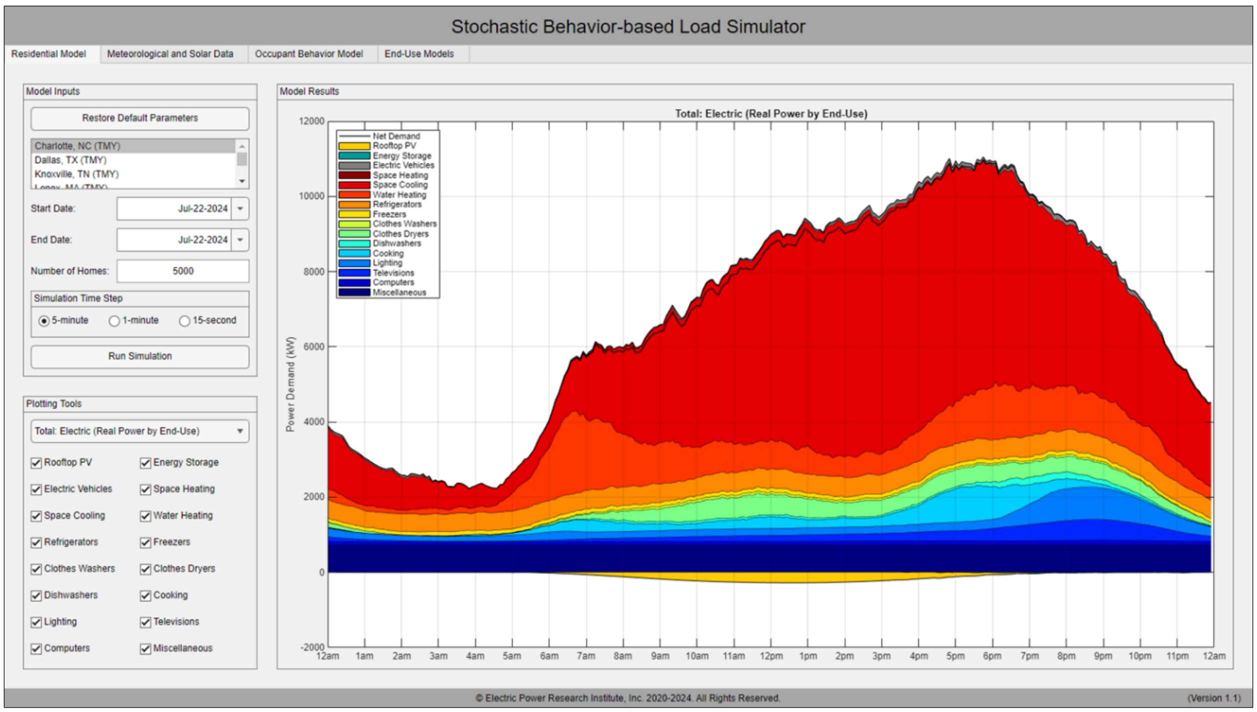
Stochastic Behavior-based Load Simulator (LoadSim): Documentation



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1 BACKGROUND

As residential energy demand continues to evolve, new and innovative modeling techniques will be essential in helping utilities anticipate demand-side changes. Modern tools will require more granularity (both spatially and temporally) and flexibility in order to adapt and answer the increasingly complex questions found in system planning. In an effort to address these challenges, EPRI developed a detailed bottom-up modeling framework, later dubbed LoadSim (short for Stochastic Behavior-based Load Simulator), in which the characteristics of the home, its individual end-uses, and the behavior of its occupants are modeled in tandem [1]. This holistic approach allows for the development of highly resolved (sub-hourly) disaggregated estimates of demand. Due to the stochastic nature of the framework, simulations can be run for many homes, resulting in the smooth diversified load shapes typical of existing tools, or for a small number of homes, demonstrating the large fluctuations that may be seen by a distribution transformer or community energy system. While initial efforts focused on assembling the core components of the model, further efforts have focused on extending LoadSim to provide a more complete representation of household energy trends, along with a validation of the framework [2].

To date, this framework has been used for a variety of applications:

- Generation of synthetic load shapes based on differences in residential demand driven by behavioral characteristics, end-use attributes, and changing climate conditions.
- Characterization of changing coincidence and diversity factors due to electrification and energy efficiency for use in distribution planning and secondary system design.
- Utilization of loads as a resource (e.g., virtual power plants) considering the impact of demand flexibility, rooftop photovoltaics, and battery energy storage systems.
- Evaluation of the economic tradeoffs associated with changes in end-use demand.

A review of LoadSim's underlying methodology, as well as a validation and benchmarking exercise undertaken against established modeling practices, is provided as part of this document.

2 METHODOLOGY

Occupant Behavior Modeling

Within LoadSim, demand estimates are dependent on a variety of factors. These include environmental conditions, the set of end-use loads present within the home, and the use of each load. The use of each load is dependent upon the behavioral patterns of a household's occupants. These patterns can vary significantly based on the time of day and day of the week that is observed. The technique implemented here consists of using time-use data, Markov chains, and the Monte Carlo method of repeated random sampling to model occupant behavior [3].

American Time Use Survey

Time-use data is available from a variety sources (both nationally and internationally) and is typically collected through surveys in which individuals self-report the activities they participate in throughout the day. These surveys, often conducted by universities and governmental organizations, aim to provide researchers with a reliable source of data describing how people utilize their time. Within LoadSim, data from the American Time Use Survey (ATUS) is used. This survey, sponsored by the U.S. Bureau of Labor Statistics and conducted annually by the U.S. Census Bureau since 2003, measures the amount of time people spend doing various activities, such as sleeping, cooking, and driving [4]. Information collected by the ATUS includes the start and end times of each activity (in minutes), where each activity occurred (at home or away), and whether the activity was done for one's job. Additional demographic information for each respondent, including age, sex, employment status, and region of residence, is also available.

Data collected from the 2003-2023 surveys are used to create the statistically driven occupant behavior models used as part of this framework. Survey results include data from 245,139 respondents with a total of 4,740,486 recorded activities. By analyzing this data, distinct correlations between activities respondents reported participating in and their demographic characteristics become apparent. By default, occupants are segmented into five categories based on their demographics: *working male*, *nonworking male*, *working female*, *nonworking female*, and *child (ages 15–17)*. This categorization was also used in [5]. Previously, differences in behavioral patterns have been explored with respect to age, sex, household income, educational attainment, employment status, and employment type (e.g., full-time vs. part-time). Depending upon the requirements of the study, occupants can be recategorized as needed in LoadSim.

Analyzing the data available from the ATUS, based on the probability of occupants performing various activities, produces the following distribution for a working male (Figure 2.1).

