Development of Physical-Based Demand Response-Enabled Residential Load Models

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Abstract—In order to support the growing interest in demand response (DR) modeling and analysis, there is a need for physical-based residential load models. The objective of this paper is to present the development of such load models at the appliance level. These include conventional controllable loads, i.e., space cooling/space heating, water heater, clothes dryer and electric vehicle. Validation of the appliance-level load models is carried out by comparing the models’ output with the real electricity consumption data for the associated appliances. The appliance-level load models are aggregated to generate load profiles for a distribution circuit, which are validated against the load profiles of an actual distribution circuit. The DR-sensitive load models can be used to study changes in electricity consumption both at the household and the distribution circuit levels, given a set of customer behaviors and/or signals from a utility.

Index Terms—Appliance-level load model, demand response (DR) and distribution circuit, electric vehicle, physical-based.

I. INTRODUCTION

THERE has been a lot of interest in load modeling in the past several decades. Scale of load models can vary, ranging from the appliance level to the power grid level. In 1995, IEEE provided a load model bibliography for power flow and dynamic performance simulation. This bibliography covered almost all relevant load modeling work in late 20th century [1]. The classic load models defined load as a function of voltage and frequency, which are referred to as “static” load models. The “dynamic” load models were developed for transient studies. To better guide the load modeling work, authors in [2] provides the basic definitions and concepts. Obviously, different simulations need different load model representations.

In order to study demand management, published work has focused on physical-based load models, especially on heating, ventilation, and air conditioning (HVAC) loads and water heating loads [3]–[7]. Physical-based load models for residential HVAC were developed in [8], [9] and tested against utility data. The models captured thermodynamic principles of building structures and the diversification was created by random distribution functions when building the distribution circuit load profile. These load models have been mostly used for direct load control (DLC) studies [10]–[12]. Other than a physical-based methodology, load models were developed based on consumer’s behavior [13]. Load models built from statistical survey data and historical measurements were presented in [14]–[16] with proper random functions designed for aggregation diversity.

With the development of the smart grid, there is a need for load models that can facilitate the study of changes in electricity consumption in response to customer behavior and/or signals from a utility. Such load models are useful to evaluate the impact of demand response (DR) at a distribution circuit level. For the load models to represent DR activities, the following characteristics are required, which have not all been all addressed in the published literature:

• Comprehensive—the models should cover all major types of controllable loads so that DR can be simulated considering consumer choices instead of simple load curtailment.
• Physically based—the models should be built according to the physical and operational characteristics of the appliances to reflect the real-world situation.
• Interactive—the models should allow interfaces for external signals to simulate the DR control actions.
• Reasonably aggregated—the algorithm should provide reasonable load diversification and aggregation to represent the distribution circuit load profile.

This paper proposes a set of DR-enabled load models at the appliance level, including space cooling/heating, water heating, clothes drying and electric vehicle loads, for a residential distribution circuit (“Comprehensive”). The models are designed based on their physical characteristics (“physical-based”) and can be controlled externally (“interactive”) to reflect any desired DR strategies. At the same time, these models are aggregated using a stochastic method to create load profiles of a distribution circuit (“reasonably aggregated”). The resulting load profiles are validated against the utility measurement data in both summer and winter to show representativeness of the proposed load model. In addition, the developed load models are easy to use as the models’ parameters are easily adjustable to fit different network sizes present in different locations.

II. LOAD CATEGORIZATION

Hourly load curves of an average household by load type are available from the RELOAD database [17], which is used by the Electricity Module of the National Energy Modeling System (NEMS) [18]. The load data are available for twelve months (January to December), and three day types (typical weekday, typical weekend and typical peak day). Based on the RELOAD database, residential loads are classified by the following load types: space cooling/heating, water heating, cloth drying, cooking, refrigeration, freezer, lighting and others. For the purpose of this study, these load types are classified into two categories: controllable and critical. Controllable loads
III. DR-ENABLED SPACE COOLING/HEATING LOAD MODEL

This section presents the development of a DR-enabled space cooling/heating load model, together with its validation and aggregation to create the load profile at a distribution circuit level.

