)$. This is calculated using (3) for each appliance at each instant

$$PSI_{ij} = 1 - \left| \frac{\text{Appliance Load} - \text{Req Avg Load Adjustment}}{\text{Appliance Load}} \right|. \quad (3)$$

For example, in a peak day, if a transformer is overloaded by 120 kVA, then on an average 1 kVA is to be adjusted in each house with the assumption of 120 houses. This required load adjustment is compared with the rating of each appliance to calculate PSI_{ij}. For each house, the appliance with the highest PSI is the most appropriate for the adjustment. Table VI illustrates how PSI is used to select a particular load for adjustment. If 1 kVA load were to be adjusted, then the washer load, which has a highest PSI of 0.9091 compared to all other loads in that house, should be adjusted. Whereas, if 2 kVA load were to be adjusted, then AC load (PSI is 0.8696) should be chosen. Selection of AC for the necessary 2 kVA adjustment is much better than the selection of any other combination of appliances which add approximately 2 kVA power level (e.g., washer 1.1 kW and dryer 1.3 kW). Here, 2 control commands are reduced into 1, which means the control algorithm chooses only one load at a step. Hence the 2 kVA load is chosen for load adjustment instead of

TABLE VI
PSI CALCULATION OF HOUSE-1 FOR A PARTICULAR INSTANT.

Average Load Adjustment per House	Power Similarity Index (PSI)		
	AC (2.3 kW)	Water Heater (3.6 kW)	Washer (1.1 kW)
1kVA	0.4348	0.2778	**0.9091**
2kVA	**0.8696**	0.5556	0.1818

two loads with 1.1 kW and 1.3 kW. This explains the effectiveness of PSI.

PSI is required to select the closest and most appropriate load to be adjusted to eliminate overload. Use of PSI will minimize overall control commands in the network.

5) High Power Consumption Index (HPCI): HPCI aims at identifying the house which is consuming the highest power at a time when load adjustment is required. HPCI is calculated as in (4) and is used as the criteria index $C(i,j,5)$. For example, if a house has 5 kVA of connected load and the load consumption is 5 kVA at that time, then HPCI is 1 at that time. At other time instants, if load consumption is 3 kVA, HPCI is 0.6 ($=3/5$). HPCI is one way to socialize the load adjustment such that network overload is effectively mitigated

$$HPCI_{ij} = \frac{\text{Total load of } i^{th} \text{ house}}{\text{House load with max consumption in the network}}. \quad (4)$$

C. Using House Ranking and Criteria Indices for the Selection of Appropriate Load Adjustment in the Network

Houses are ranked with a factor to replicate the impact of load on voltage violation. The random selection of house loads will result in a number of unnecessary load adjustments when voltage violation exists. Hence, this ranking mechanism is introduced for each house to avoid unnecessary load adjustment during voltage problems. Traditionally, the sensitivity method [25], [26] has been used for load ranking and can be used here to choose the most suitable house for required load adjustment.

Rank for each house at each instant is calculated using the voltage magnitude and angle of each house from a three-phase unbalance load flow program. Voltage sensitivity is considered as an appropriate voltage measure in this process. Voltage sensitivity parameter (ρ) is the average change in the voltages of all houses in a feeder due to load adjustment at that house. Inverse Jacobian matrix parameters are used to calculate the voltage sensitivity at each house. The parameter ρ of the i^{th} house in the p^{th} phase for a three-phase unbalanced system is derived using (5)

$$\rho_i^p = \frac{\sum_{h=1}^{n}\sum_{m=1}^{3}\left(\frac{\partial \Delta V_h^m}{\partial \Delta P_i^p}\Delta P_i^p + \frac{\partial \Delta V_h^m}{\partial \Delta Q_i^p}\Delta Q_i^p\right)}{3n} \quad (5)$$

where n is the total of number of houses in one phase. Maximum and minimum values of the sensitivity parameter in each phase is calculated and used in (6) to define rank, R_{ij}^p, for the i^{th} house and the j^{th} appliance in the p^{th} phase. e_{ij} is the appliance status (On/Off) signal at a particular time for the i^{th} house and the j^{th} appliance and can be obtained from smart meters. The value of e_{ij} is 1 if the appliance is on at a particular time and 0 otherwise.

$$R_{ij}^p = \left(\frac{\rho_i^p - \min_i(\rho_i^p)}{\max_i(\rho_i^p) - \min_i(\rho_i^p)}\right)\cdot e_{ij}. \quad (6)$$

The overall control process maintains voltage and network power levels within limits. Here, 0.94 p.u. and 1.06 p.u. are the minimum and maximum voltage levels, respectively, because $+/-6\%$ are the Australian standards. Also, network power limits are taken as the capacity of the transformer (chosen here as 500 kVA). Power flow equations used during the three-phase unbalanced load flow program is provided here. The derived mismatch equations for the load buses are (7)–(8)

$$\Delta P_i^p = P_i^p + \sum_{h=1}^{n}\sum_{m=1}^{3}|V_i^p||V_h^m|\{G_{ih}^{pm}\cos(\theta_i^p - \theta_h^m) + B_{ih}^{pm}\sin(\theta_i^p - \theta_h^m)\} \quad (7)$$

$$\Delta Q_i^p = Q_i^p + \sum_{h=1}^{n}\sum_{m=1}^{3}|V_i^p||V_h^m|\{G_{ih}^{pm}\sin(\theta_i^p - \theta_h^m) - B_{ih}^{pm}\cos(\theta_i^p - \theta_h^m)\}. \quad (8)$$

Here, G_{ih}^{pm} and B_{ih}^{pm} are conductance and susceptance of the feeder connecting the i^{th} and the h^{th} house in phase p due to the effect of phase m, respectively; θ_i^p is the bus angle at the i^{th} house in phase p; P and Q are real and reactive power, respectively; and V is the bus voltage. The rank of each house is then multiplied with the decision value for the appropriate selection of load.

