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Supplemental information

Distribution grids may be a barrier to residential electrification

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Supplemental Notes: Distribution Grids May Be a Barrier to Residential Electrification

Contents

1	Building models	1
1.1	Housing types	1
1.2	Floor areas	2
1.3	Insulation and air sealing	2
1.4	Miscellaneous electrical load	4
2	Heating equipment	5
2.1	Heat pump efficiencies	5
2.2	Heat pump sizing	6
2.3	Heat distribution	7
2.4	Heating fuels	7
2.5	Water heating	7
3	Electric vehicles	7
3.1	Commutes	7
3.2	Numbers of vehicles	8
3.3	Vehicle types	8
3.4	Vehicle efficiencies	8
4	Model validation	10
5	Device coordination	11
6	Sensitivity to modeling choices	11

1 Building models

1.1 Housing types

Housing types in the United States vary regionally. For example, Fig. S1 (left) shows that multi-family housing dominates Bronx County and Kings County in New York. By contrast, almost all counties in Colorado (right) have mostly single-family detached houses. These differences in housing configurations affect heating and cooling demand. In winter, detached homes lose more heat because all of their exterior walls are exposed to the outside environment, unlike attached housing units (such as apartments, row houses, and condominiums) that share walls with adjacent housing. Therefore, it is important to understand the distribution of housing types at the county level across the United States. EDGIE categorizes housing as either attached or detached, with the distribution of housing types in each county based on data from ResStock.

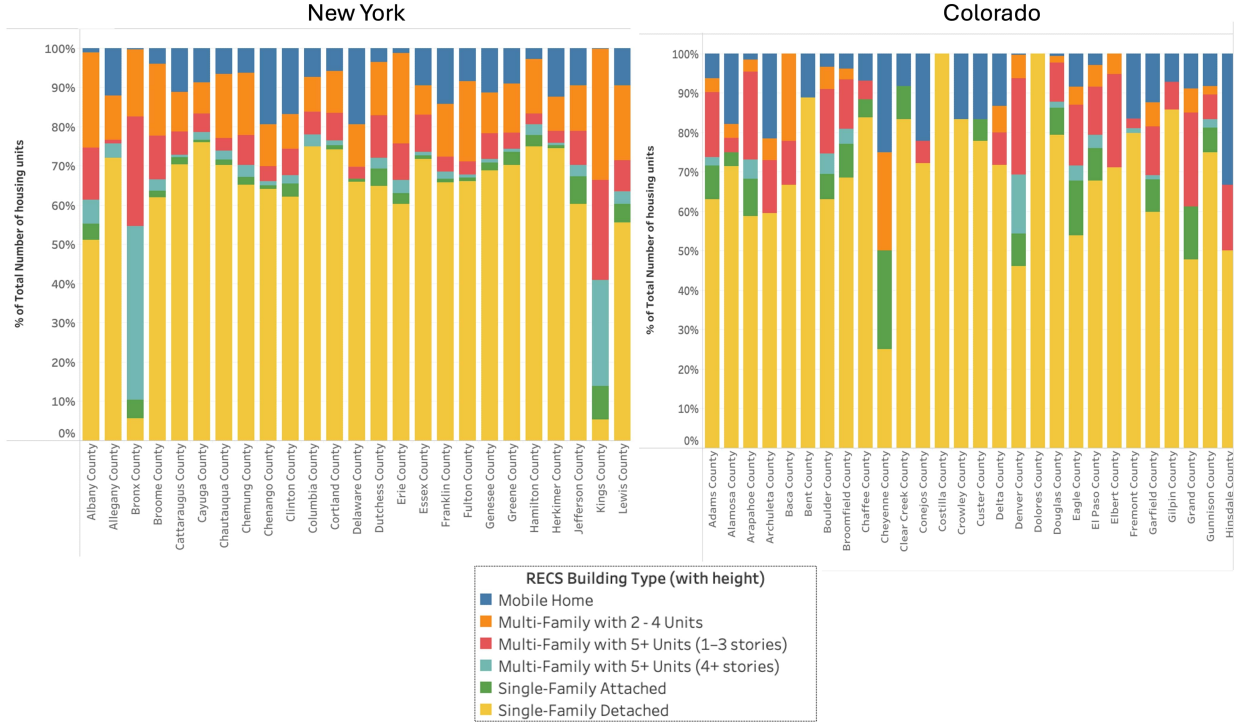


Figure S1: Housing types in New York (left) and Colorado (right).

1.2 Floor areas

ResStock provides county-level floor area information obtained from the from the Residential Energy Consumption Survey and the American Housing Survey. Fig. S2 shows the floor area distribution for attached housing and detached housing. To ensure the analysis reflects typical housing sizes, outliers are removed by capping floor areas: 400-1,700 ft² (38-158 m²) for attached homes and 1,000-3,000 ft² (92-278 m²) for detached homes. Within each housing type (attached or detached), the floor area follows the same Gaussian distribution in each county.

1.3 Insulation and air sealing

The thermal resistance between the indoor air and outdoor air depends on the resistance to heat transfer through the roof, walls, and windows, as well as the infiltration rate of outdoor air. Below is a summary of the components and their respective contributions to the overall thermal resistance:

1. Roof thermal transmittance, U_r (kW/m²/°C): This represents the rate of heat transfer through the roof per unit area and per unit temperature difference.
2. Outward-facing roof surface area, A_r (m²): The area of the roof that is exposed to the external environment.
3. Wall/window thermal transmittance, U_w (kW/m²/°C): Similar to U_r , but U_w represents the normalized rate of heat transfer through the vertical walls and windows.
4. Outward-facing wall/window surface area, A_w (m²): The total exterior-facing surface area of the walls and windows that are exposed to the outdoors.

