# Grid Integration of Electric Vehicles and Demand Response With Customer Choice

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***Abstract*—As electric vehicles (EVs) take a greater share in the personal automobile market, their penetration may bring higher peak demand at the distribution level. This may cause potential transformer overloads, feeder congestions, and undue circuit faults. This paper focuses on the impact of charging EVs on a residential distribution circuit. Different EV penetration levels, EV types, and charging profiles are considered. In order to minimize the impact of charging EVs on a distribution circuit, a demand response strategy is proposed in the context of a smart distribution network. In the proposed DR strategy, consumers will have their own choices to determine which load to control and when. Consumer comfort indices are introduced to measure the impact of demand response on consumers' lifestyle. The proposed indices can provide electric utilities a better estimation of the customer acceptance of a DR program, and the capability of a distribution circuit to accommodate EV penetration.**

***Index Terms*—Customer choice, demand response (DR), distribution circuit, electric vehicle (EV), home area network (HAN).**

## I. Introduction

SEVERAL automobile manufactures are introducing electric vehicles (EV) to the mass market. While the widespread adoption of EVs brings potential social and economic benefits, the impact of EVs on electric power systems cannot be overlooked. Analysis needs to be carried out at the distribution level to evaluate the potential impact of the additional EV load [1].

Majority of previous work regarding the impact of EV penetration on electric power systems focuses at the transmission level [2]–[4]. The Oak Ridge National Laboratory (ORNL) [5] performed a thorough analysis of EV penetration into the regional power grid, and reported that all regions would need additional generation to serve the extra EV demand. However, in a large system where many EV fleets are present, the problem may not be visible unless everyone charges their EVs at the same time. Recent research started to turn to the distribution level. This is because the EV penetration shows more severe problems in a smaller area due to a possible cluster effect [6]. The authors in [1] provided an analytical framework to evaluate the impact of plug-in hybrid electric vehicle (PHEV) loading on a distribution system and [7] used stochastic methods to study the possible impacts of charging EVs on distribution network components. The authors in [8] considered case studies with different EV penetration levels and charging patterns and estimated the maximum number of EVs that a distribution network can accommodate based on an N-1 contingency condition. The authors in [9] and [10] focused on the distribution system losses due to EV charging. In [9] an optimal EV fleet charging profile is proposed for minimizing the distribution system power losses. For even smaller sized networks, authors in [11] and [12] emphasized on the integration of EVs at the distribution transformer level serving a few houses and proposed household load control strategies to tackle the transformer overloading problem.

While the literature review suggests that the analysis of EV penetration into the distribution network is quite extensive, there is still a need to take into consideration the vehicle driving patterns. A more important contribution could be to develop a demand response strategy that will accommodate EV fleets and make the EV penetration invisible to the system. That is to maintain the original peak demand level experienced without EVs.

Over the last several decades electric utilities around the world have deployed various types of demand response (DR) programs to reduce their peak loads during stressed conditions [13]. With advanced sensing and control technologies, the development of demand response programs can be more creative and flexible with many more possible options [14]–[17]. The authors in [18] provided an overview of DR strategies in commercial buildings. A scoping study was provided in [19] that summarized and evaluated the existing methods for residential demand response. While demand response applications in industrial and commercial sectors have been well studied in [17] and [20]–[22], the residential demand response strategy taking into account the consumer comfort still needs an in-depth study. At the same time, there is the lack of indices to measure the impacts of demand response on consumer convenience.

This paper proposes a demand response (DR) strategy for use to manage the load in a residential distribution circuit. This is in order to accommodate EV charging while keeping the peak demand unchanged. The consumers will have the freedom to choose what kind of household loads to be controlled, and when. Consumer comfort indices are proposed to measure the impact of DR on residential consumers. This proposed DR approach can be customized to perform demand response in various segments and sizes of the network.

According to Federal Energy Regulatory Commission (FERC) staff report [23], demand response programs can be categorized into incentive-based and time (price)-based. The report shows that the potential peak demand reduction mostly comes from the incentive-based DR programs. Therefore this paper focuses on the technical aspects of incentive-based DR

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strategy design that takes into account customers' preferences, comfort levels, and load priorities.

## II. Modeling of Circuit Load and EV Charge Profiles

In this section, the load profiles of a distribution circuit and an EV charge profile are modeled for the purpose of this study. The load profiles of the distribution circuit are classified by load types. The EV charge profile is created based on the driving pattern, home arrival times, and EV types using a stochastic method.

### A. Modeling of the Distribution Circuit Load

In this paper, a distribution circuit is chosen for the study and previously developed load models in [24] are used in the simulations. Hourly load curves of an average household are available from the RELOAD database [25], which is used by the Electricity Module of the National Energy Modeling System (NEMS) [26]. Based on the RELOAD database, residential loads are classified by the following nine types: space cooling, space heating, water heating, cloth drying, cooking refrigeration, freezer, lighting, others.