Overall, the above parameters provide the decision for load adjustment. These indices (as discussed in Section II-B) along with the appropriate rank (as discussed in this Section) for each house are used in decision matrix calculation. D_{ij}, the decision for the i^{th} house and the j^{th} controllable load, is defined as in (9)

$$D_{ij} = R_{ij}^p \sum_{k=1}^{5} C(i,j,k). \quad (9)$$

Where, $C(i,j,k)$ is the criteria raking matrix for the k^{th} criteria index of the i^{th} house and the j^{th} controllable load ($C(i,j,k) \in [0,1]$). An efficient solution can be achieved with the combination of multiple criteria indices into a single criterion by multiplying each criterion with a positive weight and summing the weighted criteria [27]. For simplicity, this paper considers unity weights for all five criteria.

For the i_0^{th} house in the p_0^{th} phase, if ρ_{i0}^{p0} is the minimum ρ in that phase, then $R_{ij}^p = 0$ and hence $D_{ij} = 0$. This means that the corresponding appliance will not be selected for load adjustment at that time instant. This is reasonable because at that time instant, the i_0^{th} house is the least sensitive to the voltage violation in the feeder. Since the voltage sensitivity depends on house locations as well as load consumption, at other time instants the same house may not have the minimum sensitivity and hence the corresponding load can be selected for adjustment at that time.

D. Customer Reward (CR) Scheme

CR scheme provides rebates to residential customers for their participation in the demand response. The proposed rebate is a function of both shifted energy and voltage improvement due to load adjustments as shown in (10). The shifted energy of the house is the sum of the product of all load adjustments and the respective waiting times. Here, waiting time is the time that is delayed by the controller to re-connect the appliance to the system. The effective change in voltage within the network due to a particular load adjustment is taken as the ratio of voltage deviation of the i^{th} house to the voltage improvement from the lower limit

$$\begin{aligned} R_i &= f(shifted\ energy, voltage\ improvement) \\ &= \alpha \cdot \left(\exp\left(\sum_{l=1}^{Nadj} \frac{E_i^l}{E_{\lim}} \right) - 1 \right) \\ &\quad + \beta \cdot \sum_{l=1}^{Nadj} \left(\frac{\Delta V_i^l}{\Delta V_{i,\lim}^l} + \sum_{m=1 \neq i}^{Nv} \frac{\Delta V_m^l}{\Delta V_{m,\lim}^l} \right). \quad (10) \end{aligned}$$

Here, R_i is the rebate in \$/day for i^{th} house; E_i^l is the shifted energy for the i^{th} house measured at the l^{th} load adjustment; E_{lim} is the limit of maximum shifted energy (chosen to be 12 kWhr in this case); ΔV_i^l is the voltage deviation in p.u. and $\Delta V_{i,lim}^l$ is the voltage improvement (from lower limit of 0.94) in p.u of the i^{th} house measured at the l^{th} load adjustment; N_{adj} is the total number of load adjustments per day for the i^{th} house; N_v is the number of houses with voltage violations in the same feeder as the i^{th} house; α and β are cost coefficients for shifted energy and voltage improvement chosen here as 20 and 1, respectively.

An exponential function for shifted energy is chosen to provide increased benefit to customers who are willing to participate in load adjustments for a longer time. The rebate for voltage improvement due to load adjustment of a house has two components, i.e., one resulting in the voltage improvement of that particular house whose load is adjusted and the second being the improvement in voltage profile in all other houses down the feeder. This is important since load adjustment in the house which happens to be at the beginning of the feeder would inadvertently improve the voltage of other houses down the feeder and therefore should be rewarded accordingly.

In particular, each house will be benefitted by the load adjustment at the end of the day with rebates.

E. Implementation and Operation of Load Control Algorithm

The load control process of CR scheme is shown in Figs. 2 and 3. As shown in Fig. 2, the signal from the smart meters is received every four minutes. Data processing and identification of load adjustments are achieved offline in 2 minutes and then signals are sent for load adjustment.

Communication network like WiMAX has a bit rate in between 5–25 Mbps where it has a tendency to vary with distance. Also, 900 MHz system and ZigBee network have a bit rate of 20 and 250 kbps, respectively. Hence, it takes less than a second for signal transfer. Further, the data process time calculated in our program is roughly 10–15 seconds. Here, 2 minutes time frame is selected as a reasonable time for data collection and processing and another 2 minutes for sending back data and load curtailment. Hence, load curtailment happens every 4 minutes. The 4-minute time window is chosen in this research to make it roughly aligned with the DMS updates, which usually occur every tens of seconds to a few minutes.

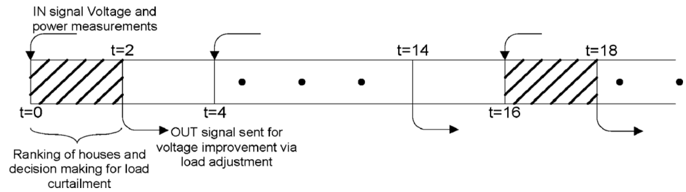

Fig. 2. Time schematic of the load control process.

From time $t = 0$ minute, at each instant $t = t_1$, signals from the primary controllers (smart meters) are received by a secondary controller. Received appliance state and power data are used in the load flow program to calculate voltage at each house. Total network power and voltage at each house are checked to insure that they are kept within standard limits. The above measurement and data processing occurs every 2 minutes.