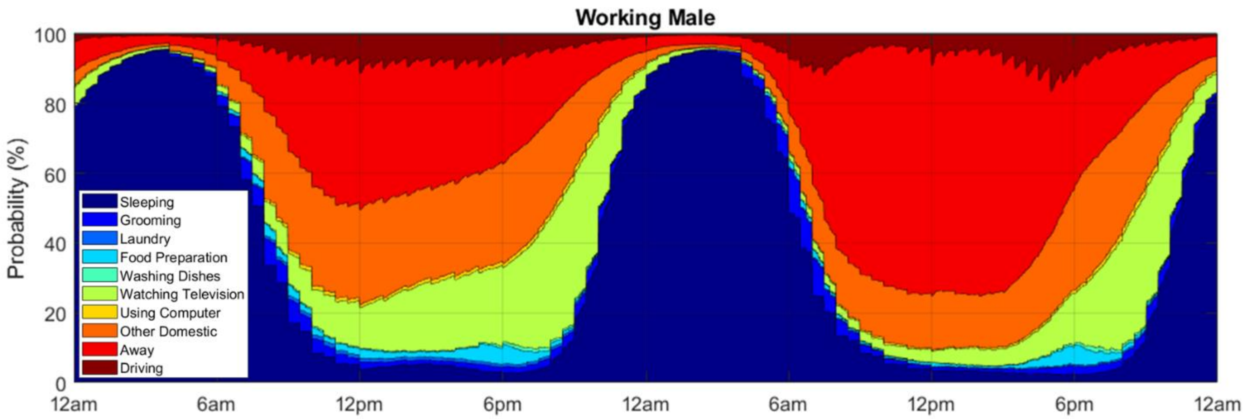


Figure 2.1 Activity distribution of a working male occupant (Sunday-Monday)

Due to the tendency of those surveyed by the ATUS to report the start and end times of their activities to the nearest 15- or 30-minute increment (e.g., 12:00 am, 12:15 am), a simple moving average filter is applied over a 60-minute time span to smooth the results (Figure 2.2).

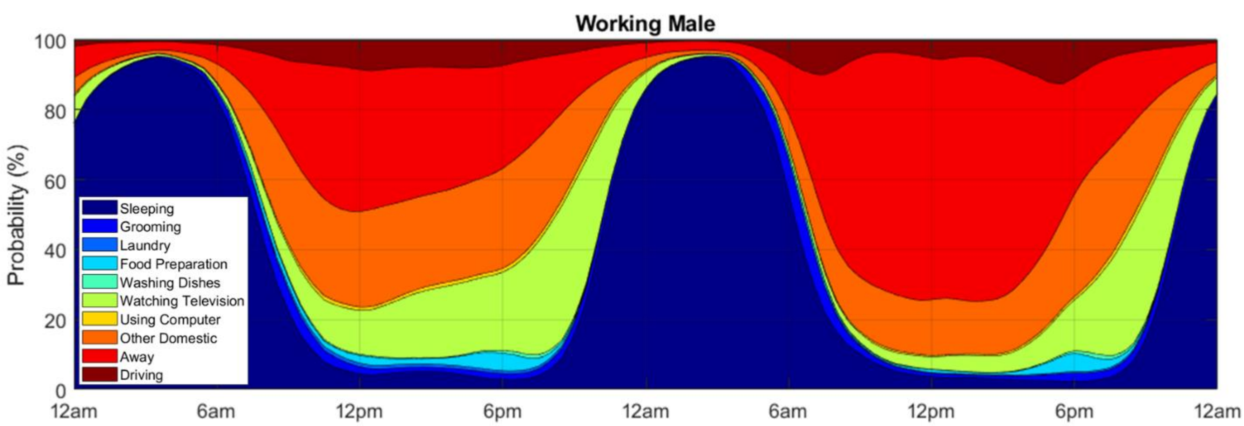


Figure 2.2 Filtered activity distribution of a working male occupant (Sunday-Monday)

Markov Chain Behavior Model

ATUS data is used to construct a series of Markov chains, a stochastic process which utilizes transition probabilities (i.e., the probability of transitioning from one state to another) to determine which state to transition to next. Transition probabilities depend solely upon the current state and not upon the sequence of states preceding the current state (i.e., memoryless). A visual representation of a two-state Markov chain is shown in Figure 2.3, with states drawn as circles and the probabilities of transitioning from one state to another drawn as arrows between the states (e.g., the probability of transitioning from $State\ 1$ to $State\ 2$ is given by $P_{1,2}$).

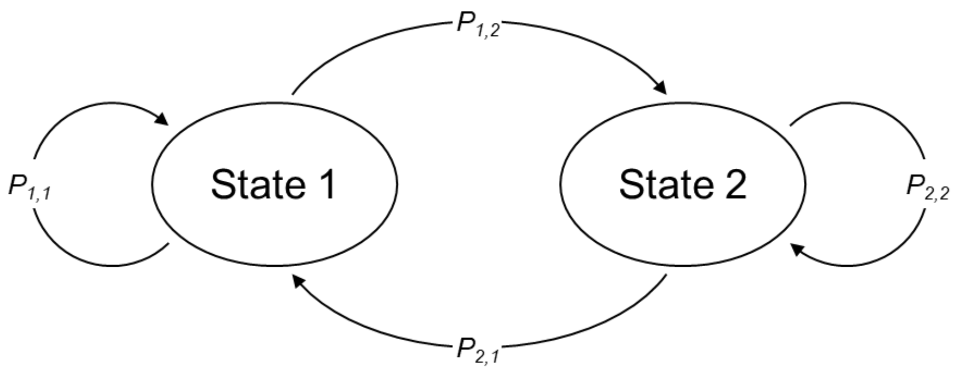


Figure 2.3 Example of a two-state Markov chain

For the behavior models used in LoadSim, ten states (or activities) are defined. These activities were chosen based on data availability and their relationship to the most energy intensive residential end-uses. These activities, and their corresponding end-uses, are listed in Table 2.1.

Table 2.1 Activities (Markov chain states) and corresponding residential end-uses

ACTIVITY CATEGORY	RESIDENTIAL END-USES
1. Sleeping	Lighting
2. Grooming	Water Heater
3. Laundry	Washer, Dryer, Water Heater
4. Food Preparation	Cooking, Refrigerator, Freezer, Water Heater
5. Washing Dishes	Dishwasher, Water Heater
6. Watching Television	Television
7. Using Computer	Computer
8. Other Domestic	N/A
9. Away	Lighting
10. Driving	Electric Vehicle, Lighting

Because the likelihood of participating in each activity varies throughout the day, time varying Markov chains are developed on a one-minute time scale for each day of the week. First, each of the activities recorded by the ATUS is assigned to one of the ten categories shown above. Next, activity transitions are recorded to develop Markov chain matrices for each minute of the week. Mathematically, the probability of transitioning from one activity at time t, to another at time $t+1$, can be represented as $P_{i,j}^{d,m}$, where i is the current activity, j is the next activity, d is the current day of the week, and m is the current minute of the day [5]. The transition probabilities of a time varying Markov chain at any given time can be expressed as a $n \times n$ matrix, where n is the number of possible states. In Figure 2.4, transition probabilities for an activity change occurring between 6:59 pm and 7:00 pm on a Sunday are shown. Each row represents the current activity state of an occupant, while the columns represent the next possible activity state.