A. Model Development for the Space Cooling/Heating Load

Fig. 1 illustrates the block diagram of the DR-enabled space cooling/space heating load model.

Inputs to the model are the DR control signal \( C_{AC,i} \), time series outdoor temperature data \( T_{out,i} \), thermostat set point \( T_s \), and time series room temperature data \( T_i \). The model outputs are the time series electric power consumption \( p_{AC,i} \) in kilowatts of the space cooling/space heating unit, and the room temperature \( T_{i+1} \) at the next time step. The room temperature output is used as an input to the load model at the next time step. The model needs additional house parameters, including house structures, number of people dwelling and the electrical characteristics of the space cooling/space heating unit.

1) Calculation of the Electric Power Demand \( p_{AC,i} \):

A central space cooling/space heating unit with a thermostat works in an “on-off” mode and will simply run at its rated power when turned on. In general, the thermostat control is set such that the room temperature \( T_i \) will fluctuate around the thermostat set point \( T_s \) within the dead band of \( \Delta T \). For each time step \( i \), the demand for electricity of the space cooling/space heating unit \( p_{AC,i} \) is calculated as

\[
p_{AC,i} = P_{AC} \cdot w_{AC,i}
\]

where \( P_{AC} \) is the rated power of the space cooling/space heating system (kW), and \( w_{AC,i} \) is the status of the space cooling/space heating unit in time slot \( i \), 0 = OFF, 1 = ON.

For space cooling, the unit is ON when the room temperature increases above the set point, plus the threshold. The unit is OFF when the room temperature decreases below a certain value. The status of the unit remains the same if the room temperature is within the acceptable band. This relationship is presented in (2):

\[
w_{AC,i} = \begin{cases} 
0, & T_i < (T_s + c_{AC,i}) - \Delta T \\
1, & T_i > (T_s + c_{AC,i}) + \Delta T \\
w_{AC,i-1}, & T_s - \Delta T \leq T_i - c_{AC,i} \leq T_s + \Delta T 
\end{cases}
\]

(2)

For space heating, the operation is similar to above:

\[
w_{AC,i} = \begin{cases} 
0, & T_i > (T_s + c_{AC,i}) - \Delta T \\
1, & T_i < (T_s + c_{AC,i}) + \Delta T \\
w_{AC,i-1}, & T_s - \Delta T \leq T_i - c_{AC,i} \leq T_s + \Delta T 
\end{cases}
\]

(3)

where \( c_{AC,i} \) is the DR control signal for the space cooling/space heating unit in time slot \( i \) (°F).

The electric power demand also depends on the DR control signal \( c_{AC,i} \). This \( c_{AC,i} \) signal is implicitly derived from the revised thermostat set point preset by a homeowner during a DR event. This scenario is possible with the use of a home energy management (HEM) controller. For example, if during a normal operating condition the homeowner sets the thermostat set point at 74°F, but pre-determine that during a DR event his/her new set point should be set at 78°F, this implies the \( c_{AC,i} \) signal of 4°F. \( c_{AC,i} \) is positive for space cooling and negative for space heating. Note that with a HEM controller, the \( c_{AC,i} \) value can be configured to allow demand response implementation that takes into account the priority of all end-use loads in a house, and customer comfort levels. This topic is not in the scope of this paper. More information about a possible DR strategy is reported in [19].

2) Determination of Room Temperature \( T_i \): For each time step \( i \), the room temperature is calculated as

\[
T_{i+1} = T_i + \Delta t \cdot \frac{G_i}{C_{HV,AC}} + \Delta t \cdot \frac{C_{HV,AC}}{\Delta c} \cdot w_{AC,i} - \Delta T \quad (T_0 = T_s)
\]

(4)

where

\[
\begin{align*}
T_i & \quad \text{room temperature in time slot } i \text{ (°F)}; \\
\Delta t & \quad \text{length of time slot } i \text{ (hour)}; \\
G_i & \quad \text{heat gain rate of the house during time slot } i, \text{ positive value results in an increase in room temperature; and negative value results in a decrease in room temperature (Btu/h)}; \\
C_{HV,AC} & \quad \text{cooling/heating capacity, positive for heating and negative for cooling (Btu/h)}; \\
\Delta c & \quad \text{energy needed to change the temperature of the air in the room by } 1^\circ F (\text{Btu}/^\circ F) \\
\end{align*}
\]