For the purpose of this study, all residential loads are classified into two categories: controllable and critical. Controllable loads are defined as the loads that can be controlled without noticeable impacts on consumer's life style. The critical category contains loads that are either very important (critical loads) or loads that cannot be controlled. For residential houses, space cooling/heating, water heater, and clothes dryer loads are controllable; all other loads are considered either critical or noncontrollable.

In the previous study by the authors [27], physical-based load models are developed for all types of controllable loads. The model takes into consideration the consumer ownership rate [28], which can be found in [29]. Data from the RELOAD database are used to construct the critical load profiles.

### B. Modeling of EV Fleet Charge

To create an EV fleet charge profile, it is critical to get the information on how long and how far the vehicles are driven, and where and how long they are parked. According to the 2001 National Household Travel Survey [30], vehicles are parked for more than 90% of the time. As this paper is looking at a residential distribution circuit, it is reasonable to assume that EV owners leave for work and return home at different times, which impacts the charging profile. The authors in [31] analyze survey data on the vehicle coming home time (plug-in time for EVs). The finding indicates that the EV plug-in time is close to a normal distribution curve. For this reason, this paper uses a normal probability distribution function to describe the EV fleet plug-in time.

EV driving patterns are used to determine the state of charge in the EV. Fig. 1 shows the American daily driving distance distribution [30]. This study uses the Monte Carlo method to simulate the daily driving distances for each EV in the distribution circuit based on the data in [30].

In addition to the driving patterns, battery usable capacities and the charging power requirements (kW) are also used to build the EV fleet charge profile. Table I shows the basic battery charge data of three popular EVs in the U.S. market.

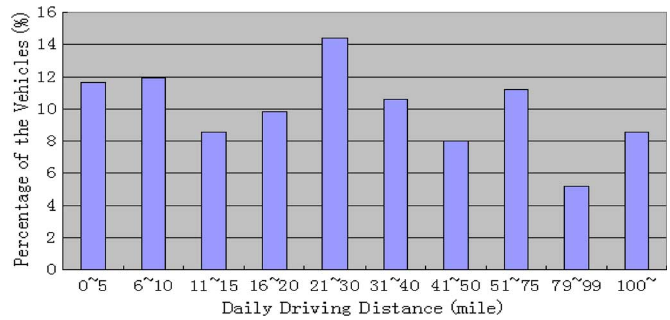


Fig. 1. American daily driving distance distribution [30].

TABLE I
EVs in the U.S. Market [32]–[36]

| Make & Model | Battery Size | Energy Available | All Electric Range | Charge Power |
|---|---|---|---|---|
| **GM Chevy Volt** | 16kWh | 8kWh | 40 mi | 1.9kW<br>3.3kW* |
| **Nissan LEAF** | 24kWh | 19.2kWh | 100 mi<br>(LA4 mode) | 1.8kW<br>3.3kW*<br>49kW (fast) |
| **Tesla Roadster** | 53kWh | 37.1kWh | 244 mi<br>(Experiment) | 1.8kW<br>9.6kW*<br>16.8kW |

* Recommended charging rate

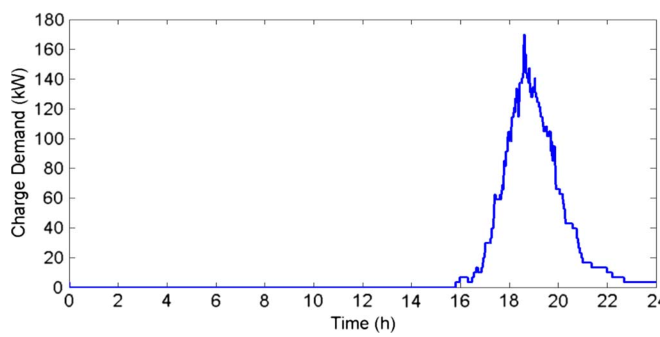


Fig. 2. EV Fleet charging profile.

Fig. 2 shows an example charging profile of a group of 100 EVs with the mix of 40% Chevy Volt, 40% Nissan LEAF, and 20% Tesla Roadster. Each type of EV has different charging rates according to Table I. The recommended charging power rates (*) are used to generate the simulation results presented in Fig. 2. The EVs are assumed to come back home and plugged in at different time according to a normal probability distribution function with the mean at 18:00 and the variance of 1 h.

Note that EVs can be charged anywhere with charging stations installed. As our focus is to deal with excessive load during peak hours for a residential distribution circuit, evening hours are of interest. Therefore we only consider the time period that is likely to be impacted by EV charging at home in the evening.

## III. Demand Response Strategy Design

The proposed demand response strategy is designed in two layers: the neighborhood area network (NAN) and the home area network (HAN). DR is designed to accommodate EV fleets plugged into a distribution circuit while ensuring that the original peak demand can be maintained with different EV penetration levels.