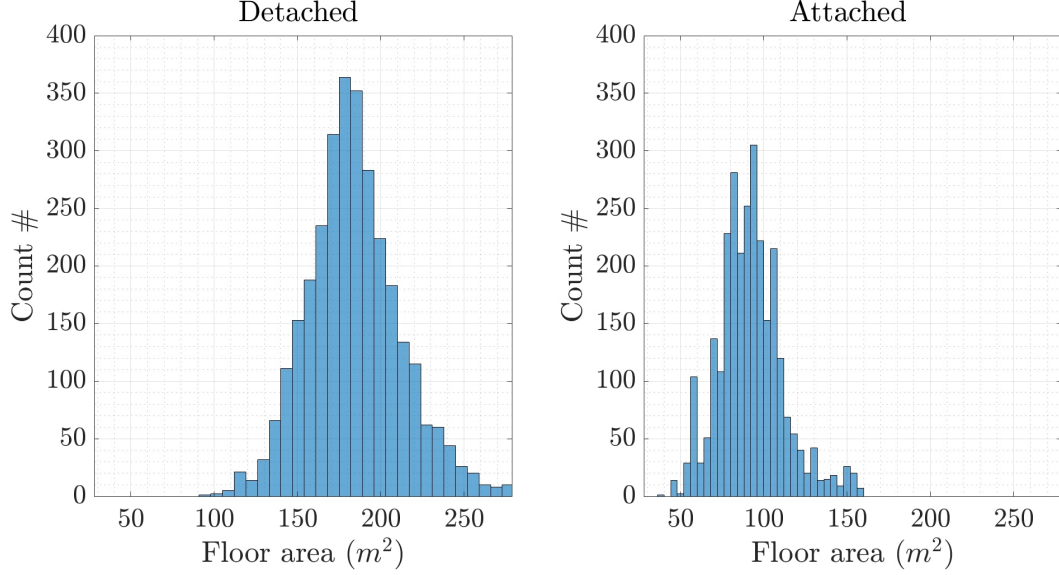


Figure S2: Floor area distributions for detached (left) and attached (right) housing.

5. Infiltration mass flow rate, $\dot{m}$ (kg/s): The product of the density of air and the volumetric flow rate of air exchange between the indoors and outdoors.

6. Specific heat capacity of air at constant pressure, c_p (kJ/kg/°C): The amount of heat transfer required to raise the temperature of a unit mass of air by one degree Celsius in a constant-pressure process.

The overall thermal resistance R (°C/kW) between the indoor and outdoor air includes the roof, walls/windows, and air infiltration:

$$R = \frac{1}{U_r A_r + U_w A_w + \dot{m} c_p}. \quad (1)$$

For a wall assembly with exterior surface area composed of $100\lambda\%$ windows and $100(1 - \lambda)\%$ opaque walls, the overall thermal transmittance U_w is a weighted average of the window transmittance U_{window} and the wall transmittance U_{wall} :

$$U_w = \lambda U_{\text{window}} + (1 - \lambda) U_{\text{wall}}.$$

For typical wall assemblies, the fenestration ratio λ (the ratio of the window area to the total area of the wall-plus-window assembly) ranges from about 0.1 to 0.3. For a box-shaped building with N stories, each with length ℓ (m) and floor aspect ratio α , the total floor area is $A_f = \alpha N \ell^2$. Equivalently, $\ell = \sqrt{A_f / (\alpha N)}$. The total wall area is

$$A_w = 2(1 + \alpha) h N \ell = 2(1 + \alpha) h \sqrt{\frac{N A_f}{\alpha}} \approx 4h \sqrt{N A_f},$$

where h (m) is the height of one story. The approximation $(1 + \alpha) / \sqrt{\alpha} \approx 2$ is exact for $\alpha = 1$ (meaning the box-shaped building has a square footprint) and is accurate within at most 10% relative error for all $\alpha \in [1, 2.5]$. The roof area is $A_r = A_f / N$.

Outdoor air can infiltrate a building through gaps in doors, windows, wall assemblies, etc. As air outflows typically balance air inflows, we assume that indoor air exits the building at the infiltration mass flow rate $\dot{m}$. Associated with this mass transfer is an effective heat transfer rate of $\dot{m} c_p (\theta - T)$, where θ (°C) is the outdoor air temperature and T (°C) is the indoor air temperature. The air change frequency ν (Hz) represents the number of air changes per second, where one air change corresponds to outdoor air filling the building's volume $A_f N h$ once. We randomize air change frequencies across housing units over the range

of 0.2 to 1.5 per hour, informed by^{1,2}. (Unless stated otherwise, all random variables mentioned in this document are drawn from independent symmetric triangular distributions over the ranges we specify.) The mean air change frequency is $\nu = 0.85$ per hour $= 2.36 \times 10^{-4}$ Hz. The mean value matches the mean value of Residential Leakage Data collected from over 135,000 homes in the United States by Lawrence Berkeley National Laboratory³. The infiltration mass flow rate is $\dot{m} = \nu \rho A_f N h$, where ρ (kg/m³) is the density of air.

The thermal transmittances of walls and windows, U_{wall} and U_{window} , vary across climate zones, reflecting regional differences in building codes and construction practices. The Table S1 shows the thermal transmittance values we use for the seven climate zones in the lower 48 United States. For reference, typical values of U_{window} are roughly 1, 2.5, and 5 W/m²/°C for triple-, double-, and single-pane windows, respectively.