	Sleeping (7:00 pm)	Grooming (7:00 pm)	Laundry (7:00 pm)	Driving (7:00 pm)
Sleeping (6:59 pm)	**99.20%**	0.07%	0.01%	0.07%
Grooming (6:59 pm)	0.14%	**95.18%**	0.03%	1.09%
Laundry (6:59 pm)	0.00%	0.00%	**98.01%**	0.15%
Food Preparation (6:59 pm)	0.00%	0.06%	0.01%	0.04%
Washing Dishes (6:59 pm)	0.04%	0.15%	0.04%	0.34%
Watching Television (6:59 pm)	0.03%	0.05%	0.01%	0.12%
Using Computer (6:59 pm)	0.08%	0.12%	0.06%	0.23%
Other Domestic (6:59 pm)	0.03%	0.15%	0.02%	0.23%
Away (6:59 pm)	0.00%	0.04%	0.00%	1.05%
Driving (6:59 pm)	0.03%	0.42%	0.03%	**95.21%**

Figure 2.4 Time varying Markov chain matrix

Occupants are simulated using the Monte Carlo method of repeated random sampling. At each time step, a uniformly distributed pseudorandom number is generated and compared to the cumulative distribution of the possible activity transition probabilities to determine which activity transition occurs. Because occupant activity transitions are chosen stochastically, each simulation yields a distinct behavior pattern, which is valuable for exploring possible outcomes.

Residential End-Use Modeling

To make use of these behavior models, residential end-use models are developed based on technical characterizations of individual end-uses and their interactions with environmental conditions and occupant behaviors. End-uses modeled explicitly include space heating, space cooling, water heating, refrigerators, freezers, electric vehicle charging, clothes washers, clothes dryers, dishwashers, cooking, lighting, and various electronic devices. These end-uses can be broadly grouped into three categories (thermostatically controlled, deferable, and uninterruptible), each sharing similarities regarding their basic modeling approaches. Distributed energy resources (i.e., rooftop photovoltaics and battery energy storage), are also modeled.

Thermostatically Controlled End-Uses

Thermostatically controlled end-uses are those that are directly controlled by thermostat settings and indirectly controlled by environmental factors and occupant behavior. Within the residential sector, the largest and most common of these end-uses are space heating, space cooling, water heating, refrigerators, and freezers. From a modeling perspective, thermostatically controlled end-uses are the most complex to develop due to the need to model their unique thermal properties. Here, each of the developed models is composed of a series of first-order differential equations relating change in temperature to the temperature of the surroundings, the thermal properties of the system, and the amount of heat added or removed from the system.

Home/HVAC

Within LoadSim, the thermal properties of a structure are characterized based on an equivalent thermal parameter model (often referred to as an RC model). Here, detailed parameters such as wall/roof/window insulation, thermal mass, and air infiltration are represented as a network of resistors and capacitors. Changes in temperature are related to internal heating gains (from occupants and loads), solar heating gains, heat added or removed by the HVAC system, and gains/losses between individual nodes. This general framework is commonly referenced in literature and other similar models (with varying levels of complexity) [6], [7], [8]. A 3R3C network is utilized in LoadSim, with nodes representing the air inside the home, internal mass of the contents of the home, and exterior surface area (i.e., envelope) of the home (Figure 2.5).

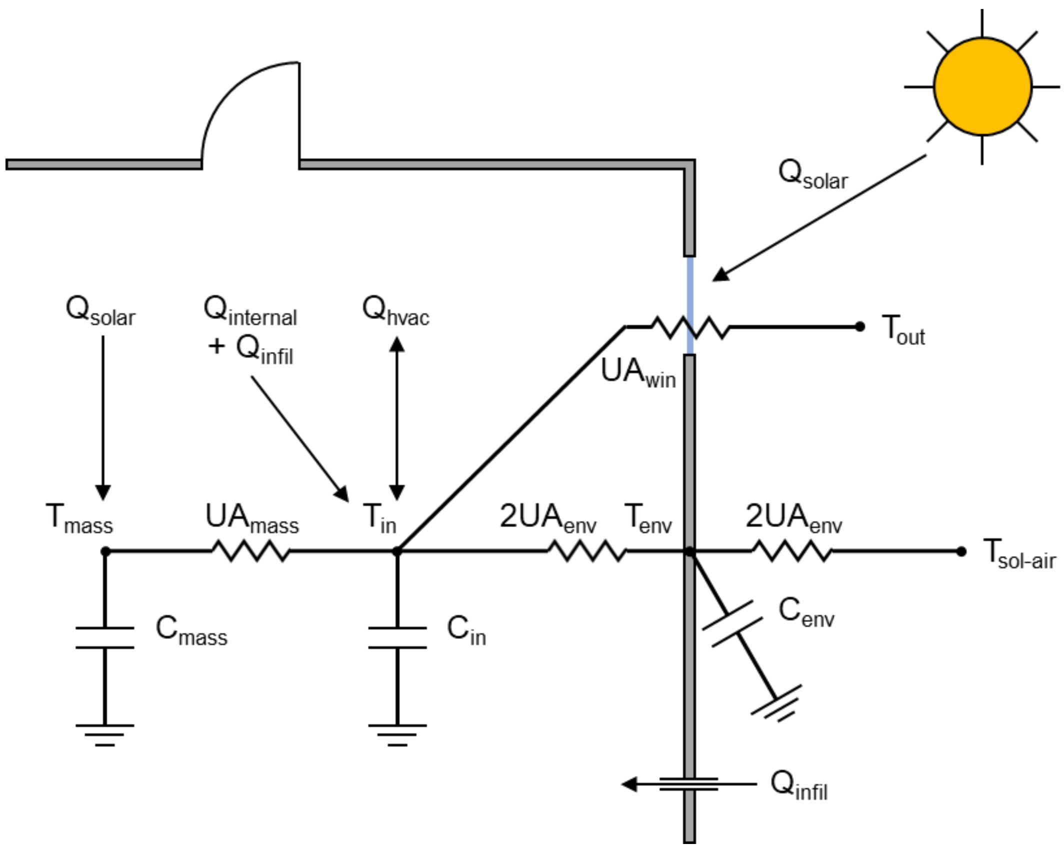


Figure 2.5 Equivalent thermal parameter model of a home (3R3C network)

Parameters captured include: outdoor air temperature, T_{out}, sol-air temperature, $T_{sol-air}$, indoor air temperature, T_{in}, temperature of the home's internal mass, T_{mass}, temperature of the home's envelope, T_{env}, thermal mass of the air in the home, C_{in}, thermal mass of the home's internal mass, C_{mass}, thermal mass of the home's envelope, C_{env}, thermal conductance of the home's internal mass, UA_{mass}, thermal conductance of the home's envelope, UA_{env}, thermal conductance of the home's windows, UA_{win}, heat transfers to indoor air (from internal gains, infiltration, and HVAC), Q_{air}, and heat transfers to the home's internal mass (from solar), Q_{mass}.