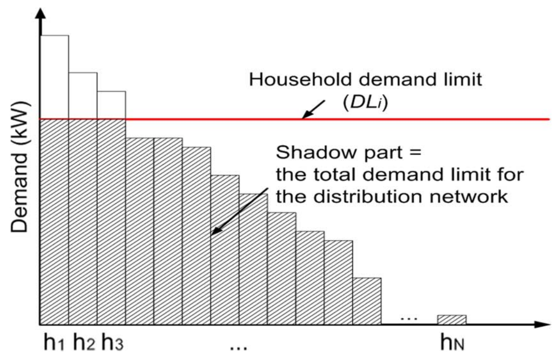


Fig. 3. Sketch of sorted consumption queue and demand limit for each house.

### A. Demand Limit Allocation for Each House at NAN

To make the EV penetration transparent when EVs are added to a distribution network, the original load peak (before EV penetration) should be set as the demand limit for the whole circuit. Once the circuit-level demand limit is set, the demand limit for each house is determined according to the methodology presented below. Then, each house is assigned its demand limit to make sure the aggregated circuit demand stays within the circuit-level demand limit.

Fig. 3 shows the methodology to determine the demand limit amount allocated to each household in the distribution circuit of interest. This methodology can be described as follows: Firstly, the NAN control center sorts all reported demand (kW) within a distribution circuit. Then, the household demand limit ($\mathrm{DL}_i$, red line) is set at the point where the summation of all household demand to be served (shadow area) is equal to or less than the peak load without EVs. As demonstrated in Fig. 3, the demand limit will only be applied to the houses that have their electricity consumption exceed the household demand limit. The houses with lower consumption than this limit will not be affected.

$\mathrm{DL}_i$ can be determined by solving the optimization problem as shown in (1).

$$\begin{aligned} &\max(\mathrm{DL}_i)\\ &\text{Subject to}:\\ &\sum_{m=1}^{N} D_{m,i} \le \mathrm{DL}_{\mathrm{total},i}\\ &D_{m,i} = \begin{cases} L_{m,i}, & L_{m,i} < \mathrm{DL}_i \\ \mathrm{DL}_i, & L_{m,i} \ge \mathrm{DL}_i \end{cases} \quad m = 1, 2, \ldots, N \end{aligned} \tag{1}$$

where:

| | |
|---|---|
| $\mathrm{DL}_i$ | household demand limit (kW) assigned to all houses in time slot $i$; |
| $D_{m,i}$ | demand of the $m^{\text{th}}$ house after DR (kW) in time slot $i$; |
| $\mathrm{DL}_{\mathrm{total},i}$ | available supply (kW) of the distribution circuit of interest in time slot $i$; |
| $L_{m,i}$ | original demand of the $m^{\text{th}}$ house (kW) in time slot $i$. |

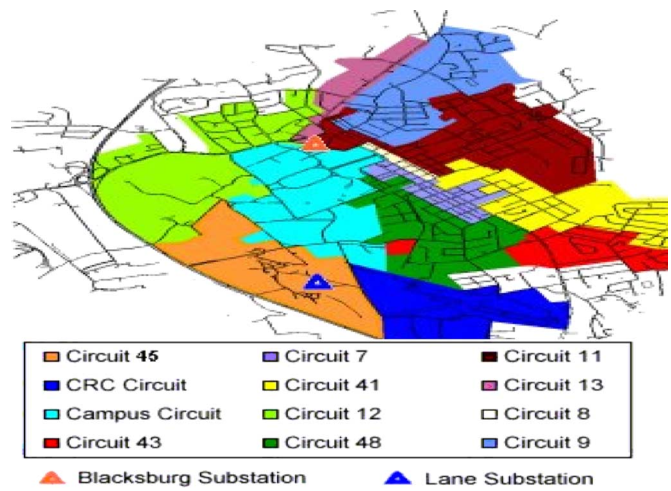


Fig. 4. Virginia Tech Electric Service (VTES) for case study [39].

### B. Demand Response Strategy in HAN

Household loads are divided into two categories according to Section II: critical and controllable. The critical loads will not be controlled only report their status. The controllable loads will be controlled by the HAN control center according to the assigned demand limit. The DR strategy for a residential house is that when there is a demand limit, HAN the control center will check if the household demand in the next time interval will be over the assigned limit. If yes, the control center will deny demand requests from some noncritical smart appliances according to customer pre set preferences [37].

If the HAN control center sees the total household demand to exceed the demand limit, demand response actions will take place. The demand response in the HAN is performed as follows:

Step 1) Customers set the load priority for each appliance. For example, water heater may be of the highest priority, heating, ventilation, and air conditioning (HVAC) may be of the second, and clothes dryer may be of the lowest priority.