Table S1: Thermal transmittance values of walls and windows in different climatic zones

Climate zone	U_{wall} (W/m ² /°C)	R_{wall} (°Fft ² h/BTU)	U_{window} (W/m ² /°C)	R_{window} (°Fft ² h/BTU)
1 (hottest)	0.5	11.35	3.8	1.49
2	0.47	12.08	3.8	1.49
3	0.47	12.08	2.7	2.11
4	0.33	17.20	2.0	2.84
5	0.33	17.20	2.0	2.84
6	0.25	22.71	2.0	2.84
7 (coldest)	0.2	28.39	2.0	2.84

For roofs, we use U - and R -values of 0.35 W/m²/°C and 16 °Fft²h/BTU. We assume that direct thermal coupling between the indoors and the the ground is negligible. This assumption is exact for units in multifamily housing that share no surfaces with the ground. For other housing units, this assumption is reasonably accurate if basements are well-insulated and/or temperature differences between basements and the ground are small. Future EDGIE versions may adjust the overall thermal resistance calculations to explicitly account for direct thermal coupling to the ground.

The table above contains representative values of U_{wall} and U_{window} for each climate zone. For each housing unit, we combine the corresponding climate zone’s values of U_{wall} and U_{window} into the wall/window thermal transmittance, $U_w = \lambda U_{\text{window}} + (1 - \lambda)U_{\text{wall}}$, using a fenestration ratio λ randomized between 0.2 and 0.3. We then further randomize U_w by $\pm 20\%$ to reflect building-to-building differences in insulation, air sealing, and fenestration ratios. Due to variation in the fenestration ratio λ , wall/window thermal transmittance U_w , floor area A_f (and therefore the wall/window area A_w and roof area A_r), and air change frequency ν (and therefore the infiltration mass flow rate $\dot{m}$, the overall thermal resistance R in Eq. (1) varies significantly both within and across climate zones and building types. Future EDGIE versions may adjust the overall thermal resistance randomization to occasionally represent homes that have little or no wall insulation, as this case is not uncommon in older United States housing.

We tuned building models to data on the total input energy to the heating plant. This input energy includes both useful heat delivered to the space and heat lost through ducts. For this reason, our models may modestly overestimate electricity used by ductless mini-split heat pumps, which supply heat directly to the space and are not subject to duct losses. Our tuning process uses the National Renewable Energy Laboratory’s ResStock database. ResStock is a residential building energy modeling tool that has been validated through comparison with measured aggregate loads at the state level and at the utility level [chapter 4 of⁴]. We tuned our underlying thermal resistance distributions by comparing 15-minute input energy profiles from EDGIE with those from ResStock for the same locations and weather conditions.

1.4 Miscellaneous electrical load

By miscellaneous electrical load (MEL), we mean all electricity use other than space heating/cooling, water heating, and vehicle charging. MEL includes refrigerators, freezers, dishwashers, clothes washers and dryers,

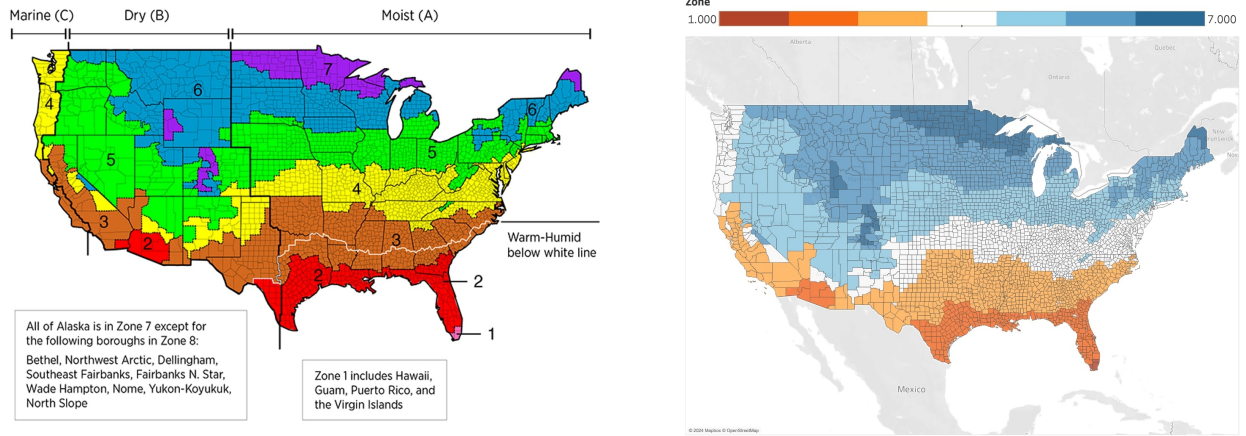


Figure S3: Climate zones as defined by ASHRAE/IECC⁷ (left) and as mapped into EDGIE (right)

lights, televisions, computers, networking equipment, etc. We simulate each housing unit's MEL as follows.

1. Get the time-average MEL intensity (in units of kW per household) from the Residential Energy Consumption Survey (RECS)⁵ data for the appropriate housing type (attached or detached) and geographic region (Midwest, Northeast, South, or West).
2. Randomly sample one MEL time series from the Multi-Family Residential Electricity Dataset⁶, which contains measurements from 390 apartments in New York City.
3. Rescale the time series such that its time-average equals the time-average MEL from step 1.

This process retains the temporal structure of real MEL data while matching population-level energy statistics for the housing type and geographic region. Our method of resampling MFRED profiles, rescaled to match annual MEL consumption from RECS, could lead to unrealistically high MEL demand peaks. This could happen, for example, when rescaling an MFRED profile with low mean but high variance to match a high annual mean from RECS. While our averaging over 1,000 homes mitigates this issue, it could be significant when simulating a small number of homes.