Heat transfers within the home can be described by a set of first-order differential equations:

$$C_{in} \cdot \frac{dT_{in}}{dt} = Q_{air} - UA_{mass} \cdot (T_{in} - T_{mass}) - 2 \cdot UA_{env} \cdot (T_{in} - T_{env}) \\ -UA_{win} \cdot (T_{in} - T_{out}) \tag{2.1}$$

$$C_{mass} \cdot \frac{dT_{mass}}{dt} = Q_{mass} - UA_{mass} \cdot (T_{mass} - T_{in}) \tag{2.2}$$

$$C_{env} \cdot \frac{dT_{env}}{dt} = -2 \cdot UA_{env} \cdot (T_{env} - T_{in}) - 2 \cdot UA_{env} \cdot (T_{env} - T_{sol-air}) \tag{2.3}$$

Thermal mass is calculated as shown in (2.4), (2.5), and (2.6), where V_{home} is the volume of the home, c_p is the specific heat of air (0.2403 Btu/lbm·°F), ρ_{air} is the density of the air in the home (0.075 lbm/ft^3), and A_{home} is the square footage of the home. In (2.4), the 4× multiplier was determined empirically to reflect typical HVAC cycling times. The total thermal mass per floor area, κ_{mass}, is estimated based on the product of an assumed internal mass of 8 lbm/ft^2 [9] and a specific heat of 0.3 Btu/lbm·°F [10]. Finally, assuming average construction, the thermal mass of the home's envelope, κ_{env}, is set to a default value of 6 Btu/°F·ft^2. This varies greatly by construction type (e.g., 2-3 Btu/°F·ft^2 for wood/siding, 8-16 Btu/°F·ft^2 for brick/concrete).

$$C_{in} = 4 \cdot V_{home} \cdot c_p \cdot \rho_{air} \tag{2.4}$$

$$C_{mass} = \kappa_{mass} \cdot A_{home} \tag{2.5}$$

$$C_{env} = \kappa_{env} \cdot \left(A_{wall} + A_{roof} + A_{door}\right) \tag{2.6}$$

Thermal conductance is calculated as shown in (2.7), (2.8), and (2.9). These equations take into account the insulation of the exterior walls, R_{wall}, roof, R_{roof}, doors, R_{door}, and windows, R_{win}, as well as the interior heat transfer, h_i, for a vertical surface in still air (1.46 Btu/hr·°F·ft^2) [11]. Additionally, lightweight furniture covering 40% of the home's floor area is assumed [9].

$$UA_{mass} = h_i \cdot 0.4 \cdot A_{home} \tag{2.7}$$

$$UA_{env} = \frac{A_{wall}}{R_{wall}} + \frac{A_{roof}}{R_{roof}} + \frac{A_{door}}{R_{door}} \tag{2.8}$$

$$UA_{win} = \frac{A_{win}}{R_{win}} \tag{2.9}$$

To inform the logic used for sizing HVAC systems (described later in more detail), a design thermal conductance is also derived, combing UA_{env}, UA_{win}, and air infiltration (or leakage). Here, I_{design} represents the design infiltration volumetric air exchange rate (in air changes per hour).

$$UA_{design} = \frac{A_{wall}}{R_{wall}} + \frac{A_{roof}}{R_{roof}} + \frac{A_{door}}{R_{door}} + \frac{A_{win}}{R_{win}} + I_{design} \cdot V_{home} \cdot c_p \cdot \rho_{air} \tag{2.10}$$

To model different housing types, physical properties are generalized, greatly simplifying the structural components needing to be defined (a barrier in similar tools). Of note, parameters for the shape of the home (ratio of depth to width), number of floors, and ceiling height are used to determine a home's total exterior surface area. For single-family attached and multi-family dwellings, walls/roofs shared with adjacent housing units are ignored, decreasing exposure to environmental factors. Structures with fewer exposed surfaces tend to be internally dominated, with higher internal heat gains relative to gains/losses from the environment. Conversely envelope dominated structures are more strongly affected by environmental conditions.

Table 2.2 Assumed physical characteristics by housing type

PARAMETER	SINGLE-FAMILY (DETACHED)	SINGLE-FAMILY (ATTACHED)[1]	MULTI-FAMILY (LOW-RISE)[2]	DESCRIPTION
$\boldsymbol{Shape}$	0.67	1.5	1.5	Shape of Home
$\boldsymbol{N_{floors}}$	2	2	1	Number of Floors
$\boldsymbol{N_{doors}}$	3	2	0	Number of Exterior Doors
$\boldsymbol{h_{ceiling}}$	8.5 ft	8.5 ft	8.5 ft	Ceiling Height
$\boldsymbol{EWF}$	1	0.6	0.35	Exterior Wall Fraction
$\boldsymbol{ERF}$	1	1	0 (67%), 1 (33%)	Exterior Roof Fraction
$\boldsymbol{WWR}$	0.15	0.15	0.30	Window/Exterior Wall Ratio

These assumptions are used to calculate the home's remaining structural metrics, including the surface area of exterior walls, windows, and doors, A_{total}, surface area of the exterior roof, A_{roof}, surface area of exterior doors (assuming an average door size of 36"×80", or 20 ft^2), A_{door}, surface area of exterior windows, A_{win}, and surface area of exterior walls, A_{walls}.

$$V_{home} = A_{home} \cdot h_{ceiling} \tag{2.11}$$

$$A_{total} = 2 \cdot N_{floors} \cdot h_{ceiling} \cdot (\text{Shape} + 1) \cdot \sqrt{A_{home}/\left(N_{floors} \cdot \text{Shape}\right)} \cdot \text{EWF} \tag{2.12}$$

$$A_{roof} = \left(A_{home}/N_{floors}\right) \cdot \text{ERF} \tag{2.13}$$

$$A_{door} = 20 \cdot N_{doors} \tag{2.14}$$

$$A_{win} = A_{total} \cdot \text{WWR} \tag{2.15}$$

$$A_{wall} = A_{total} - (A_{door} + A_{win}) \tag{2.16}$$

While the representation of a home's physical properties are somewhat simplified in LoadSim, the dynamics that are captured have been found to sufficiently model key demand impacts.

[1] Assumes a two-story structure comprised of three adjacent housing units (with shared side walls).

[2] Assumes a three-story structure comprised of twenty-four single-story dwellings (with shared walls/roofs).

Heat transferred to the air inside the home and the internal mass of the home are calculated using (2.17) and (2.18), where $Q_{internal}$ represents the internal heat gains (from occupants and loads), Q_{infil} represents the gains/losses due to infiltration , Q_{hvac} represents the heat added or removed by the HVAC system, and Q_{solar} represents the heat gains from solar radiation.

$$Q_{air} = Q_{internal} + Q_{infil} + Q_{hvac} \tag{2.17}$$

$$Q_{mass} = Q_{solar} \tag{2.18}$$

Internal heating gains are approximated as the sum of all sensible heating gains from occupants and loads (2.19). Heating gains from occupants (who are present in the home) are defined as a constant 220 Btu/hr per occupant [9]. Heating gains from end-use loads are estimated by multiplying the device's current real power demand by a predefined heat gain fraction.

$$Q_{internal} = 220 \cdot N_{occupants} + \sum P_{load} \cdot Heat\ Gain\ Fraction_{load} \tag{2.19}$$

The values provided in Table 2.3 are largely based on the sensible load fractions defined in [9].