Step 2) Customers perform preference settings for each appliance. For example, clothes drying job may have to be finished by midnight, room temperature should not be higher than 81 °F.
The proposed DR strategy allows customers to change or reschedule their load priority and preference settings at different times of the day.

Step 3) Perform demand response based on the preset load priority and preferences. When the HAN control center sees the preferences are being violated, the corresponding loads' priorities will be temporarily raised to the highest possible level.
- For HVACs, the DR strategy is:
  - — Change the temperature set point once the demand limit signal is received and the HVAC is not of high priority.
  - — Set back the default temperature set point when the room temperature exceeds the preset comfort range.
- For water heaters, the DR strategy is:

— Turn the water heater OFF once the demand limit signal is received and the water heater load is not of high priority.
— Force the unit ON when the hot water temperature falls below the preset comfort range.
- For clothes dryers:
— Turn OFF the heating coil in the clothes dryer once the demand limit signal is received and the clothes drying load is not of high priority.
— Force the unit ON when the HAN control center foresees that a) the clothes drying job will not finish within the preset duration; b) the heating coil's off time reaches the maximum limit. Note that the motor load will keep on running
- For electric vehicles:
— Stop charging the EV once the demand limit signal is received and the EV is not of high priority.
— Resume charging when the HAN control center foresees that the EV charging cannot be finished within the preset time duration.

The smart appliances will have two-way communication with the HAN control center. Each smart appliance has an IC built in to report the status and to receive the control signal. Recently, some home electronic companies such as General Electric have already started to produce smart appliances with IP based remote control signal receiver [38].

## IV. Consumer Comfort Level Indices

To evaluate the DR impacts on consumer daily life, comfort indices are needed to measure consumer comfort levels. The consumer convenience indices are defined based on the severity, scale, and duration of convenience violations for each controllable appliance.

### A. Severity Indices

The severity indices are used to measure how severely the consumer comfort levels are violated. The indices are based on the maximum percentage deviation from the original settings.

*1) Severity Indices for HVACs:* For HVACs, the severity index $I_{se,\mathrm{HVAC}}$ is defined as the largest room temperature deviation in percentage taking into account all homes in a distribution circuit. $T_{i,\mathrm{HVAC}}$ is the actual room temperature while $T_{s,\mathrm{HVAC}}$ is the room temperature setting.

$$I_{se,\mathrm{HVAC}} = \max\left(\left|\frac{T_{i,\mathrm{HVAC}} - T_{s,\mathrm{HVAC}}}{T_{s,\mathrm{HVAC}}}\right| \times 100\%\right) \quad (2)$$

*2) Severity Indices for Water Heaters:* For water heaters, the severity index $I_{se,\mathrm{WH}}$ is defined as the largest hot water temperature deviation in percentage taking into account all homes in a distribution circuit. $T_{i,\mathrm{WH}}$ is the actual outlet hot water temperature while $T_{s,\mathrm{WH}}$ is the hot water temperature setting.

$$I_{se,\mathrm{WH}} = \max\left(\left|\frac{T_{i,\mathrm{WH}} - T_{s,\mathrm{WH}}}{T_{s,\mathrm{WH}}}\right| \times 100\%\right) \quad (3)$$

*3) Severity Indices for Clothes Dryers:* For clothes dryers, the severity index $I_{se,\mathrm{CD}}$ is defined as the longest clothes drying time delay in percentage taking into account all homes in a distribution circuit. $t_{i,\mathrm{CD}}$ is the actual clothes drying time while $t_{s,\mathrm{CD}}$ is the original setting for the clothes drying time.

$$I_{se,\mathrm{CD}} = \max\left(\frac{t_{i,\mathrm{CD}} - t_{s,\mathrm{CD}}}{t_{s,\mathrm{CD}}} \times 100\%\right) \quad (4)$$

*4) Severity Indices for Electric Vehicles:* For electric vehicles, the severity index $I_{se,\mathrm{EV}}$ is defined as the longest EV charging time delay in percentage taking into account all homes distribution circuit. $t_{i,\mathrm{EV}}$ is the actual EV charging time while $t_{s,\mathrm{EV}}$ is the original EV charging time without DR.

$$I_{se,\mathrm{EV}} = \max\left(\frac{t_{i,\mathrm{EV}} - t_{s,\mathrm{EV}}}{t_{s,\mathrm{EV}}} \times 100\%\right) \quad (5)$$

*5) Severity Indices for Electric Vehicles:* For EV charging at home, the delay is usually not a problem unless the user needs the EV in the evening, for which they will set a higher priority for the EV. In that case, EV charging will be guaranteed. Therefore the severity indices are not applicable to EVs.