2 Heating equipment

2.1 Heat pump efficiencies

EDGIE models heat pump coefficients of performance (COPs) as piecewise linear functions of the outdoor temperature. Heating COPs are capped below at a floor of unity: When the COP reaches unity, the heating system switches to resistance backup heat. EDGIE selects heat pump COPs based on the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) and International Energy Conservation Code (IECC) climate zones shown in Fig. S3. In the all-electric future scenario, EDGIE selects cold-climate heat pumps in climate zones 5, 6, and 7. The minimum COPs of these cold-climate heat pumps are 2.2 to 2.4 under heating design conditions, consistent with the Department of Energy's Cold-Climate Heat Pump Challenge specifications⁸. In the baseline case, which includes a small but nonzero number of heat pumps, heat pumps in zones 5, 6, and 7 still have higher COPs than heat pumps in warmer climate zones, but their design heating COPs (minimum COP 1.5 to 1.8) are not as high as in the all-electric future scenario.

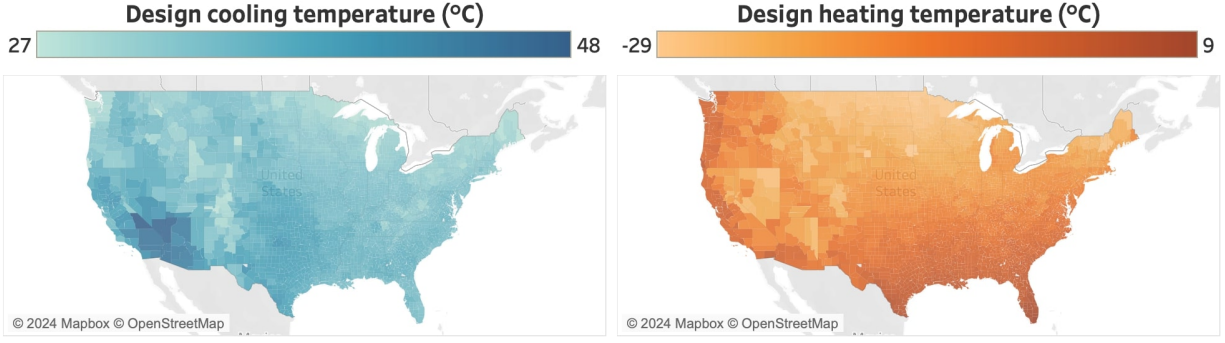


Figure S4: Design outdoor temperatures for cooling (left) and heating (right).

2.2 Heat pump sizing

EDGIE sizes heat pumps based on steady-state design heating and cooling load calculations that correspond to the Air Conditioning Contractors of America *Manual J Residential Load Calculation* procedure. EDGIE implements the following steps.

1. Obtain the outdoor temperatures under design heating and cooling outdoor temperatures, $\theta_{\text{des,h}}$ and $\theta_{\text{des,c}}$ ($^{\circ}\text{C}$), for the specific location. Fig. S4 shows the design heating and cooling outdoor temperatures for each county as prescribed by the American Society of Heating, Refrigeration, and Air-Conditioning Engineers *2017 Handbook of Fundamentals* and the Air Conditioning Contractors of America *Manual J Design Conditions 8th Edition*.
2. Set the design indoor temperatures for heating and cooling, $T_{\text{des,h}}$ and $T_{\text{des,c}}$ ($^{\circ}\text{C}$), to the occupant preferences (distributed according to Residential Energy Consumption Survey data).
3. Estimate plausible exogenous thermal powers under design heating and cooling conditions, $w_{\text{des,h}}$ and $w_{\text{des,c}}$ (kW). Exogenous thermal powers are estimated as the sum of heat transfer rates from sunlight and occupants' bodies, plus heat transfer from miscellaneous electrical loads. Thermal power from sunlight is zero at heating design conditions (which generally occur in the coldest hours of the night). For cooling design conditions, thermal power from sunlight is based on solar irradiance measurements and window areas.
4. Compute the thermal loads under design heating conditions,

$$q_{\text{des,h}} = r \left(\frac{T_{\text{des,h}} - \theta_{\text{des,h}}}{R} - w_{\text{des,h}} \right),$$

and under design cooling conditions,

$$q_{\text{des,c}} = \frac{r}{s} \left(\frac{\theta_{\text{des,c}} - T_{\text{des,c}}}{R} + w_{\text{des,c}} \right).$$

Here r is the oversize ratio (randomized between 1.2 and 1.3) and s is the heat pump's sensible heat ratio, meaning the ratio of the temperature-change component of its cooling output to its total (temperature-change plus humidity-change) cooling output.

5. Select an appropriate heat pump from a finite set of available heat pumps. To size for heating, we select the heat pump whose maximum heating capacity at the heating design outdoor temperature $\theta_{\text{des,h}}$ is closest to the design heating load $q_{\text{des,h}}$. To size for cooling, we select the heat pump whose

maximum cooling capacity at $\theta_{\text{des,c}}$ is closest to $q_{\text{des,c}}$. For both heating and cooling, if the design load exceeds the maximum capacity of all available central heat pumps, we select a mini-split heat pump such that the maximum capacity of the combined (central plus mini-split) system at the design outdoor temperature is as close as possible to the design load.

In this study, the set of available heat pumps includes 11 central heat pumps from (three major manufacturers), three mini-split heat pumps (from one major manufacturer), and nine combinations thereof (each manufacturer’s largest central heat pump combined with each of the mini-splits). We model each heat pump’s maximum heating and cooling capacities as linear functions of the outdoor temperature. We fit capacity models to data from the Northeast Energy Efficiency Partnerships and manufacturer specification sheets.