Table 2.3 Assumed heat gain fractions by end-use

END-USE	HEAT GAIN FRACTION	END-USE	HEAT GAIN FRACTION
HVAC Fan	1.0	**Dishwasher**	0.6
Water Heater	-	**Cooking**	0.6 (Electric), 0.3 (Fossil Fuel)
Refrigerator	1.0	**Lighting**	0.9
Freezer	0.5	**Electronics**	1.0
Electric Vehicle	-	**Miscellaneous**	0.9
Clothes Washer	0.8	**Rooftop PV**	-
Clothes Dryer	0.15 or 1.0 (Electric), 0.1 (FF)	**Energy Storage**	-

Infiltration, due to air leakage in a home's envelope, is calculated based on the design infiltration volumetric air exchange rate, volume of air in the home, and temperature differential between the indoor and outdoor air (with additional adjustments based on wind speed (in m/s) [12]).

$$Q_{infil} = I_{design} \cdot V_{home} \cdot c_p \cdot \rho_{air} \cdot 0.224 \cdot v_{wind} \cdot (T_{out} - T_{in}) \tag{2.20}$$

The process for calculating solar heating gains through windows is simplified by considering only the diffuse and ground reflected irradiance components. Use of the direct component would require assumptions for both the orientation of the home and location of its windows. In (2.21), I_{DHI} is diffuse horizontal irradiance, I_{GHI} is global horizontal irradiance, ρ_g is surface albedo, and SHGC is the solar heat gain coefficient. A window/exterior transmission coefficient, WETC, of 0.6 (representing the approximate shading due to an insect screen) is also assumed [Ref].

$$Q_{solar} = \left(\frac{I_{DHI}}{2} + \frac{I_{GHI} \cdot \rho_g}{2}\right) \cdot A_{win} \cdot \mathrm{SHGC} \cdot \mathrm{WETC} \tag{2.21}$$

Similarly, sol-air temperature, which is used to account for solar heating gains through the envelope of the home, is calculated based on the assumption that vertical surfaces are shaded from the direct component (which is greatest during sunrise/sunset). Because the home's envelope is treated as a single lumped parameter, irradiance incident to both the horizontal and vertical surfaces of the home are weighted based on relative surface area. Additional parameters which must be defined include the exterior heat absorption fraction (set to 0.6), α, and exterior heat transfer coefficient (6.0 Btu/hr·°F·ft^2 in winter and 4.0 Btu/hr·°F·ft^2 in summer), h_o [11].

$$T_{sol-air} = T_{out} + \frac{\alpha \cdot I_{GHI}}{h_o} \cdot \frac{A_{roof}}{A_{wall} + A_{roof} + A_{door}} + \frac{\alpha \cdot \left(\frac{I_{DHI}}{2} + \frac{I_{GHI} \cdot \rho_g}{2}\right)}{h_o} \cdot \left(1 - \frac{A_{roof}}{A_{wall} + A_{roof} + A_{door}}\right) \tag{2.22}$$

Heat added or removed from the home by the HVAC system is calculated differently depending on the type of heating and cooling system present. Within LoadSim, a home's heating and cooling equipment are sized based on the methodology outlined in [6]. A summary of this sizing logic is provided on the following page, with required input parameters described in Table 2.4.

Table 2.4 HVAC sizing parameters

PARAMETER	VALUE/EQUATION	DESCRIPTION
$\boldsymbol{OSF}$	0.2	Oversizing Factor
$\boldsymbol{LLF}$	0.3	Latent Load Fraction
$\boldsymbol{T_{heat}}$	Varies by Location (based on ASHRAE)	Heating Design Temperature
$\boldsymbol{T_{heat,set}}$	70 °F	Heating Design Thermostat Setpoint
$\boldsymbol{T_{cool}}$	Varies by Location (based on ASHRAE)	Cooling Design Temperature
$\boldsymbol{T_{cool,set}}$	75 °F	Cooling Design Thermostat Setpoint
$\boldsymbol{Q_{dig}}$	$167.09 \cdot A_{home}{}^{0.442}$	Design Internal Gains[3]
$\boldsymbol{I_{dps}}$	$195 \cdot A_{win} \cdot \mathrm{SHGC} \cdot \mathrm{WETC}$	Design Peak Solar Radiation[4]

More Coming Soon…

[3] Approximated against mean annual End-Use Load and Consumer Assessment Program consumption data [6].

[4] 195 Btu/hr·ft^2 assumes typical clear sky incident solar radiation for a latitude of 35 degrees [6].

Water Heater

Coming Soon…

Refrigerator/Freezer

Coming Soon…

Deferable End-Uses

Deferrable end-uses refer to any device that requires a specific amount of energy but allows for flexibility on when that energy can be supplied. Residential end-uses that can be placed into this category include electric vehicle charging, clothes washers, clothes dryers, and dishwashers.

Electric Vehicle

Coming Soon…

Clothes Washer

Coming Soon…

Clothes Dryer

Coming Soon…

Dishwasher

Coming Soon…

Uninterruptible End-Uses

Uninterruptible end-uses include those that demand energy continuously while in operation, but typically lack the flexibility of deferable end-uses. Cooking, lighting, and electronic devices, like televisions and computers, can be considered uninterruptible. Of these, lighting is the most complex and is tied to both occupant behavior and natural lighting levels. Cooking and electronics are the most simplistic, with energy demand being tied directly to occupant behaviors.

Cooking

Cooking end-uses include many different residential appliances such as conventional ovens, ranges, stoves, microwaves, and a variety of other countertop devices. Rather than modeling each of these individually, which would require extremely detailed time use data or assumptions relating to the probability of each appliance being used, cooking is modeled as a constant instantaneous load which demands energy whenever an occupant is in the food preparation activity. While less detailed, this was found to be a sufficiently accurate approximation in [13].

Both electric and hybrid (i.e., electric and fossil fuel) options are modeled based on the assumed rated demand values provided in Table 2.5. Demand ratings of individual pieces of equipment may differ significantly from the values listed here, which were calibrated against [14]. For cooking, reactive demand is approximated based on a constant power factor of 0.95.