Offline load flow studies are performed to obtain the appropriate load adjustments in the case that the power level and/or voltage at each house are violated. The offline load flow block is an iterative process that selects multiple sets of loads for adjustment in that time step as summarized in Fig. 3. The criteria indices and rankings and hence decision value (D_{ij}) are calculated for each iteration. The maximum value of D_{ij} is used to find the corresponding j_0^{th} load of the i_0^{th} house for load adjustment. The power and voltages are recalculated after this load is adjusted in the offline load flow program. If violations exist, another load is selected for adjustment by recalculating the updated criteria indices and decision values. This process is repeated until violations are removed. At the end of the "offline selection of load" block, multiple sets of appliances that need to be adjusted are identified to keep the voltage and power within limits.

All selected appliances for adjustments are saved and signals are sent at $t = t + 2$ minutes to relevant smart meters. If loads are adjustable (such as AC and water heater loads), then the AC set point is increased by 1°C and the water heater set point is decreased by 1°C for 15 minutes. Whereas, the non-adjustable loads are switched off for 4 minutes. The process is repeated for the whole day and after 24 hours. Rebates to the customer are calculated as per (10). Set point adjustments would result in the reduction of power consumption, which will be used along with associated waiting time to calculate the shifted power. Fig. 3 summarizes the load control process with CR scheme for a particular day.

Most of the appliances that do turn ON, run for a certain time as a constant power load and then turn OFF. This replicates a discrete event. Once the control signal for adjustment is sent for certain loads, such as hysteresis type ACs, inverter type ACs, and water heaters, another signal is not sent for the next 15 minutes. For example, at time instant $t = 2$, the control signal is sent

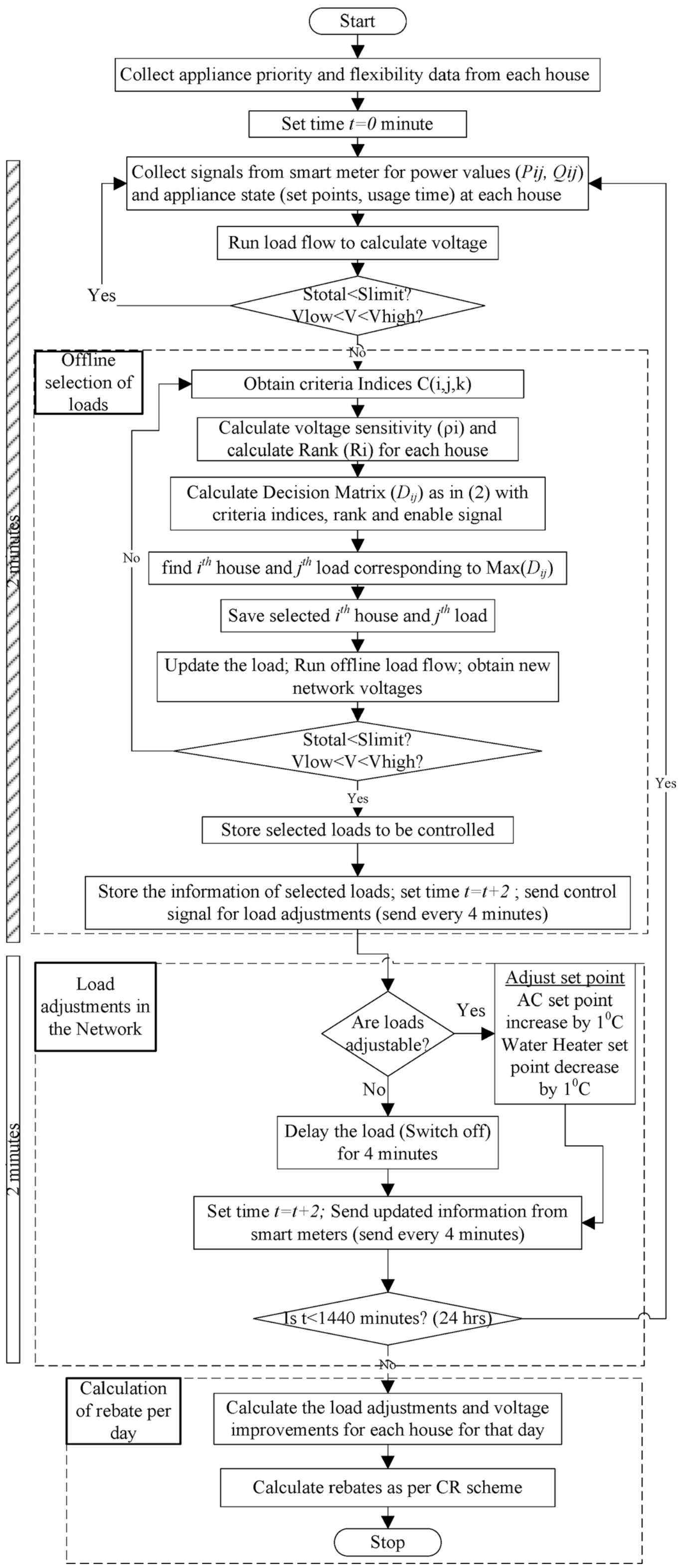

Fig. 3. Summary of Load control process with CR scheme for a particular day.

for adjusting the water heater of House#4 (say). Once the measurements are obtained at $t = 4$, the decision matrix is calculated as per (9), and the control signals are sent again at $t = 6$ for another set of load adjustment. This signal would not adjust the water heater of House#4 until after $t = 16$, where the measurements are taken again. The decision matrix is again calculated at $t = 16$ and if the water heater is required to be adjusted, then the signal would contain a message to adjust the water heater of House#4 at $t = 18$ (as illustrated in Fig. 2).