2.3 Heat distribution

We do not distinguish between housing with forced-air vs. hydronic distribution or between housing with existing ducts vs. without. We implicitly assume that either a) the air-to-air and air-to-water heat pumps that serve forced-air and hydronic systems, respectively, have the same COP distributions; or b) housing with hydronic distribution gets renovated with air-to-air heat pumps and forced-air distribution, or with ductless mini-split heat pumps. This is similar to ResStock’s approach, which assumes that 100% of ducts in single-story homes are in unconditioned space and 75% for multi-story homes. Modeling more detailed duct configurations—including duct sealing, insulation, and routing through semi-conditioned or conditioned spaces—is left for future work. Capturing these details could improve estimates of heating demand and retrofit impacts in specific housing types.

2.4 Heating fuels

ResStock⁹ uses sampling methods that reflect Residential Energy Consumption Survey data on fuels used for space and water heating. In the baseline case, EDGIE selects space and water heating fuels for each housing unit in each county according to the ResStock distributions. In particular, electric heating in the baseline simulations includes an appropriate mix of heat pumps and electric resistance.

2.5 Water heating

Water withdrawals come from the Building America Domestic Hot Water Event Schedule Generator, which generates plausible hot water withdrawals using the method in¹⁰. The temperature of inlet water to the tank varies sinusoidally with a one-year period, mean of 10 °C, and amplitude of 5 °C. This inlet water temperature profile follows the empirical data reported in¹¹. The cylindrical water tanks modeled here have capacities ranging from 50 to 80 gallons (0.23–0.36 m³) volumes. The thermal capacitance of each tank is the product of the density of water, the specific heat of water, and the tank volume. The thermal resistance between the water and the surrounding air is determined by dividing an R-value between 6 and 8°F ft²/BTU/h (1060–1410 °C m²/kW) by the tank’s surface area. Each water heater has a heat pump with a COP of 2.5 to 3 and 4.5 kW of resistance backup heat.

3 Electric vehicles

3.1 Commutes

Commute durations in each county are obtained from the census survey¹² and multiplied by state-average commute speeds¹³ to estimate commute distances. In EDGIE’s electric vehicle model, vehicles travel between home and work and charge at either location when the battery energy drops below a minimum threshold. Commute distances influence the energy consumed during commutes. Fig. S5 shows the average commute

distance for each county (left) and state (right). The state-level commute distances shown in Fig. S5 are unweighted averages over each state's counties. Morning departure times vary from 5 to 11 AM. Evening return times vary from 4 to 11 PM. At-home and at-work charging opportunities depend on individual commute schedules.

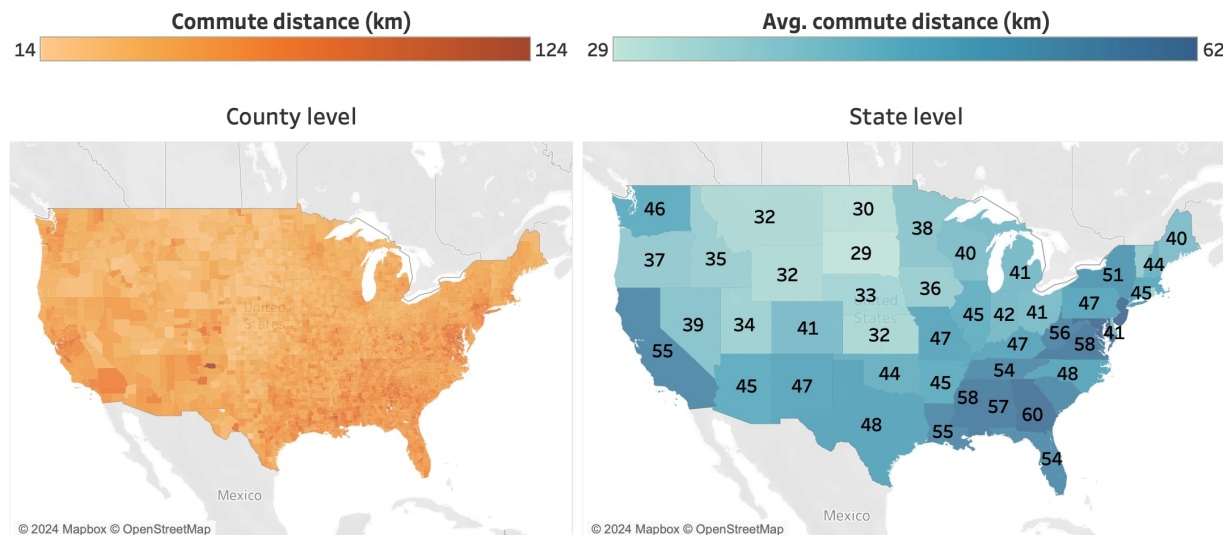


Figure S5: Average commute distances by county (left) and state (right) from census data.

3.2 Numbers of vehicles

EDGIE tunes the number of vehicles per housing unit in each county to census data. Census data indicate how many homes have zero, one, two, or 'three or more' cars. To simplify analysis, homes with 'three or more' cars are assumed to have three cars. Fig. S6 shows the variation of the number of cars per home in sample counties in Arizona.

3.3 Vehicle types

The used car sales company iSeeCars¹⁴ analyzed over 21 million used vehicle sales from April 2022 through March 2023. The shares of trucks, SUVs, minivans, and passenger cars (sedans, coupes, convertibles, hatchbacks, station wagons) within each state were calculated. Fig. S7 shows the distribution of vehicles in a few sample states. Since these data are not available at the county level, EDGIE uses the same distribution across all counties within a given state. Vehicle type distributions vary across states, however.