Table 2.5 Cooking model parameters

PARAMETER	RATED DEMAND
Cooking (Electric)	1,500 W
Cooking (Electric/Fossil Fuel)	600 W (Electric), 6,500 Btu/hr (Fossil Fuel)

Lighting

Lighting demand is modeled based on the approach outlined in [15]. Here, three different lighting states are defined: Φ_{active}, when an occupant is present in the home and awake, $\Phi_{inactive}$, when an occupant is present in the home and asleep, and Φ_{absent}, when an occupant is away from the home. Constant lighting demand is assumed for both the inactive and absent states, while lighting demand in the active state is defined as shown in (2.23), where Φ_{min} and Φ_{max} represent the minimum and maximum lighting levels demanded by a home's occupants, E_{solar} is the incident solar illuminance, and E_{limit} is an empirically estimated limiting factor of 5,000 lux (which is allowed to vary by a maximum of ±3 standard deviations per household, σ = 500 lux).

$$\Phi_{active} = \begin{cases} \Phi_{min} \cdot \dfrac{E_{solar}}{E_{limit}} + \Phi_{max} \cdot \left(1 - \dfrac{E_{solar}}{E_{limit}}\right) & E_{solar} < E_{limit} \\ \Phi_{min} & E_{solar} \geq E_{limit} \end{cases} \tag{2.23}$$

Using this approach, demand for lighting is limited by the current level of daylight. As a result, in the middle of the day when the sky is brightest, occupants will demand less artificial lighting than in the evening hours when natural lighting levels are minimal. Because occupants do not adjust lighting levels immediately following a change in daylight levels, lighting is adjusted incrementally based on an assumed probability (approximately once every 15 minutes). While an occupant is in an active state, lighting levels are only altered if an incremental adjustment of $\Delta\Phi$ will bring the current lighting level closer to an occupant's desired lighting level. Instantaneous lighting level adjustments occur when an occupant transitions from an active state to an inactive or absent state, or vice versa. This corresponds to an immediate change in lighting levels whenever an occupant goes to sleep, wakes up, leaves, or returns home. A summary of the values used in this model is given in Table 2.6. These values are assigned on an occupant-by-occupant basis, with the percentage of occupants assigned a specific value shown in parentheses.

Table 2.6 Lighting model parameters

PARAMETER	VALUES
$\boldsymbol{\Phi_{inactive}}$	0 lm (60%), 800 lm (40%)
$\boldsymbol{\Phi_{absent}}$	0 lm (60%), 800 lm (40%)
$\boldsymbol{\Phi_{min}}$	800 lm (80%), 1,600 lm (20%)
$\boldsymbol{\Phi_{max}}$	3,200 lm (60%), 4,000 lm (40%)
$\Delta\boldsymbol{\Phi}$	800 lm

To estimate incident solar illuminance from the available meteorological data, various methods for calculating luminous efficacy (a measure of how well a light source produces visible light) were considered. In [16], it is explained that assuming a constant value for solar luminous efficacy can produce reasonably accurate results in most instances. For this reason, a constant luminous efficacy of 120 lm/W is assumed for sunlight. Solar illuminance incident to vertical surfaces (i.e., windows) is calculated based on (2.24), where I_{DHI}, is diffuse horizontal irradiance, I_{GHI}, is global horizontal irradiance, and ρ_g is the surface albedo. The direct irradiance component is assumed to be shaded, as accounting for this would require assumptions for both the orientation of the home and location of its windows. A window/exterior transmission coefficient, WETC, of 0.6 (representing the approximate shading due to an insect screen) is also assumed [Ref].

$$E_{solar} = 120 \cdot \left(\frac{I_{DHI}}{2} + \frac{I_{GHI} \cdot \rho_g}{2}\right) \cdot \mathrm{WETC} \tag{2.24}$$

To build upon approach described in [15] and model different lighting types, the power required to produce an output of 800 lm, $\Delta\Phi$, is defined by lighting type (60 W for incandescent, 43 W for halogen, 14 W for compact fluorescent, 12 W for linear fluorescent, and 9 W for LED). Lighting is then assigned in a home on a light-by-light basis for each occupant and adjusted incrementally as described. Reactive power is approximated based on assumed constant power factors of 1.00 (incandescent and halogen), 0.92 (compact fluorescent), 0.95 (linear fluorescent), and 0.90 (LED). Finally, demand values are scaled by a factor of 1.2, based on a calibration against [17].

Electronics

As with cooking, modeling every electronic device would require either extremely detailed time use data or many different assumptions with regards to the use of each device. Additionally, because most electronics have a relatively small impact on the overall demand of the residential sector, only the most common electronic devices have been modeled. Televisions and computers are represented as constant power instantaneous loads. Whenever an occupant is engaged in these activities, the rated power is demanded. When these devices are not in use, they are assumed to be in standby mode [18]. As a result, demand can be represented by (2.25)

$$P = \begin{cases} P_{rated} & In\ Use \\ P_{standby} & Not\ in\ Use \end{cases} \tag{2.25}$$

A maximum of two televisions (for > 3 occupants) and one computer are allowed to be active in a home at any given time. Assumed demand values are provided in Table 2.7. For both televisions and computers, reactive demand is approximated based on a constant power factor of 0.90.

Table 2.7 Electronic model parameters

PARAMETER	RATED DEMAND
Television	180 W (Rated), 0 W (Standby)
Computer	200 W (Rated), 20 W (Standby)

Miscellaneous

While the largest and most common residential end-uses are considered in LoadSim, it is both impractical and unnecessary to model every possible load. As a result, some level of demand will remain unaccounted for. To address this, an additional demand of 60 W per occupant is defined. This value is derived against [14] and remains constant over time (i.e., is not affected by occupant behavior). Reactive demand is approximated based on a constant power factor of 0.90.

Distributed Energy Resources

Coming Soon…

Rooftop Photovoltaics

Coming Soon…

Energy Storage

Coming Soon…

Energy Management

Coming Soon…

3 SIMULATION AND VALIDATION

Simulation Structure

LoadSim can be used to evaluate residential demand by end-use on a daily (e.g., peak conditions) or even annual basis. The framework utilizes a variable simulation time step, with a focus on evaluating sub-hourly impacts, and is typically run at a 1- or 5-minute resolution. Simulations can be run for many homes, resulting in smooth diversified load shapes typical of existing tools, or for a small number of homes, demonstrating the large fluctuations that may be seen by a distribution transformer or community energy system. Required meteorological and solar data is obtained from [19]. Demographic data from the U.S. Census Bureau and U.S. Bureau of Labor Statistics are used to set the number and type of occupants in each simulation, while technology saturation data from [14] and [17] are used to set the share of each technology type.

To demonstrate the potential applications of LoadSim, a variety of modeling use-cases are described in [1] and [2]. Examples of those outputs are shown in Figure 3.1 and Figure 3.2.