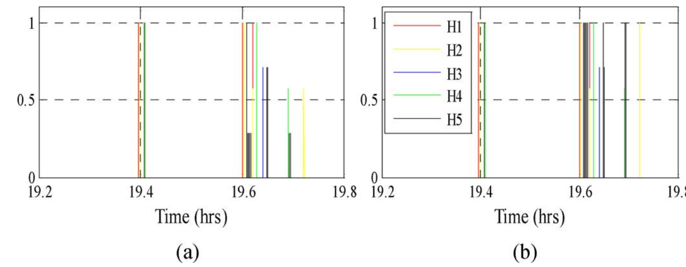

Fig. 4. API during each control (a) without (b) with API in decision process.

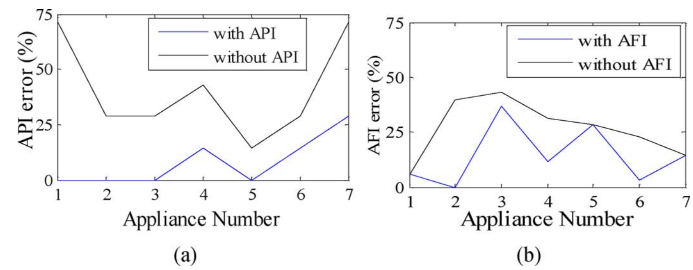

Fig. 5. Error in (a) API (b) AFI when API (or AFI) is considered or not considered during decision making.

III. Critical Assessment of CR Scheme

This section critically assesses various aspects of the demand response and evaluates the necessity of indices, CR, and challenges in the implementation of the proposed scheme.

A. *Significance of Indices in Control Scheme*

As discussed in the previous section, customer information is used to define five indices for effective load control. Here, each index is critically evaluated to justify its necessity in the load adjustment algorithm.

A single-phase five-house radial network is considered for this purpose. All houses are assumed to have seven similar controllable appliances. Initially, two different decision processes are analyzed; one with API and the other without API. As shown in Fig. 4, customer priority deviates more if API is not considered during decision making. That is, appliances with higher customer priority are also selected for adjustment.

Further, the average selection of loads for 30 random days is observed. The selection of loads deviates from the reference API values as in Fig. 5(a), violating customer preferences. A similar study is done using AFI and results are shown in Fig. 5(b). Hence, these indices are important in maintaining customer preferences. Here, all houses are assumed to have the same reference values for API and AFI. Also, ranks of houses are kept constant. Actual API and AFI are calculated based on the number of controls within the day without API and AFI in decision process. Appliance selection deviates from the customer specified value if these indices are removed from the decision process.

Moreover, ASI is significant because it reduces the selection of appliances which are in the middle of operation. An experiment with and without ASI during decision process is conducted

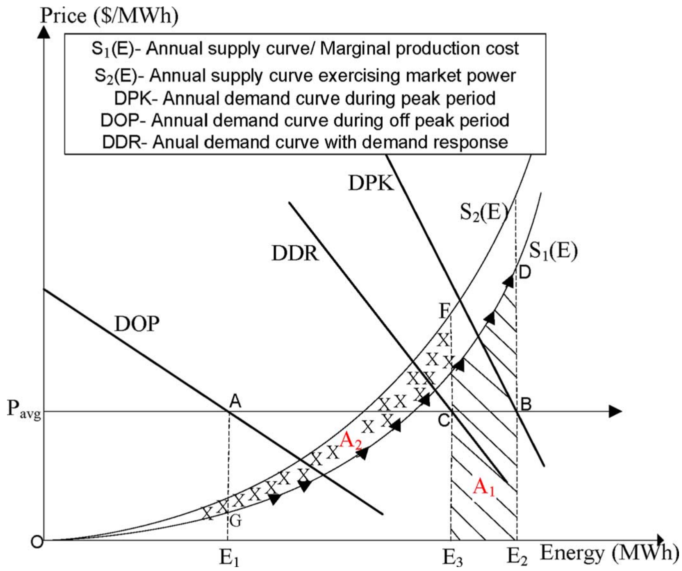

Fig. 6. Supply and demand curve with and without CR scheme.

for 30 days and results are compared. The percentage of appliances such as washing machines, dish washers, and dryers interrupted in the middle of operation is 2–5% whereas it is 12.5% without ASI. Hence, it prevents these appliances from being interrupted in the middle of their operation cycle.

The significance of PSI is analyzed in a case study with and without PSI. It is observed that controls reduce from 39 to 32 in a significant day. On an average 15–25% of controls are reduced by the use of PSI. Hence PSI is an effective factor in the decision process. HPCI is important in selecting house with maximum consumption that lead to network problems. It provides benefits to the customers who have an average consumption schedule and do not considerably violate the network. If HPCI is not included in decision process, a house with maximum consumption is likely to be selected only 20–30% of the time. This shows that each criteria index is complementary and necessary for effective load adjustment.

B. Evaluation of Cost Coefficients for CR

Annual supply and demand curves are used to find cost coefficients of the rebate function in (10). The supply curve is dependent on the marginal operating costs of various generators in the electricity market. The demand curve changes according to the consumption pattern of customers. These curves can be obtained from utilities and market operators and have daily (peak and off peak) as well as seasonal (summer and winter) variations [28]. For simplicity, the monotonically decreasing demand curve and monotonically increasing supply curve, as shown in Fig. 6, are considered for the calculation of α and β.

During off-peak time, demand is lower and is represented by the curve DOP, whereas the increase in demand at peak time can be shown by curve DPK. For a constant tariff (flat rate), the price is fixed at P_{avg} and therefore the market during off-peak time operates at point A for quantity demanded E_1. The increase in demand causes a shortage of supply, which leads to an increase in price. Due to the increased price, the utility will increase the quantity of supply from point G to point D, as shown in Fig. 6, to cater to the increase in quantity demanded from E_1 to E_2. However, due to flat rate, the market operates at point B. The demand response will reduce the demand and shift the demand curve to the left, which can be represented as DDR [29]. At the same time, the supply price increases and shifts the supply curve to S_2. This is because the suppliers are provided with reduced incentives to exercise market power [30]. Finally, the market operates at point C after demand response achieves the reduction from E_2 to E_3.