3.4 Vehicle efficiencies

Different vehicle types use different amounts of energy per unit distance driven. An electric vehicle's energy intensity (the amount of energy it uses to drive a unit distance) also depends on the outdoor air temperature¹⁵. Energy intensities increase in both cold and hot weather due to increased energy demand for cabin conditioning, as well as temperature-dependent battery chemistries. EDGIE bins vehicles as either small (such as sedans) or large (such as pickups or SUVs). Small and large vehicle parameters follow the characteristics of the Tesla Model S (higher efficiency) and Ford F-150 Lightning (lower efficiency), respectively. The energy intensity is obtained from¹⁶ and adjusted for outdoor temperature using the model from¹⁵. Fig. S8 shows the energy intensity of driving small and large vehicles as functions of the outdoor temperature.

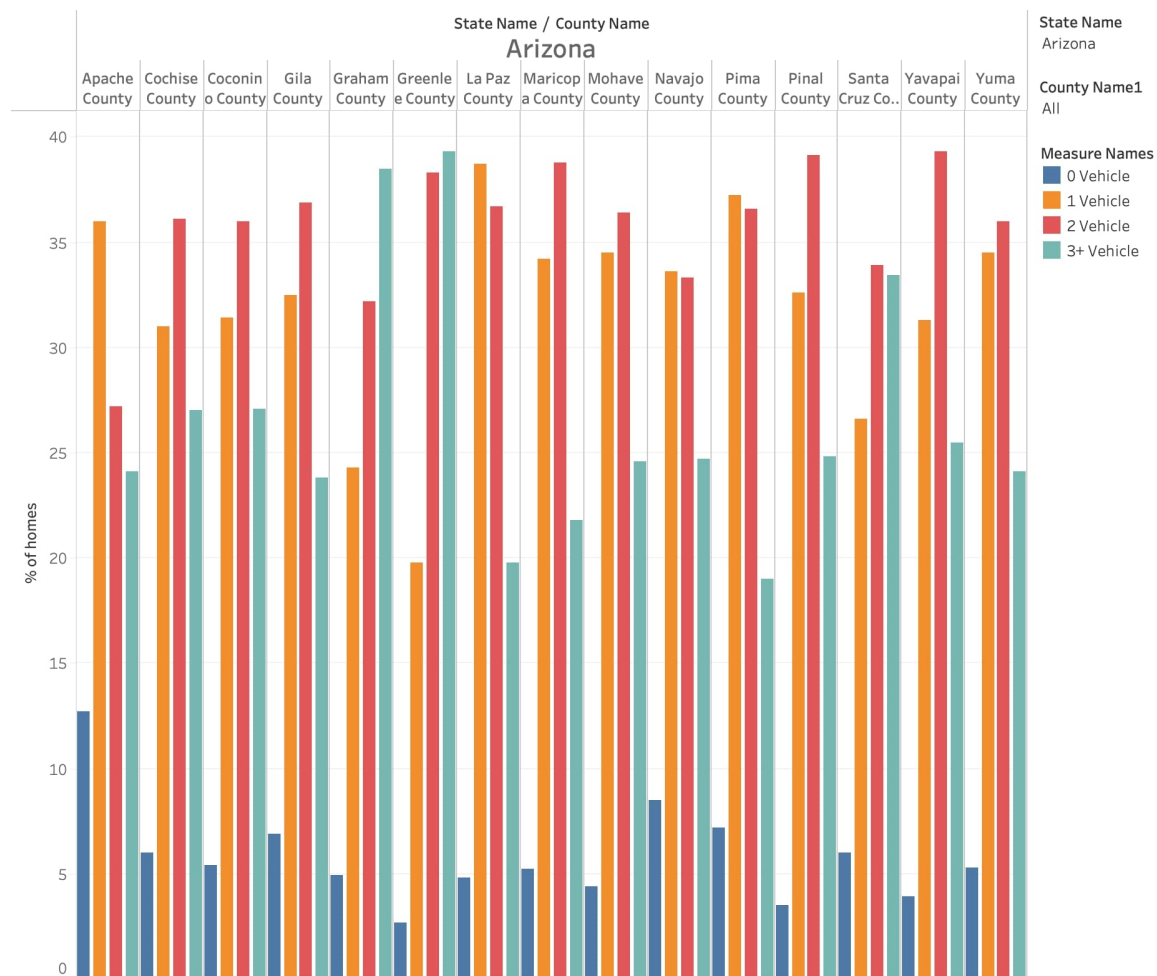


Figure S6: Number of vehicles per home in sample counties in Arizona.

228 The modeled electric vehicles have charging and discharging efficiencies of 0.9 to 0.95 and energy capacities
 229 of 54 to 82 kWh.