TABLE II
Distribution Circuit Peak Demand at Different EV Penetration Levels

| | Original peak loads | New peak loads | |
|---|---|---|---|
| | | w/ 50 EVs | w/ 100 EVs |
| **Summer** | 1.60MW | 1.66MW | 1.75MW |
| **Winter** | 2.60MW | 2.67MW | 2.80MW |

### B. Scale Indices

The scale indices are used to measure the number consumers whose comfort levels are violated as a percentage of a total household in the distribution circuit of interest.

*1) Scale Indices for HVACs:* For HVACs, the scale index $I_{sc,\mathrm{HVAC}}$ is defined as the maximum ratio, considering all time slots in the study period, of number of homes with room temperatures out of the comfort ranges in each time slot to the total number of homes with HVAC in a distribution circuit. See (6), where $n_{\mathrm{HVAC}}$ is the number of homes with the room temperatures out of preset comfort ranges in each time slot. $N$ is the total number of consumers in a distribution circuit and $\mathrm{OR}_{\mathrm{AC}}$ is the ownership rate of HVACs.

$$I_{sc,\mathrm{HVAC}} = \max\left(\frac{n_{\mathrm{HVAC}}}{N \times \mathrm{OR}_{\mathrm{AC}}} \times 100\%\right) \quad (6)$$

*2) Scale Indices for Water Heaters:* For water heaters, the scale index $I_{sc,\mathrm{WH}}$ is defined as the maximum ratio, considering all time slots in the study period, of the number of homes with hot water temperatures out of the comfort ranges in each time slot to the total number of homes in a distribution circuit. See (7), where $n_{\mathrm{WH}}$ is the number of homes with the hot water temperature out of preset comfort ranges in each time slot. $N$ is the total number of consumers in a distribution circuit and $\mathrm{OR}_{\mathrm{WH}}$ is the ownership rate of water heaters.

$$I_{sc,\mathrm{WH}} = \max\left(\frac{n_{\mathrm{WH}}}{N \times \mathrm{OR}_{\mathrm{WH}}} \times 100\%\right) \quad (7)$$

*3) Scale Indices for Clothes Dryers:* For clothes dryers, the scale index $I_{sc,\mathrm{CD}}$ is defined as the ratio of the number of homes with clothes drying job delayed to the total number of homes with electric clothes dryers in a distribution circuit. See (8), where $n_{\mathrm{CD}}$ is the number of homes with clothes drying job delayed charge delayed longer than a preset comfort level. $N$ is the total number of consumers in a distribution circuit and $\mathrm{OR}_{\mathrm{CD}}$ is the ownership rate of clothes dryers.

$$I_{sc,\mathrm{CD}} = \frac{n_{\mathrm{CD}}}{N \times \mathrm{OR}_{\mathrm{CD}}} \times 100\% \quad (8)$$

*4) Scale Indices for Electric Vehicles:* For EVs, the scale index $I_{sc,\mathrm{EV}}$ is defined as the ratio of the number of homes with EV charging delayed to the total number of homes with EVs in a distribution circuit. See (9) where $n_{\mathrm{EV}}$ is the number of homes with EV charge delayed longer than a preset comfort level. $N$ is the total number of consumers in a distribution circuit and $\mathrm{OR}_{\mathrm{EV}}$ is the ownership rate of electric vehicles.

$$I_{sc,\mathrm{EV}} = \frac{n_{\mathrm{EV}}}{N \times \mathrm{OR}_{\mathrm{EV}}} \times 100\% \quad (9)$$

### C. Duration Indices

The duration indices are to describe the length of the inconvenient period for HVAC and water heater. (As the severity indices for clothes dryer and EV are already measured by duration, this type of indices is not applicable to them.)

*1) Duration Indices for HVACs:* For HVACs, the duration index $I_{d,\mathrm{HVAC}}$ is defined as the longest duration of room temperature violating the pre set comfort level. $t_{\mathrm{HVAC}}$ is the duration that the room temperature is out of the comfort range, in minutes.

$$I_{d,\mathrm{HVAC}} = \max(t_{\mathrm{HVAC}}) \quad (10)$$

*2) Duration Indices for Water Heaters:* For water heaters, the duration index $I_{d,\mathrm{WH}}$ is defined as the longest duration of hot water temperature violating the pre set comfort level. $t_{\mathrm{WH}}$ is the duration that the hot water temperature is out of the comfort range, in minutes.

$$I_{d,\mathrm{WH}} = \max(t_{\mathrm{WH}}) \quad (11)$$

## V. Case Study

To study the impact of the multilayer demand response strategy on load shape, a distribution circuit in the Virginia Tech Electric Service (VTES) area in Blacksburg, VA, is taken as a case study.

### A. Cast Study Description

A distribution circuit noted as Circuit 9 in the VTES service area, is chosen as the case study platform as shown in Fig. 6. There are 34 laterals with 117 transformers serving 780 customers. As most consumers served by this circuit are residential, the circuit is considered to be a residential distribution circuit.