The cost of supply due to demand response is reduced and it is the difference between ODE_2 (area under the supply curve S_1) and OFE_3 (area under supply curve S_2). For simplicity, it can be represented as $(\mathrm{A}_1 - \mathrm{A}_2)$ as shown in Fig. 6.

Energy values E_1, E_2, and E_3 are found using annual supply curves mapped to the intersection of demand curves with a fixed price. A_1 and A_2 are found after the computation of E_2 and E_3, respectively.

The total rebate in the network for a day should be less than the reduction in cost of supply due to demand response. Hence, the total rebate for the network, R_{total}, that can be offered by the utilities to their customers should be less than the cost savings because of demand response. That is, $(\mathrm{A}_1 - \mathrm{A}_2)$ should satisfy (11)

$$\left\{R_{total} = N \cdot (\alpha \cdot E^{avg}_{shift} + \beta \cdot V^{avg}_{imp}) \text{ and } R_{total} < (A_1 - A_2)\right\}. \tag{11}$$

Here, N is the number of houses in the network. E^{avg}_{shift} and ΔV^{avg}_{imp} are components related to the average shift in energy and voltage improvement that is calculated from offline load flow studies using the annual demand and supply curves.

For example, if a 500 kVA network is overloaded by 150 kVA, then E_2 and E_3 are 650 kVA and 500 kVA, respectively. The reduction in cost, i.e., $(\mathrm{A}_1 - \mathrm{A}_2)$, is \$100 using a sample supply curves from [31]. E^{avg}_{shift} and ΔV^{avg}_{imp} are found to be 0.041 and 2.0, respectively, for an average house using offline load flow studies. If β is kept at 1.0, the value of α is found to be 20 to satisfy (11). Note that the utility can choose appropriate values of α and β to incentivize the increase of customer participation. This depends on the network layout, the number of customers, and the existing tariff. The rebate pattern can be changed by the utility for every quadrant of the year to accommodate seasonal load changes.

C. Customer Rewards

A single-phase five-house model is considered to evaluate rebate calculations. For simplicity, houses are assumed to have similar appliances of 1 kVA each. The power consumption profile in each house is assumed to be the same. API and AFI are fixed in every house as in Tables III and IV.

A rebate for each house is calculated every 24 hours by the utility to provide benefit to the customers as discussed in Section II.D. The results obtained for 5 houses are tabulated in Table VII. H2 pool pump (#2) and electric vehicle (#5) are adjusted for 12 minutes and for 4 minutes with 1 kW of shifted power, respectively. Hence, the rebate for the total shifted energy and the voltage improvement is \$0.45 and \$0.51, respectively. So, H2 will get a total rebate of \$0.96 (\$0.45 + \$0.51). It shows an increased rebate towards the end of the feeder in case 1. Customers towards the end of the feeder

TABLE VII
DETAILED CALCULATION OF REBATE FOR 5 HOUSES IN ONE FEEDER

House No#	Appliance No #* (Power (kW),Time(min))	Energy Shift, E_i (kWhr)	Rebate for shifted Energy ($) $\alpha * \left(\exp\left(\sum_{l=1}^{Nadj} \frac{E_i^l}{E_{\lim}} \right) - 1 \right)$	Component of Voltage improvement of that house (p.u.) $\sum_{l=1}^{Nadj} \frac{\Delta V_i^{\ l}}{\Delta V_{i,\lim}^{\ l}}$	Component of Voltage improvement of other houses(p.u.) $\sum_{l=1}^{Nadj} \sum_{\substack{m=1 \\ \neq i}}^{Nv} \frac{\Delta V_m^{\ l}}{\Delta V_{m,\lim}^{\ l}}$	Rebate for voltage improvement ($)	Total Rebate, R_i ($)
H1	2(1,12)	0.2	0.34	0	0.18	0.18	0.52
H2	2(1,12); 5(1,4)	0.27	0.45	0	0.51	0.51	0.96
H3	2(1,12); 5(1,12);7(1,4)	0.47	0.79	0	0.82	0.82	1.61
H4	2(1,20); 5(1,12);7(1,4)	0.6	1.03	0.71	1.41	2.12	3.15
H5	2(1,8);4(1,28);5(1,8)	0.73	1.26	0.82	1.67	2.49	3.75

*Appliance No #1-Water heater; #2-swimming pool pump, #3-hysteresis type AC, #4-inverter type AC, #5-Electric Vehicle, #6-Dish Washer, #7-Cloth Washer and #8-Cloth Dryer .

TABLE VIII
COST OF ELECTRICITY CONSUMPTION IN A PEAK DAY FOR FEW HOUSES.

House No#	Without Demand Response ($)	With Traditional Demand Response (no rebates) ($)	With CR Scheme ($)
H1	10.45	9.85	9.33
H2	10.45	9.64	8.68
H3	10.45	9.04	7.43
H4	10.45	8.65	5.5
H5	10.45	8.26	4.51

will be benefitted with an increased rebate due to more load adjustments. Here, the total rebate paid by the utility to all five houses is $9.99. It is interesting to note that H1, at the beginning of the feeder, has fewer rebates for voltage improvement than H5 at the end of the feeder. H5 will have significant effect on the feeder voltage due to load adjustment and, hence, will have a higher rebate component for voltage improvement than the corresponding energy component.