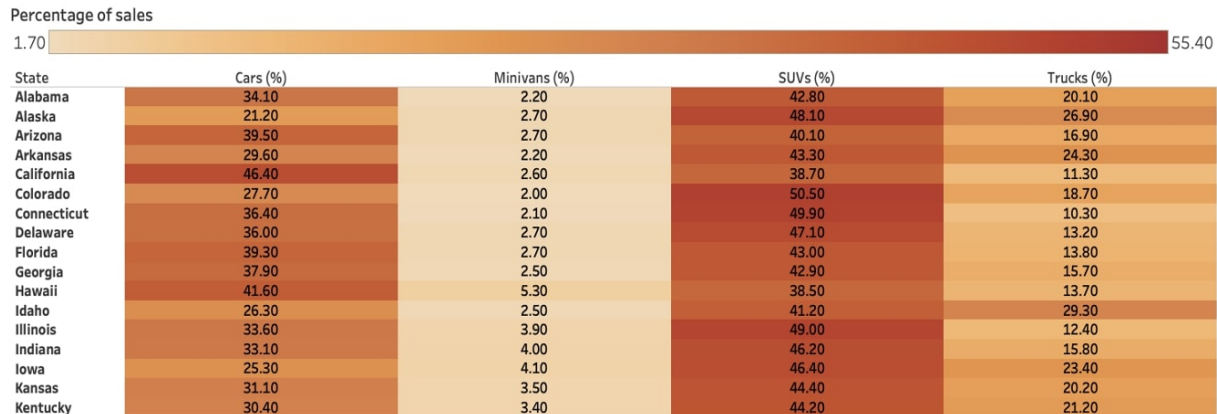


Figure S7: Vehicle type distributions in a few sample states. Darker colors mean more vehicles.

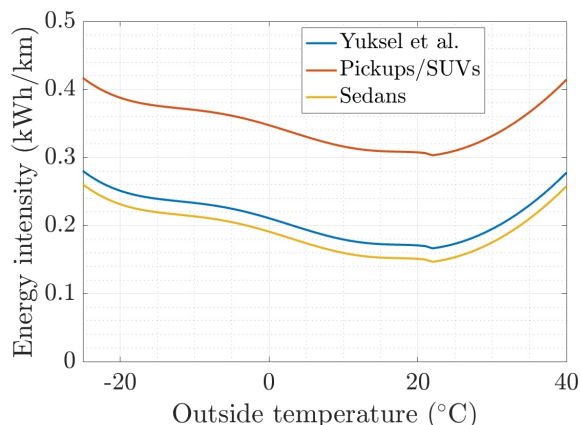


Figure S8: The energy intensity of driving depends on both the vehicle type and the outdoor temperature.

4 Model validation

For space heating, we validate EDGIE's model against two ResStock scenarios: (a) the high efficiency scenario for colder regions, where EDGIE simulates cold-climate heat pumps, and (b) the low efficiency scenario for warmer regions, where EDGIE simulates heat pumps that are not specifically designed for cold-climate efficiency. EDGIE's space heating model has also been validated against field data from an all-electric test house in Indiana¹⁷. For space cooling, we validate EDGIE's model in all regions against the high efficiency scenario from ResStock. This reflects our underlying assumptions that people in warmer regions will adopt heat pumps that are efficient for cooling but not necessarily for cold-weather heating, and that people in colder regions will adopt heat pumps that are efficient for both cooling and cold-weather heating. All ResStock results in this study are based on the 2022.1 release.

Fig. S9 compares EDGIE and ResStock estimates of peak electricity demand from space heating (top) and cooling (bottom) in five locations across diverse climates. Fig. S10 compares EDGIE and ResStock estimates of the overall peak electricity demand from all devices other than electric vehicles in the business-as-usual (top) and all-electric (bottom) scenarios. Fig. S9 includes only space heating and cooling, while Fig. S10 also includes water heating and miscellaneous electrical loads. The comparison in Fig. S10 does not include electric vehicles because they are currently not modeled in ResStock. While we do not expect the EDGIE and

ResStock results in Figs. S9 and S10 to match exactly – ResStock and EDGIE use different mathematical models, use different input data, and make different assumptions about equipment and behavior – the two modeling approaches show reasonably good agreement. The models show the same broad trends, and agree well in the colder climates (Indiana and Minnesota), where space heating dominates demand peaks. EDGIE results are based on 1,000-home simulations. ResStock’s sample sizes vary by location: 16,949 homes in Minneapolis, MN; 27,118 in Seattle, WA; 5,085 in Santa Rosa, CA; 43,100 in Indianapolis, IN; and 91,283 in Houston, TX.

5 Device coordination

Other studies have suggested that device coordination can enable load growth due to electrification without raising electricity prices. For example, one study suggested that electric vehicle adoption with coordinated charging can increase utility energy sales more than it increases the costs of transmission and distribution¹⁸. Here we investigate joint coordination of electric vehicle charging with space conditioning and water heating.

In the all-electric scenario, housing units have electric vehicles, heat pumps, and water heaters. The device coordination strategy adjusts operation of these machines to minimize their peak aggregate demand while ensuring comfortable space and water temperatures and fully charged electric vehicles by morning commute deadlines. The heat pumps and water heaters can adjust their temperature setpoints, while the electric vehicles can adjust their charging powers. Globally optimal setpoints and charging powers are computed using convex optimization with perfect forecasts and knowledge of all model parameters. Fig. S11 shows the aggregate load of a New York neighborhood without (left) and with (right) device coordination over a sample week.

In the winter device coordination optimization, each household’s indoor temperature is constrained to never drop lower than 1 °C below the temperature setpoint. During heating hours, when it is cold enough outside that heat is needed to maintain comfortable indoor conditions, the indoor temperature is constrained to never rise more than 1 °C above the temperature setpoint. During non-heating hours, such as winter afternoons with mild outdoor temperatures and ample sunshine, the indoor temperature is unconstrained above. This allows indoor temperatures to drift during warm, sunny winter conditions without forcing air conditioning equipment to turn on. Similarly, in the summer device coordination optimization, the indoor temperature can never rise more than 1 °C above the setpoint; during cooling hours, it cannot drop more than 1 °C below the setpoint.

Electric vehicles follow the same driving patterns as in the simulations without device coordination. Vehicles can charge at home or at work, using Level 2 (240 V, 24-32 A) chargers at either location. They are only permitted to charge; we do not model vehicle-to-building or vehicle-to-grid discharging.