Different EV penetration levels and EV types are taken into consideration and the consumer comfort indices are calculated. As an average number of vehicles per household is 1.9 [40], the estimated total number of vehicles for 780 homes considered in this case study is 1482. The case studies consider two EV penetration levels, 50 EVs and 100 EVs, representing 3.3% and 6.6% EV market share respectively.

In this study, it is assumed that the EV fleet is made up of 40% Chevy Volt, 40% Nissan LEAF, and 20% Tesla Roadster. This assumption is the same as the example charge profile shown in Section II. All EVs will charge at the recommended rate as indicated in Table I, i.e., Chevy Volt at 3.3 kW, Nissan LEAF at 3.3 kW, and Tesla Roadster at 9.6 kW. The driving distance and plug-in time are diversified using the Mont Carlo simulation method and normal probability distribution function, respectively.

### B. Demand Response Results

*1) Circuit Load Curves w/ and w/o Demand Response:* For this circuit, the load models developed in [24] are used to create the distribution circuit load profiles using a bottom-up approach. The results were validated with the actual circuit load profiles. The original load profile without EV and DR has the summer peak demand of 1.60 MW and the winter peak demand of 2.60 MW. This study sets the demand limit at 1.6 MW for summer and 2.6 MW for winter to perform demand response, which will make the EV penetration transparent. The simulations already take into account different consumers' priority and preference settings at different times of the day in different seasons.

Table II shows the original and new peak loads with two different EV penetration levels.

Figs. 5 and 6 show the 24-h summer and winter load profiles respectively with and without DR at EV penetration levels of (a) 50 EVs and (b) 100 EVs.

*2) Consumer Comfort Indices:* The consumer comfort zone for difference appliances is described in Table III. These numbers are based on typical consumer preference. The comfort zone may vary by areas and can be redefined according to any available concrete survey data. The simulation results of the indices are calculated and presented in Tables IV and V for summer and winter, respectively. The indices are to measure the impacts of DR on the consumer's convenience.

Fig. 7 shows the 24-h summer and winter load profiles of four load types (HVAC, water heater, clothes dryer, and EV) after the implementation of the proposed demand response strategy. As shown in Fig. 7 is the case of 100 EV penetration.

It can be seen from the simulations results that some controls are performed to all controllable load types. The controls are mainly to defer the appliance usage from about 18:00 to later. This demand deferral will maintain the distribution circuit peak load at the same level as the original peak.

The resulting consumer comfort indices as shown in Tables IV and V indicate a trend whereby the impact of DR on consumer comfort levels increase with the higher EV penetration levels. According to the indices description in Section IV, the severity indices show situation of the house experiencing the most severe impact in the whole distribution circuit, the scale indices show the percentage of houses that get out of the comfort range due to performing DR and the duration indices shows the longest DR impact duration in the network. The

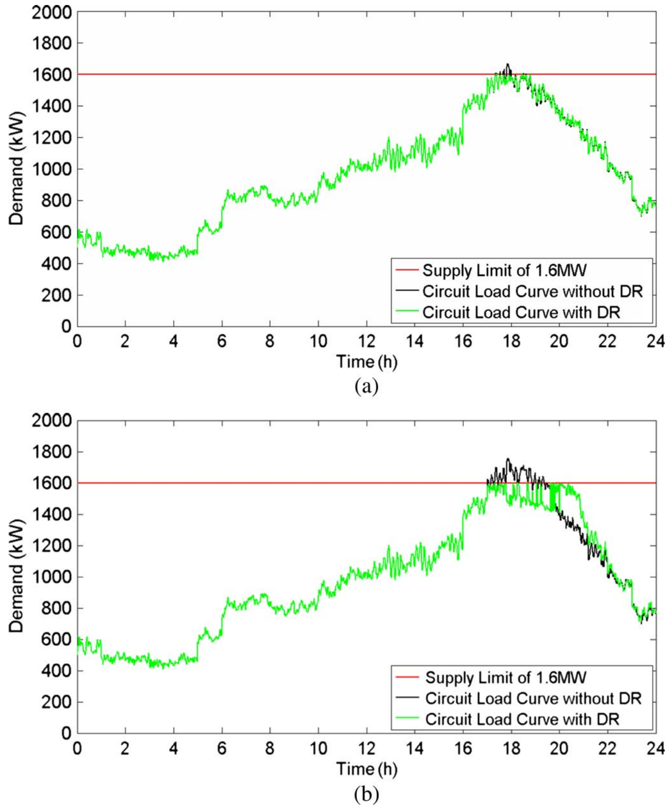


Fig. 5. Summer load profiles w/ and w/o DR at different EV penetration levels. (a) Summer load profiles with penetration of 50 EVs. (b) Summer load profiles with penetration of 100 EVs.