Scenarios with traditional demand response (no rebates) and CR scheme are compared for Australian residential tariff 11, which is 0.25 $/kWhr [32]. The cost of consumption is calculated based on the price of electricity and energy consumed every hour. Table VIII shows the cost of electricity for a few selected customers for a peak day. For instance, with constant tariff, the consumption cost of H1 is $10.45.

If H1 participates in the traditional demand response, the cost is reduced to $9.85, due to reduced or delayed load consumption on that peak day. In the absence of any rebates the customer is not rewarded for their participation in load adjustment. With the proposed CR scheme, the rebate obtained due to load adjustment of H1 is $0.52 ($9.85 − $9.33 = $0.52). Hence, H1 will pay only $9.33. Note that the rebate increases towards the end of the feeder due to significant voltage improvement component.

D. Implementation and Operations of CR Scheme

A two-level hierarchical control scheme is proposed for demand response in the residential distribution feeder. The primary control level is used to regulate the feeder voltage within an acceptable range and the secondary control level is conceived to prevent respective transformer overload. The primary controllers (smart meters) are installed at each house to collect power consumption data and communicate with the secondary controllers installed at the transformer. Each appliance in the house has appliance units (AU) and communicates usage characteristic data at each time interval. AUs collect data from other AUs and then transmit and receive data from central smart meter via WiFi or ZigBee. The role of the secondary controller is to maintain all the transformer loads below their rated values, while minimizing the negative impacts on the customer side. All controllers have low bandwidth and two way communication capabilities. Signals obtained from smart meters include ON/OFF time, power rating, and the power level of the appliances. This is feasible for houses equipped with smart meters.

Although the transient effect can be important during the demand response, voltages and currents transients caused by load change may last for no more than 50 and 20 milliseconds, respectively. In the 4 minute timeframe for load adjustment, this effect is not considered at this stage.

The step by step load control process, as discussed in the load control section above, is more efficient because it removes the rebound effect from the decision of which loads are to be curtailed. It also provides an appropriate control of power and voltage as it constantly checks for violation during the offline process.

E. Scalability

This decision process can be separated for subsystems (For example, each 500 kVA network). Load curtailment can be made separately for each subsystem when it is subject to overloads or voltage violations. This is made possible by having a main controller at each transformer level which has access to relevant smart meters in the houses. Hence, it can be deployed at a range of scales in small and large configurations easily. Data processing can be done in parallel for each system and therefore the time consumed in processing data is minimal.

F. Prevention From Customers Misusing This Scheme

Possible gaming can be avoided by restricting customer load switching by introducing an override command. This will dynamically change the API to 1 for that load and therefore it will not be selected for adjustment for the rest of the day. If a customer chooses to operate a particular load more than two times in the peak period, then the information is send back to the utility as an override and rebate would not be paid for that load shift.

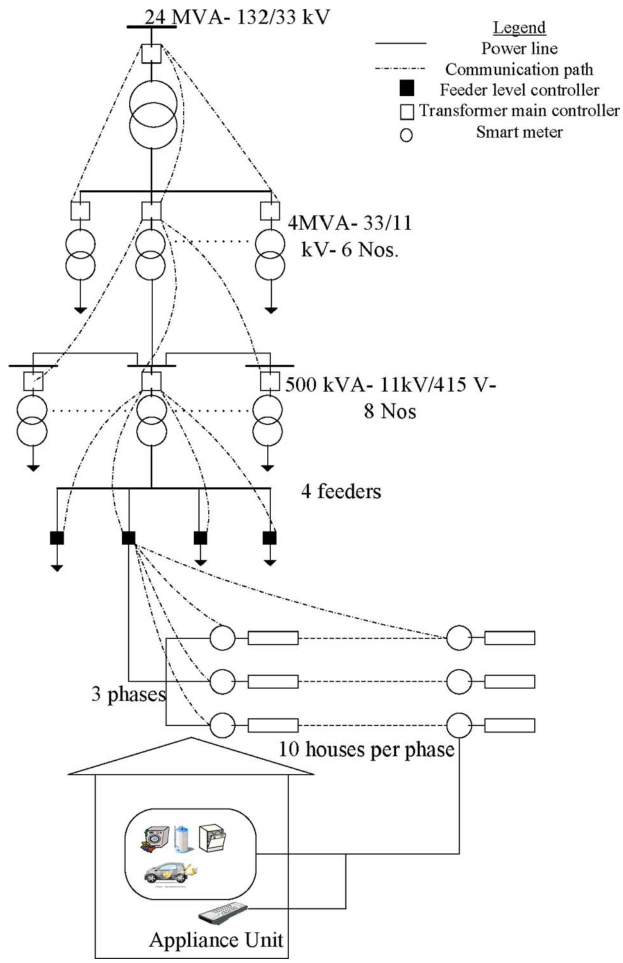

Fig. 7. Hierarchical control scheme for CR based Demand response.

IV. Case Study

Implementation of this control scheme for DLC for residential customers is shown in Fig. 7. The 11 kV/415 V, 500 kVA transformers have four feeders. Each feeder contains 30 houses evenly divided per phase. There are eight 11 kV/ 415 V transformers with controllers further controlled by the controller of a 33 kV/ 11 kV, 4 MVA transformer. Again, there will be six 33 kV/11 kV transformers which will be controlled by the controller of a 132 kV/ 33 kV, 24 MVA transformer at sub-transmission level.

An indoor thermal model for a house is used which affects the power consumed by ACs, ambient temperature, and the floor area of each house. Each appliance contains a mean power rating and a time usage pattern which closely suits the real system. A climate model is used to vary the temperature and it is linked with the time usage pattern of individual appliances. Transformer and other switch gear ratings are chosen to meet the aforementioned requirement. Further, every house is assigned with a floor area corresponding to the Australian 2008 new house data [33] which is used for the calculation of appliance loads. In order to create a realistic system, 90% of the houses are considered as unoccupied during week days (8 am to 5 pm) where most of the appliances will be unused as people are assumed to be at work. Simulations in all models maintain a fixed time step of 2 minutes of a user-defined interval to generate regular events. Network and transformer loads are calculated based on the algebraic sum of active and reactive loads.