3) Calculation of Other Parameters \( (G_i \text{ and } \Delta c) \): For each time slot \( i \), the heat gain rate of the house \( (G_i) \) is calculated as...
where \( A_{\text{wall}}, A_{\text{ceiling}}, \) and \( A_{\text{window}} \) represent the area of the wall, ceiling, and window of the house, in \( \text{ft}^2 \). \( R_{\text{wall}}, R_{\text{ceiling}}, \) and \( R_{\text{window}} \) represent the heat resistance of the wall, ceiling, and window, in \( \frac{\text{F} \cdot \text{ft}}{\text{Btu}} \) [20].

\( n_{ac} \) number of air changes in each time slot \( i \) (1/h);

\( V_{\text{house}} \) house volume, in \( \text{ft}^3 \);

\( T_{\text{out},i} \) outdoor temperature in time slot \( i \) (°F);

\( SHGC \) solar heat gain coefficient of windows [21];

\( H_{\text{solar}} \) solar radiation heat power (W/m²);

\( H_p \) heat gain from people (Btu/h).

To change the house temperature by \( 1 \)°F, the energy required (Btu/°F) is calculated as

\[
\Delta C = C_{\text{air}} \cdot V_{\text{house}}
\]

where \( C_{\text{air}} \) is the specific heat capacity of air for a typical room condition (1.0124 J/gK or 0.01195 Btu/ft³ °F), and \( V_{\text{house}} \) is the volume of the house (ft³).

**B. Model Validation for the Space Cooling/Heating Load**

To validate this model, the space cooling/space heating model is run with inputs (outdoor temperature, thermostat set point, dead band, house structure parameters, and HVAC unit size) from a real house in Virginia. Using the same inputs, the model outputs (power consumption and indoor temperature) are compared with the actual measurements. The comparisons in 1-min intervals are illustrated in Fig. 2 for two 24-h periods: (a) one in August for cooling demand; and (b) the other in January for heating demand (kW).

Fig. 2 indicates similarities between the actual power consumption and the model output. The energy difference is 1.4% for summer and 1.2% for winter. Any discrepancies may result from the assumptions associated with the house structure parameters.

**C. Aggregation of Space Cooling/Heating Loads**

The input parameters for space cooling/space heating model are divided into three categories: temperatures, building structures and the space cooling/space heating unit characteristics. These are parameters needed to be randomized for different homes in the same distribution circuit.

The temperature category includes outdoor temperatures and indoor temperature set points. The outdoor temperatures are acquired from the National Climatic Data Center (NCDC) [22], which should be the same for all houses in the same neighborhood. For the indoor temperature set points, a uniform random function is used to determine the variation in temperature set points among different houses in the same distribution circuit.

**IV. MODELING, VALIDATION, AND AGGREGATION OF WATER HEATING LOAD**

This section presents the development of a DR-enabled water heating load model, together with its validation and aggregation to obtain load profiles of the water heating load at the distribution level.

**A. Model Development for the Water Heating Load**

Fig. 3 shows the block diagram of the developed water heater model.

For each time step \( i \), the demand for electricity of the water heating unit \( (PW_i) \) is calculated as
where

\[ P_{WH,i} = \frac{w_{WH,i} \cdot P_{WH} \cdot \eta_{WH} \cdot c_{WH,i}}{f_{n}} \]  \hspace{1cm} (7)

\[ w_{WH,i} \]  \hspace{1cm} (8)

The water heater status \( w_{WH,i} \) is determined according to the following rules: when the water temperature in the hot water tank goes above the set point, it does not operate. When the water temperature drops below a lower bound, the heating coils start working again at its rated power until the outlet hot water temperature reaches the upper bound:

\[ T_{\text{outlet,i}} \]

\[ \Delta T_{w} \]

\[ T_{\text{mixed,i}} \]