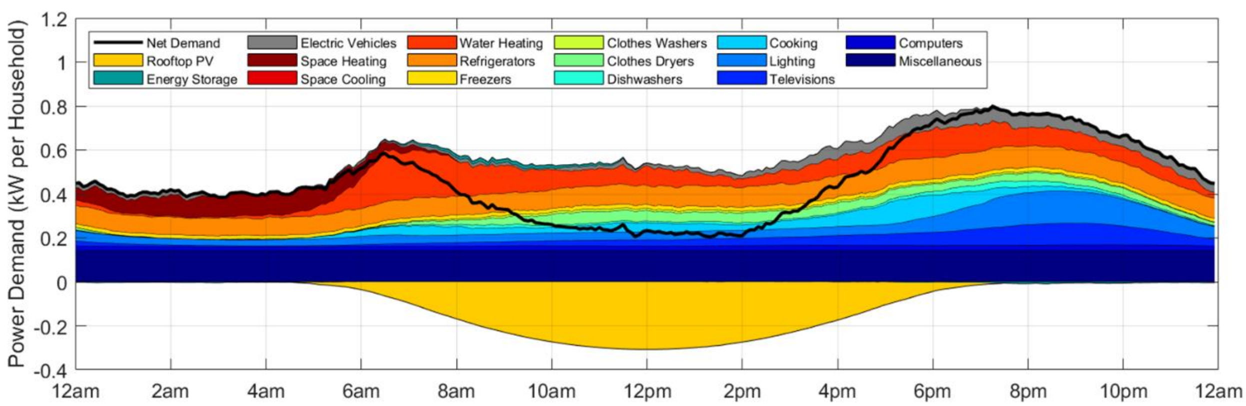


Figure 3.1 Simulated impact of rooftop PV and energy storage adoption (peak solar day)

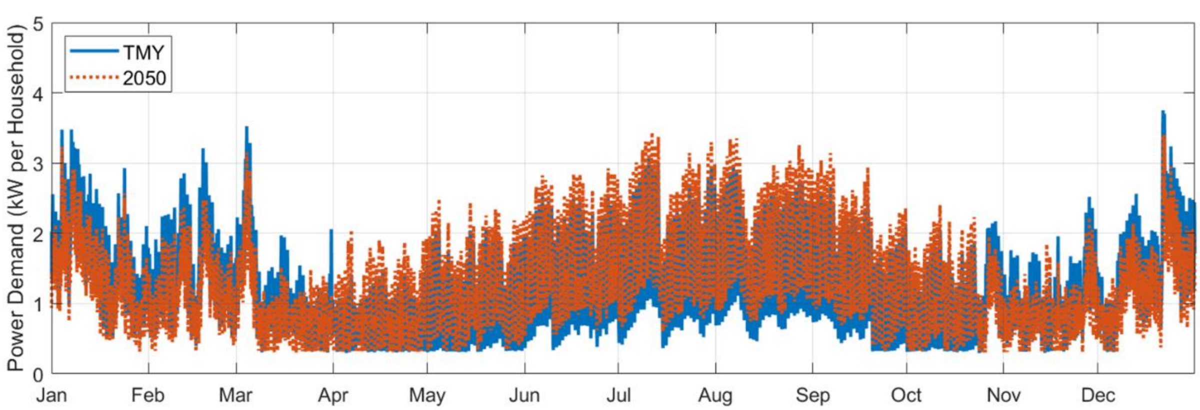


Figure 3.2 Simulated impact of changing climate conditions (annual)

Model Validation

One of the primary challenges with bottom-up modeling is the number of parameters which must be defined. While steps have been taken previously to validate end-use consumption estimates, for example the water heating model was optimized against actual lab data in [20], a comprehensive validation effort across all end-uses had not been performed. To address this shortcoming, [2] aimed to validate LoadSim based on an assessment of three key factors:

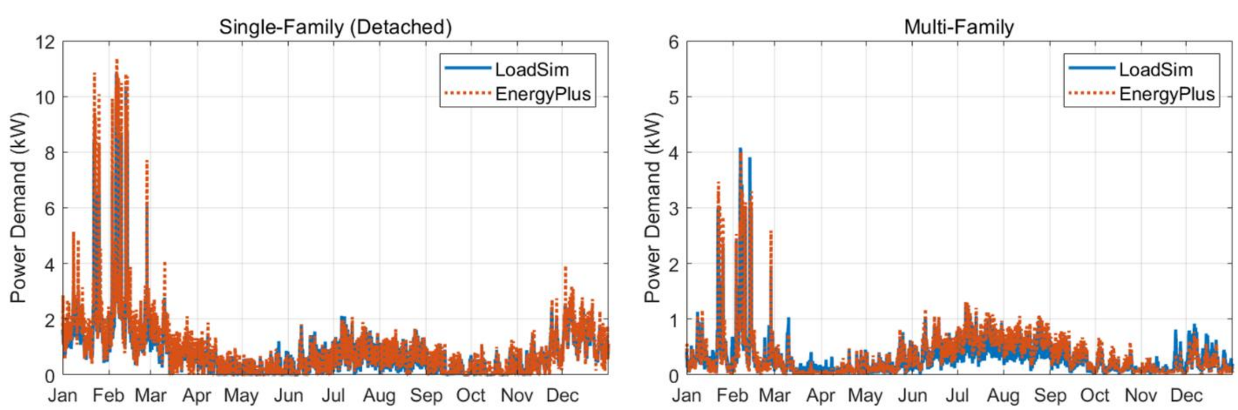
1. *Individual end-use characteristics.* As a foundational element to the bottom-up approach utilized, careful consideration is given to defining end-use specific parameters (such as rated demand, cycle duration, and cycle frequency) based on a review of various surveys, simulation protocols, and codes and standards. Because these parameters can typically be defined using real-world metrics, they are given precedence over many other aspects of the model, with only minor adjustments made during the refinement process.

2. *Annual energy consumption.* Here, a focus on accurately modeling the relative share of each end-use with respect to total household consumption is undertaken. Both electric and fossil fuel consumption estimates are evaluated against available data.

3. *Diversified load shapes.* The overall magnitude, timing, and ramp rate of demand reflects the relative responsiveness of each end-use model to external variables (i.e., behavior and environment). Fine tuning of these interactions is done on a case-by-case basis.

Space Conditioning

Space heating and cooling estimates were benchmarked against EnergyPlus, a whole building energy simulation program whose ongoing development is funded by the U.S. Department of Energy [21]. Modeled results for single and multi-family households from [22] were evaluated for New York City. Direct comparison is difficult due to the bottom-up nature requiring a significant amount of input assumptions (some of which do not have direct corollaries between the two models). Where possible, metrics shared between the two models were aligned (e.g., square footage, insulation-levels, thermostat settings, and design temperatures). A comparison of demand estimates produced by LoadSim and EnergyPlus is shown in Figure 3.3 and Figure 3.4.



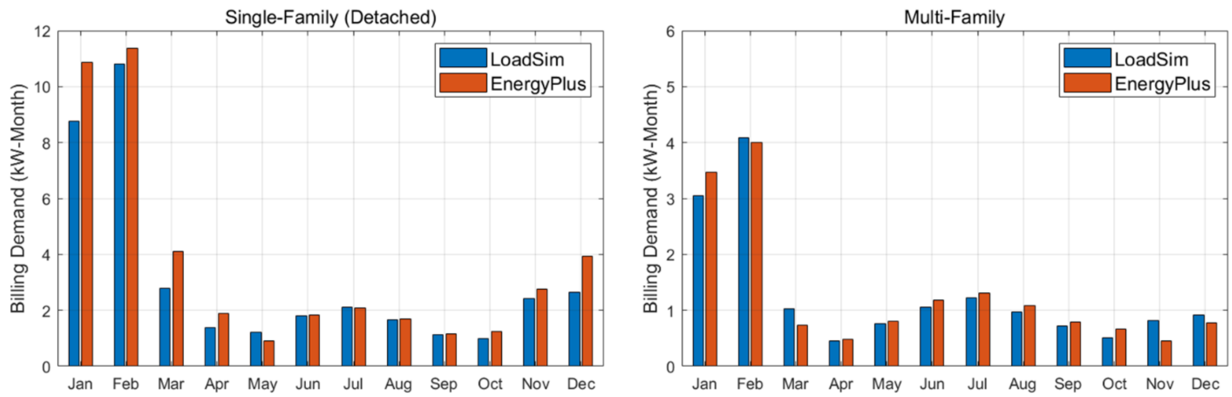


Figure 3.3 LoadSim and EnergyPlus comparison (8760 and billing demand, space conditioning)

Overall, differences between the results are minor. Both summer and winter peaks are captured well, with only minor adjustments to the default assumptions used in LoadSim. Differences are most apparent during shoulder months (where different rules for transitioning between heating and cooling modes are used) and off-peak winter months (where EnergyPlus was inadvertently set to restrict the simultaneous operation of heat pump and auxiliary heating components).