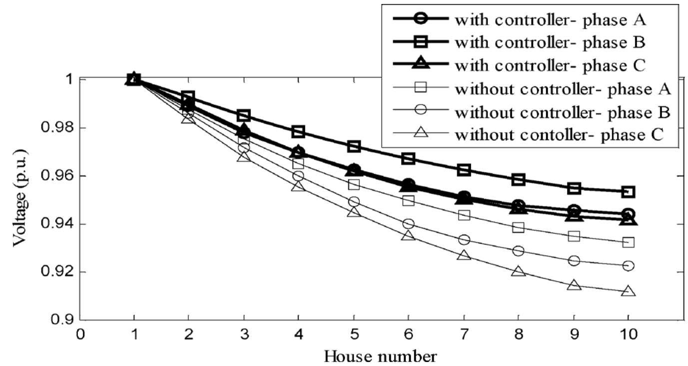

Fig. 8. The voltage profile of the residential feeder-1 without and with controller at peak time (1940 hrs).

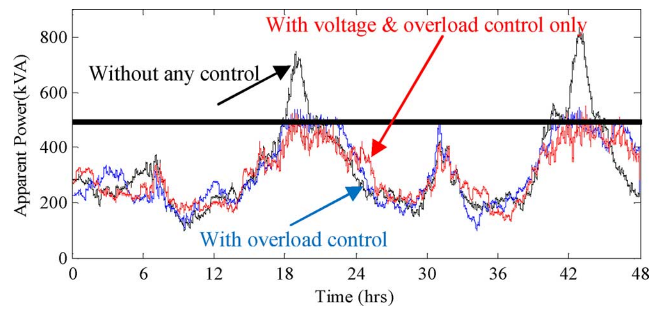

Fig. 9. Loading of 500 kVA transformer without and with controller.

A. Impact on Feeder Voltage and Transformer Overload

The voltage profile of a selected three-phase feeder with and without the proposed control scheme is shown in Fig. 8. Improvement in voltage profile is apparent, especially towards the end of the line at each phase. Similar improvement is observed in other feeders as well.

Furthermore, the network loading level is observed via the 500 kVA transformer for a 48-hour period and is shown in Fig. 9. The transformer is overloaded by approximately 50% for a 2-hour period without any control scheme. The proposed voltage controller is able to relieve the transformer overloading. Transformer overloading can still be avoided with the implementation of a simple overload (power) controller, as shown in Fig. 9.

A simple overload (power) controller uses the same load control process (as in Figs. 2 and 3) except for the limitations in voltage. Therefore, voltages in the network are not monitored and/or controlled. Fig. 10 reveals the effect of the proposed voltage controller over the simple overload (power) controller. When the voltage profile towards the feeder end is analyzed, the proposed voltage controller performance can be appreciated during peak hours, i.e., hours 18 and 42, as shown in Fig. 10. Thus, this illustrates the importance of the proposed control scheme in eliminating voltage violations.

B. Effect on Customer Loads and its Impact on ASI

The performance of this control scheme on the customer side is investigated by observing the effect on the operation of a

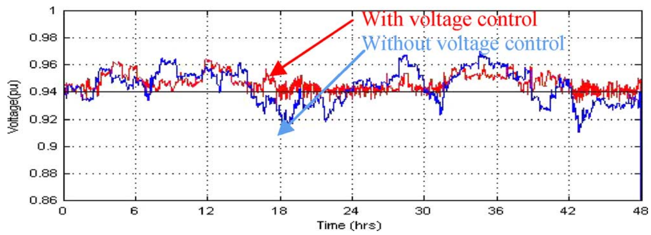

Fig. 10. Voltage profile at the end bus of feeder-1 without and with voltage controlling process.

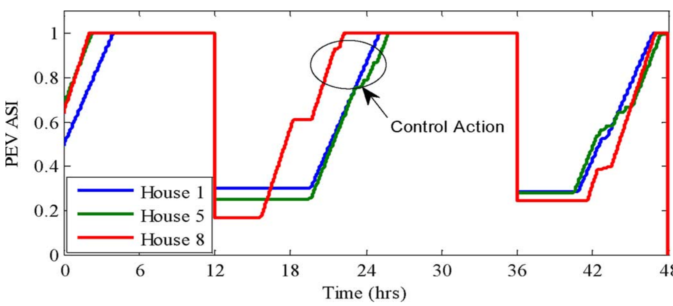

Fig. 11. ASI of 3 selected PEVs in phase- A of feeder 1.

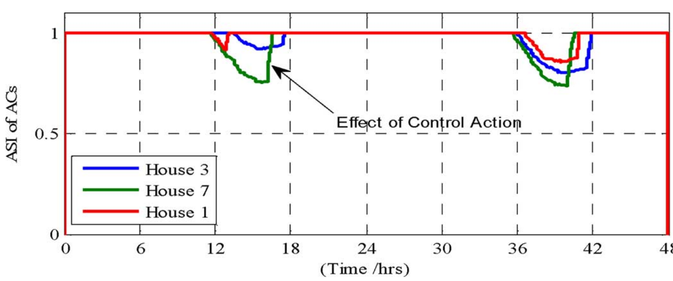

Fig. 12. ASI of Inverter type Air Conditioners in phase- A of feeder 1.

few critical controllable loads. Fig. 11 shows the waveform of the charging states, reflected by ASI, of three selected PEVs in the network. It shows that the PEVs are being charged after arriving home (hour 18) and it achieves 100% charging by midnight. Small flat line segments in the graph shows that the PEVs are disconnected due to the control action and then reconnected after 4 minutes.