The water heater status \( w_{WH,i} \) is determined according to the following rules: when the water temperature in the hot water tank goes above the set point, it does not operate. When the water temperature drops below a lower bound, the heating coils start working again at its rated power until the outlet hot water temperature reaches the upper bound:

\[ T_{\text{outlet,i}} > T_{f} \]

\[ T_{\text{outlet,i}} < T_{f} - \Delta T_{w} \]

\[ w_{WH,i} \]

\[ T_{f} \]

\[ \Delta T_{w} \]

\[ T_{\text{mixed,i}} \]

The water heater status \( w_{WH,i} \) is determined according to the following rules: when the water temperature in the hot water tank goes above the set point, it does not operate. When the water temperature drops below a lower bound, the heating coils start working again at its rated power until the outlet hot water temperature reaches the upper bound:

\[ T_{\text{outlet,i}} > T_{f} \]

\[ T_{\text{outlet,i}} < T_{f} - \Delta T_{w} \]

\[ w_{WH,i} \]

\[ T_{f} \]

\[ \Delta T_{w} \]

\[ T_{\text{mixed,i}} \]

The water temperature in the tank is calculated as

\[ T_{\text{mixed,i}+1} = T_{\text{mixed,i}} \left( 1 - \frac{V_{\text{tank}}}{V_{\text{tank}}} \cdot \frac{3412 \text{ Btu}}{kW} \cdot \frac{\eta_{WH}}{A_{\text{tank}}} \cdot \frac{T_{\text{outlet,i}} - T_{u}}{R_{\text{tank}}} \right) + \frac{1}{V_{\text{tank}}} \cdot \frac{\Delta t}{f_{\text{in}}} \cdot \frac{3412 \text{ Btu}}{kW} \cdot \frac{\eta_{WH}}{A_{\text{tank}}} \cdot \frac{T_{\text{outlet,i}} - T_{u}}{R_{\text{tank}}} \]  \hspace{1cm} (9)

where

\[ T_{\text{inlet}} \]

\[ T_{a} \]
temperature set points, a uniform random function is used to determine the variation in temperature set points among different houses in the same distribution circuit.

The lower and upper limits for the hot water temperature set points are determined based on data from [28], which specifies typical residential hot water temperature set points between 110°F and 120°F.

The water heater characteristics include the R-values, tank sizes and rated power. Similar to the hot water temperature, a uniform random function is used to determine the variation in R-values, water heater tank sizes and rated power among different houses in the same distribution circuit. The typical ranges for these values are acquired from [28] and [29].

For hot water usage, the hourly fraction data from California’s Hourly Water Heating Calculations [30] are taken as a reference. At the same time, hot water usage is categorized into different types in percentage of the daily household hot water usage [31]. Therefore for each type of hot water usage, the water consumption duration in a minute is the hot water demand in gallon divided by the flow rate in gallon per minute (gpm). Monte Carlo method is used to decide when the hot water is consumed based on the hot water hourly usage fraction shown in Fig. 5 for different residential houses.

V. MODELING, VALIDATION, AND AGGREGATION OF CLOTHES DRYER LOAD

This section presents the development of a DR-enabled clothes dryer load model, together with its validation and aggregation at the distribution level.

A. Model Development for the Clothes Drying Loads

The power consumption of a typical clothes dryer is from the motor and the heating coils. The power demand of the motor part is usually in the range of several hundred watts, but that of the heating coils can be several kilowatts.

For each time slot $i$, the demand for electricity of the clothes drying unit ($P_{CD,i}$) is calculated as

$$P_{CD,i} = k \cdot P_h \cdot w_{CD,i} \cdot c_{CD,i} + P_m \cdot w_{CD,i}$$  (10)

where

- $P_h$: rated power of clothes-dryer heating coil (kW);
- $k$: drying level ($k = 1/M, 2/M, \ldots, M/M$);
- $M$: total number of drying levels;
- $P_m$: power consumption of the dryer’s motor (kW);
- $w_{CD,i}$: status of the clothes-dryer’s heating coils in time slot $i$, 0 = OFF, 1 = ON;
- $c_{CD,i}$: DR control signal for clothes dryer in time slot $i$, 0 = OFF, 1 = ON.