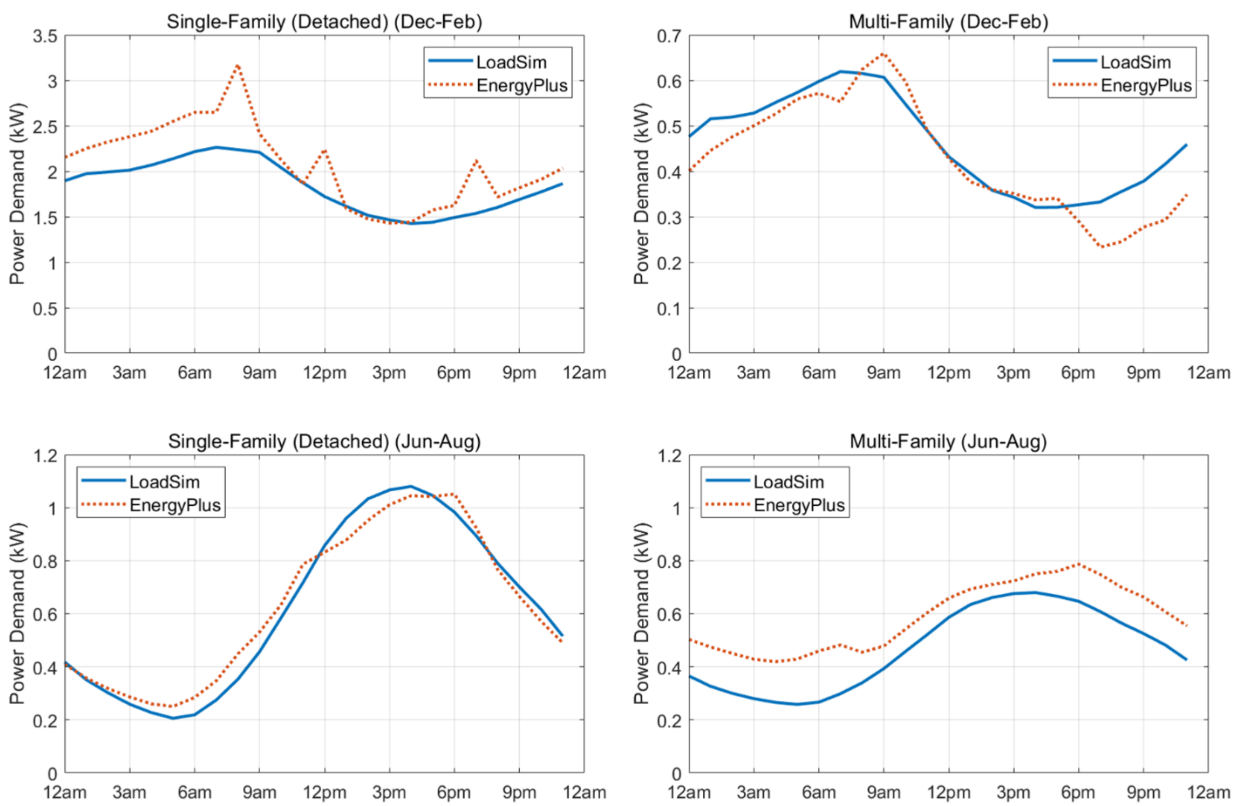


Figure 3.4 LoadSim and EnergyPlus comparison (average daily demand, space conditioning)

The magnitude, timing, and ramp rate of average daily demand over both the summer and winter seasons aligns closely as well. For multi-family dwellings, differences between how internal heat gains from occupants and loads are approximated is the main driver for variations between the two models. Comparisons for additional climate zones were completed on an annual basis, with LoadSim able to sufficiently represent the complexities of EnergyPlus in a reduced-order form.

Other End-Uses

End-use technologies which are less climate dependent, and instead driven primarily by behavioral patterns, were benchmarked against annual electric and fossil fuel consumption data from the 2020 Residential Energy Consumption Survey (RECS) and 2020 U.S. Lighting Market Characterization (LMC). A comparison of annual electric consumption is shown in Figure 3.5.

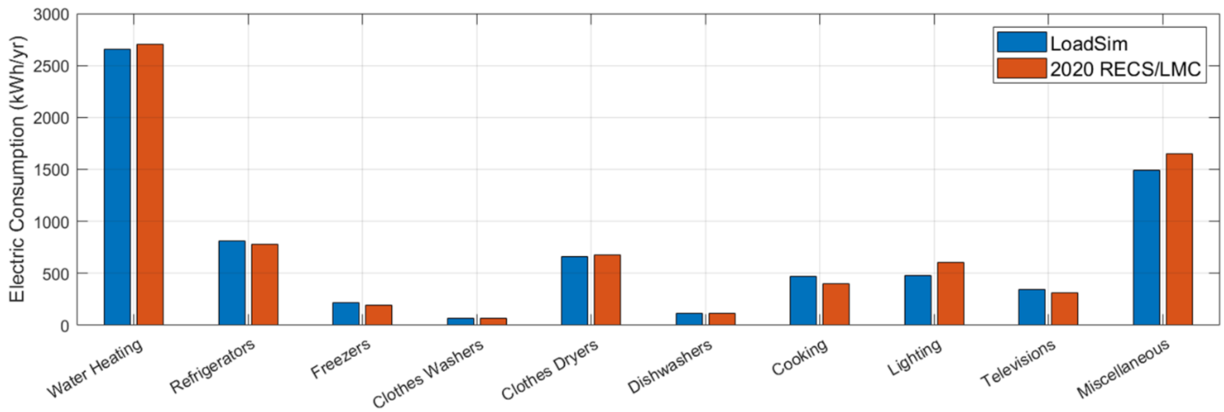


Figure 3.5 LoadSim and 2020 RECS/LMC comparison (annual electric consumption)

Average daily demand for each end-use was evaluated against profiles referenced in [9] and [23]. In some instances, adjustments were made to the interactions between various activity categories and end-uses (e.g., decreasing the likelihood of an occupant initiating a dishwasher cycle while in the washing dishes activity), further fine tuning the behavior model linkages. Only minor refinements where necessary, with modeled results closely following expected values.

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