Inverter-based ACs and water heaters are large adjustable loads where the set points of room temperature and the water tank temperature can be adjusted during the control action. ASI values of three selected ACs are shown in Fig. 12. The controller increases the temperature by 1°C during each control action and is re-adjusted (if required) after 15 minutes. The sudden variation of the temperature set point of a selected inverter type AC in phase-A during the control action is shown in Fig. 13. Considerable satisfaction, in terms of ASI for AC loads, is achieved. ASI of water heater and the tank temperature set point variation are shown in Figs. 14 and 15, respectively. Similar behavior is observed for all controllable loads in the network which confirms that the control scheme does not affect ASI adversely.

C. Effectiveness of the Proposed Scheme on Network Overloading due to Load Growth in Forthcoming Years

An annual peak demand growth of 4.36% [34] is assumed and CR scheme is tested on the 500 kVA network. The system loading level and ASI of appliances are observed for the next 15

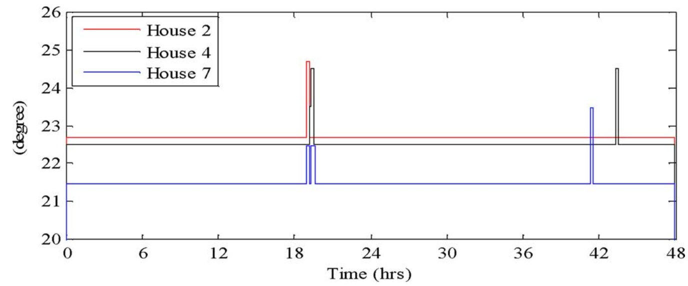

Fig. 13. Temperature Set point variation of inverter type AC in house 2, 4 and 7 of phase- A of feeder1.

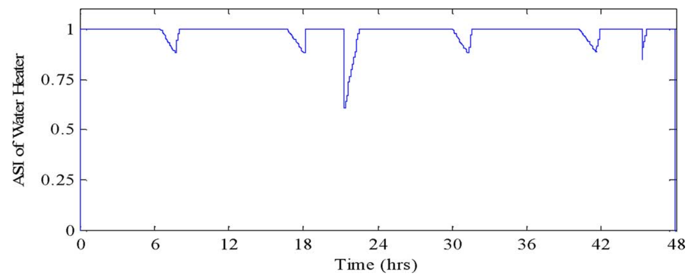

Fig. 14. ASI of a selected water heater.

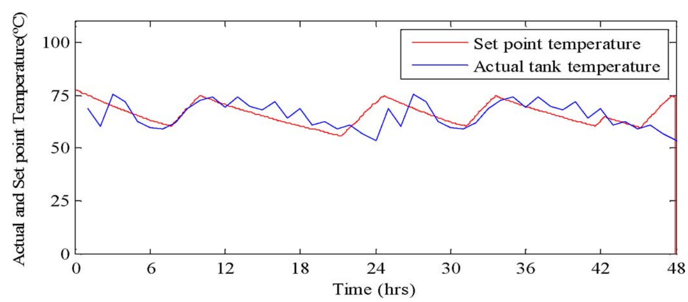

Fig. 15. Set point and actual tank temperature variation of a water heater in House 7 of Phase- A of feeder 1.

years. Simulation results can be summarized using Fig. 16. ASI of two selected appliances drops below the acceptable limit of 0.9, when the increase in peak demand reaches 299 kVA. Later, the system overloads and then diverges when peak power increase beyond 300 kVA. Therefore, the proposed demand response scheme can effectively shave the network peak for almost eleven years ($500 \times 1.0436^{11} \approx 500 + 299$), before the transformer needs to be upgraded. The proposed control scheme allows a peak increase of 299 kVA, without worsening ASI and protecting the network from overload and voltage violations.

V. CONCLUSIONS

Demand response for a residential distribution system using a Customer Reward (CR) scheme is proposed in this paper. CR deploys two-level hierarchical control schemes consisting of the primary controller (smart meters) to regulate the feeder voltage within an acceptable range and the secondary controller to prevent transformer overload. Various indices reflecting a customer's flexibility and satisfaction for controllable loads are modeled to obtain decision matrix for load adjustment. Customer engagement is encouraged through the reward mechanism. The impact of CR on network voltages, customer satisfaction indices, and appliance usage patterns are investigated. Customers are rewarded based on their participation for load

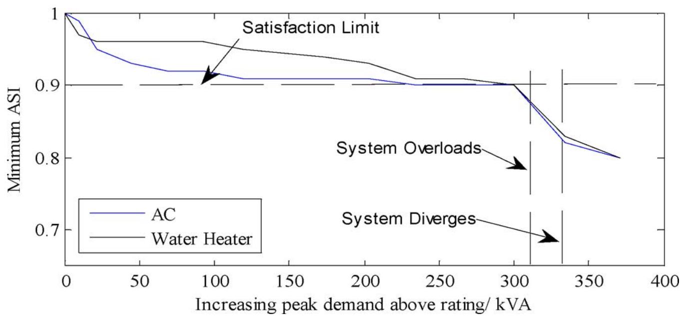

Fig. 16. Appliance Satisfaction Index vs increased peak demand.

shifting and associated voltage improvement in the feeder. The proposed demand response via CR scheme can effectively shave the network peak for several years, before the feeder transformer needs to be upgraded.

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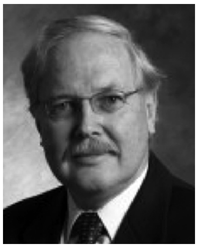

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