The electric power demand also depends on the DR control signal ($c_{CD,i}$) received from an external source, such as an in-home controller, or a utility. For the clothes dryer load, when a DR control signal is received, only the heating coil will be controlled (ON/OFF) but the motor part will not be controlled. This implies that the clothes dryer will be spinning during the control period, thus consuming only a fraction of the overall load (several kW).

B. Model Validation for the Clothes Drying Loads

For validation, the rated power of a real clothes dryer and its usage profile were used as inputs to the clothes dryer model. The clothes dryer load profile was measured in 1-min intervals during its operation using TED, and compared with the model output. Fig. 5 illustrates this comparison.

The close match between the actual and modeled power consumption characteristics of a clothes dryer implies the usefulness of the clothes dryer model for simulation and analysis.

C. Aggregation of Clothes Drying Loads

The clothes dryer load profile is developed based on a probability distribution function that is similar to the dryer power consumption profile obtained from the measurement of a home in Florida [32]. The dryer running time generally starts from late morning to midnight, with the mean in the evening. After finding out the dryers’ running time, the demand aggregation of clothes dryers is acquired by running the developed model to obtain power consumption of all dryers in the distribution circuit.

VI. MODELING AND AGGREGATION OF EV LOAD

This section presents the development of a DR-enabled EV charging load model, together with its aggregation.

A. Model Development For the Electric Vehicles (EV)

To model EV charging profiles, three parameters are essential: the rated charging power, the plug-in time and the battery state-of-charge (SOC). Equation(11) shows the calculation of the EV charging profile:

$$p_{EV,i} = P_{EV} \cdot S_{EV,i} \cdot w_{EV,i} \cdot c_{EV,i}$$  (11)

where

- $p_{EV,i}$: EV charge power in time slot $i$(kW);
- $P_{EV}$: EV rated power (kW);
- $S_{EV,i}$: EV connectivity status in time slot $i$, 0 if EV is not physically connected to the outlet and 1 if EV is connected;
- $w_{EV,i}$: uncontrolled EV charging status in time slot $i$, which depends on the battery SOC as shown in (12): 0 if EV is not being charged and 1 if EV is being charged;
- $c_{EV,i}$: DR control signal for EV in time slot $i$, 0 = OFF, 1 = ON.
The battery SOC at time slot \( i \) is a function of the SOC at the previous time slot, the energy used for driving and the battery rated capacity, which is determined by

\[
SOC_{i} = SOC_{i-1} + P_{EV} \cdot \Delta t \cdot \frac{C_{batt}}{C_{batt}}
\]

where

- \( SOC_{i} \) is the battery SOC at time slot \( i \);
- \( 
\Delta t \) is the length of time slot \( i \) (minute);
- \( P_{EV} \) is the energy used for driving (kWh);
- \( C_{batt} \) is the battery rated capacity (kWh).

The EV power demand also depends on the DR control signal \( c_{EV,i} \) received from an external source, such as an in-home controller, or a utility. The DR control signal of 0 will stop the charging of EV while the DR control signal of 1 will allow the EV to start charging. The developed EV model will extend the EV charging complete time if the EV charging is interrupted by the DR signal. That is, the EV will continue to be charged until it is fully charged.

### B. Aggregation of EV Load

To determine the EV fleet charge profile in a distribution circuit, three parameters (vehicle rated charging power, plug-in time and the battery SOC) have to be reasonably diversified.

For EV rated charging power, Table I shows the basic battery charge data of three popular EVs in the US market. The charge power presented in Table I is used to determine the charge power of EV fleet with a reasonable mix of different EV makes and models.

The EV plug-in time is derived from the National Household Travel Survey [38]. The EV plug-in time is modeled using a normal distribution with a mean and a variance derived according to the data presented in [39].

EV driving patterns are used to determine the EV energy storage status, i.e., the battery SOC. The daily driving distance for each EV in a distribution circuit is determined based on the data presented in [38] using Monte Carlo simulation. The battery SOC of each EV when plugged in is determined by (13).