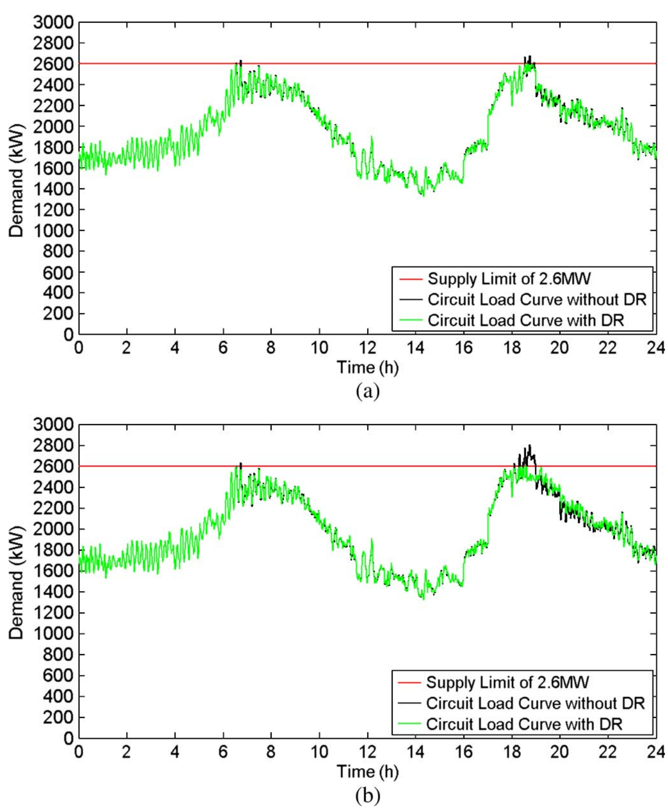


Fig. 6. Winter load profiles w/ and w/o DR at different EV penetration levels. (a) Winter load profiles with penetration of 50 EVs. (b) Winter load profiles with penetration of 100 EVs.

TABLE III
CONSUMER COMFORT ZONES FOR DIFFERENT APPLIANCES

| | HVAC | WH* | CD* | EV |
|---|---|---|---|---|
| **Comfort Zone** | ⩽±2F° difference from setting | ⩽±10F° difference from setting | ⩽30 minutes within the original charging time | ⩽30 minutes within the original charging time |

WH* represents water heater
CD* represents clothes dryer

TABLE IV
CONSUMER COMFORT INDICES RESULTS—SUMMER

| | | HVAC | WH* | CD* | EV |
|---|---|---|---|---|---|
| **50 EVs** | **Severity** | 2.75% | 15.66% | 2.17% | 7.69% |
| | **Scale** | 0% | 5.89% | 0% | 0% |
| | **Duration** | 0 min | 22 min | - | - |
| **100 EVs** | **Severity** | 4.83% | 15.66% | 2.54% | 6.67% |
| | **Scale** | 0.59% | 6.68% | 0% | 0% |
| | **Duration** | 3 min | 22 min | - | - |

WH* represents water heater
CD* represents clothes dryer

three indices are calculated to show the utilities the likelihood of receiving complains on DR programs.

## VI. CONCLUSIONS

The share of electric vehicles is expected to grow in the U.S. personal automotive market. A larger level of EV penetration into electric power systems may result in increased stress conditions in distribution circuits. This paper models EV fleet charge profiles based on driving distances and battery sizes using a Monte Carlo method. Three popular types of EVs are taken into consideration. The simulation shows that while the EV fleet charging increases the sale of the electric energy, the uncontrolled charge profile will inevitably increase the peak demand of a distribution circuit.

This paper proposes a DR strategy to help the distribution circuit to accommodate EV penetration. The proposed DR strategy can provide the utility with unchanged peak demand to avoid distribution circuit upgrade, while being able to accommodate EV charging. The proposed DR strategy is also an energy management tool within a home area network (HAN) that allows customers to control their own loads based on consumers' preference and comfort levels. Since the utility only sends the demand limit to each house and will leave all the household control decision to the consumer, the proposed DR strategy will respect the consumer's own choices and protect their privacy. A distribution circuit in Blacksburg, VA is selected for the simulation study. The control results show that the proposed DR strategy can fulfill the task of maintaining the original peak demand with different EV penetration levels.