### VII. EXAMPLE LOAD PROFILES FOR A RESIDENTIAL DISTRIBUTION CIRCUIT AND VALIDATION

To demonstrate the aggregation of the developed load model at the distribution circuit level, a distribution circuit in the Virginia Tech Electric Service (VTES) service area is taken as a case study. This circuit has 34 laterals with 117 transformers serving 780 residential/small commercial customers.

#### A. Controllable Loads

The aggregated load profile of controllable loads in a distribution circuit is created using the load models presented in Sections III and V. The parameters in Table II are used for load diversification. The percentage of the households owning each electric appliance, known as “ownership rate”, is taken into account according to the method presented in [40]. The ownership rates can be found from the survey data in [24]. EV is not included in the analysis due to the lack of EV penetration and measurement data.

#### B. Critical Loads

The aggregated load profile of critical loads is created based on the historical data of the industry-accepted database, i.e., RELOAD database. According to the categories in Section II, five load types \( \{ k = 1 – 5 \} — “cooking”, “lighting”, “refrigerator”, “freezer”, and “others” — are considered critical loads. Assuming in the distribution circuit, there are \( N \) residential houses. The critical load profile in a house in each time slot \( i \) (in 1-min interval) is derived based on (15). Note that the ownership rate has already been taken into account in the RELOAD database.
TABLE II
PARAMETERS AND FUNCTIONS FOR LOAD MODEL DIVERSIFICATION

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Parameter values/functions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Space cooling/heating</td>
<td>Temp at Roanoke Airport (ROA) [22]</td>
</tr>
<tr>
<td>$T_{inc}(^\circ F)$</td>
<td>Uniform dist. between 74-78 (summer), 66-72 (winter) [23]</td>
</tr>
<tr>
<td>$\Delta T(\circ F)$</td>
<td>Temp threshold = 1$^\circ F$</td>
</tr>
<tr>
<td>$A_{base}(B2)$</td>
<td>Normal dist. with $\mu = 1700$, $\sigma = 500$ [24]</td>
</tr>
<tr>
<td>$A_{act}(B2)$</td>
<td>Derived from $A_{base}$, assuming the height of the house is 10ft</td>
</tr>
<tr>
<td>$A_{act}(B2)$</td>
<td>Equal to $A_{base}$</td>
</tr>
<tr>
<td>$R_{act}(15°F)*2^h/Btu$</td>
<td>Uniform dist. between 13-15 [42]</td>
</tr>
<tr>
<td>$R_{act}(15°F)*2^h/Btu$</td>
<td>Uniform dist. between 0.8 - 1 [43]</td>
</tr>
<tr>
<td>$R_{act}(38-60^\circ F)*2^h/Btu$</td>
<td>Uniform dist. between 38-60 [42]</td>
</tr>
<tr>
<td>$P_{he}(kW)$, $C_{he}(Btu/h)$</td>
<td>According to ASHRAE [25]</td>
</tr>
</tbody>
</table>

C. Distribution Circuit Load Profiles and Validation

The aggregation of the controllable loads, together with the critical loads, of a distribution circuit with 780 customers is presented in Fig. 7 as solid bold lines for both (a) summer and (b) winter seasons. The actual hourly load profiles of the same circuit for several days are also presented for comparison purposes.

As shown in Fig. 7, the aggregation of the proposed load models reflects the real load profile of a residential distribution circuit reasonably well.

VIII. CONCLUSIONS

This paper presents a methodology to develop the bottom-up DR-enabled load models of space cooling/heating, water heating, clothes drying and electric vehicle loads. The models are developed at the appliance level taking into account the physical and operational characteristics of different load types. A methodology is also discussed showing how to aggregate each load type to obtain the distribution circuit load profile using a stochastic method. Each load model is validated against the real electricity consumption data of the associated load type. The comparison of the aggregated load profile at the distribution circuit level also shows similarity with the actual distribution circuit load profiles. This similarity proves that the proposed load modeling methodology can be used to create realistic distribution circuit load profile for DR studies.

With the DR-enabled load models developed and presented in this paper, researchers in academia and/or electric utilities can use the developed models to perform detailed DR studies. For example, studies of the impact of different demand response strategies and different customer behaviors on distribution circuit load shape changes can be conducted; and observations can be made at both the appliance level and the distribution circuit level.

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REFERENCES


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