Furthermore, consumer comfort indices are defined and calculated to provide a better understanding of the DR impact on the consumer's comfort level. It should be noticed that maintaining the same distribution circuit-level peak load with higher

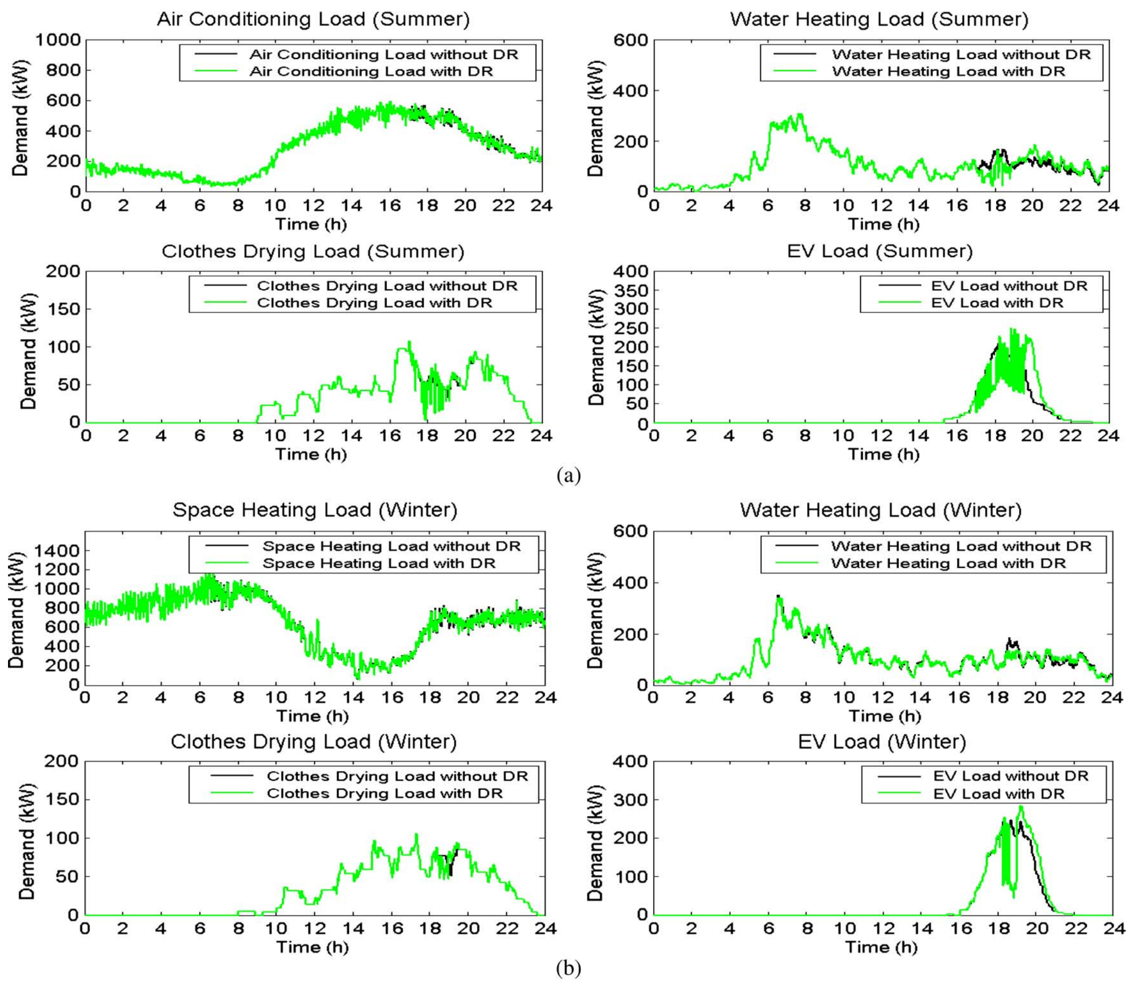


Fig. 7. 24-h summer and winter load profiles by appliance types with and without DR at the 100-EV penetration level. (a) 24-h summer load profiles by appliance types with and without DR; (b) 24-h winter load profiles by appliance types with and without DR.

TABLE V
CONSUMER COMFORT INDICES RESULTS—WINTER

| | | HVAC | WH* | CD* | EV |
|---|---|---|---|---|---|
| **50 EVs** | **Severity** | 2.59% | 14.11% | 2.22% | 5.56% |
| | **Scale** | 0% | 6.92% | 0% | 0% |
| | **Duration** | 0 min | 15 min | - | - |
| **100 EVs** | **Severity** | 7.44% | 14.11% | 2.17% | 7.69% |
| | **Scale** | 4.91% | 7.13% | 0% | 0% |
| | **Duration** | 11 min | 15 min | - | - |

WH* represents water heater
CD* represents clothes dryer

EV penetration levels may negatively impact the consumer's convenience, resulting in more complaints. Therefore, utilities can use the proposed indices to estimate the capability of demand response programs to accommodate EV fleet into a certain distribution circuit.

As the number of EVs increases, it will be more difficult to keep the household load under a given demand limit and not violating the consumer's comfort level. At that point, utilities may not be able to rely solely on demand response to shave the peak demand. When all demand resources are exploited, utilities can explore other means such as using distributed generation or equipment upgrade to address high EV penetration scenarios.

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