Optimizing device coordination for 1,000 homes in one county takes about one hour in Matlab using the CVX modeling language and the Gurobi solver on a 2.7 GHz Intel i7 processor with 16 GB of RAM. Optimizing 1,000 homes in over 3,000 counties would take nearly half a year with serial processing. Therefore, we varied the number of homes to assess the impact on peak demand reduction. Fig. S12 shows that in several sample locations, the percent peak reduction estimates for 1,000 homes were comparable to those for 100 homes. We therefore used 100-home optimization to compute the device coordination results. To further reduce computational burden, in each state, we ran the optimization in the most populous county and extrapolated the results to the remaining counties.

6 Sensitivity to modeling choices

This section provides information on the sensitivity analyses presented in the main paper.

Less efficient heat pumps. In the central case, heat pump efficiencies and sizing follow the methodology outlined in Sections 2.1 and 2.2. In the central case, heat pumps have COPs at -15 °C that range from 1.5 to 2 in the warmer climate zones 1-4, and from 2.2 to 2.4 in the colder climate zones 5-7. In the ‘less



Figure S9: Peak 15-minute electricity demand per housing unit (calculated by aggregating over all housing units, then taking the maximum over time) from space heating (top) and space cooling (bottom). EDGIE's space heating model is validated against ResStock's high efficiency scenario in colder regions and low efficiency scenario in warmer regions. The space cooling model is validated against ResStock's high efficiency scenario in all regions.



Figure S10: Peak 15-minute electricity demand per housing unit (calculated by aggregating over all housing units, then taking the maximum over time) in the business-as-usual (top) and all-electric (bottom) scenarios. EDGIE's space heating model is validated against ResStock's high efficiency scenario in colder regions and low efficiency scenario in warmer regions. The space cooling model is validated against ResStock's high efficiency scenario in all regions.

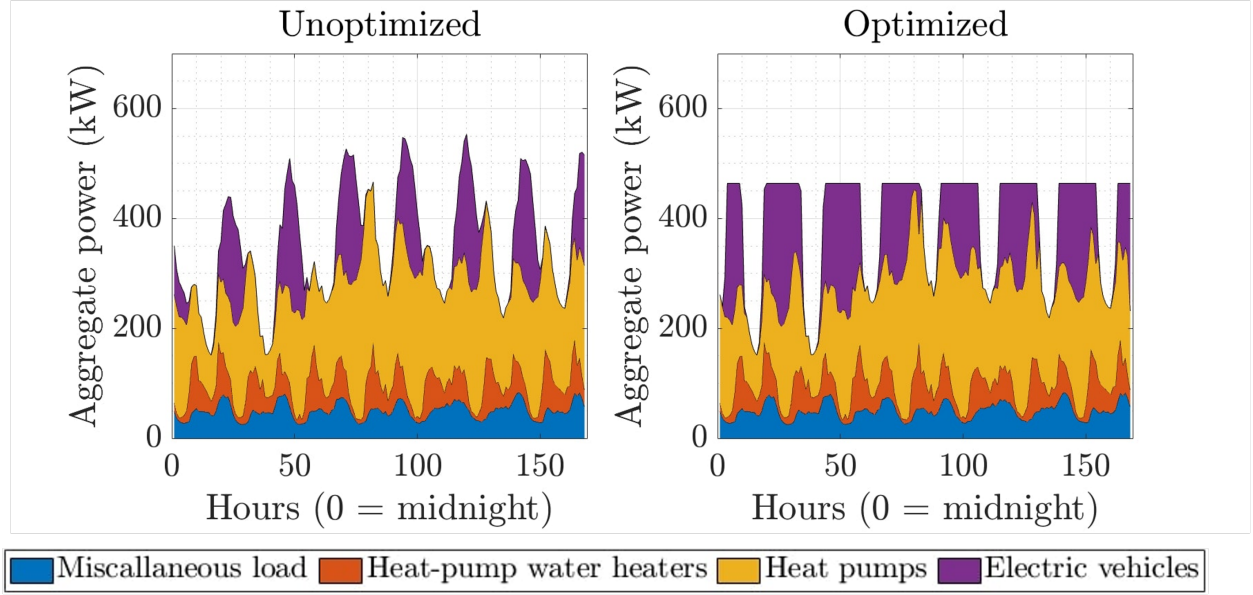


Figure S11: Peak shaving through device coordination.

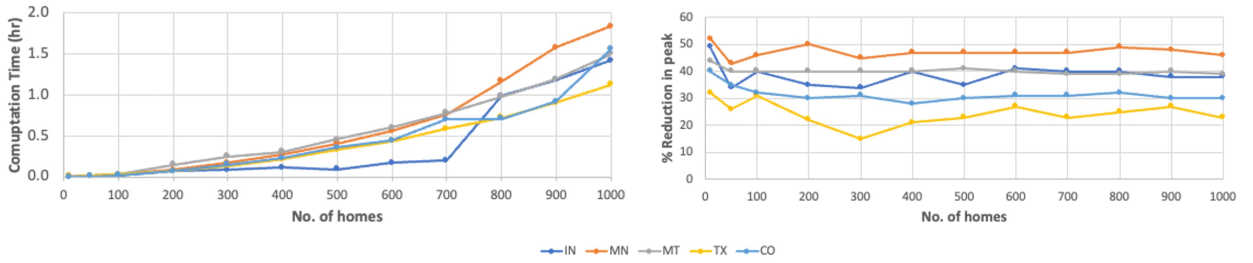


Figure S12: Computation time and peak demand reduction vs. the number of homes included in the device coordination optimization.

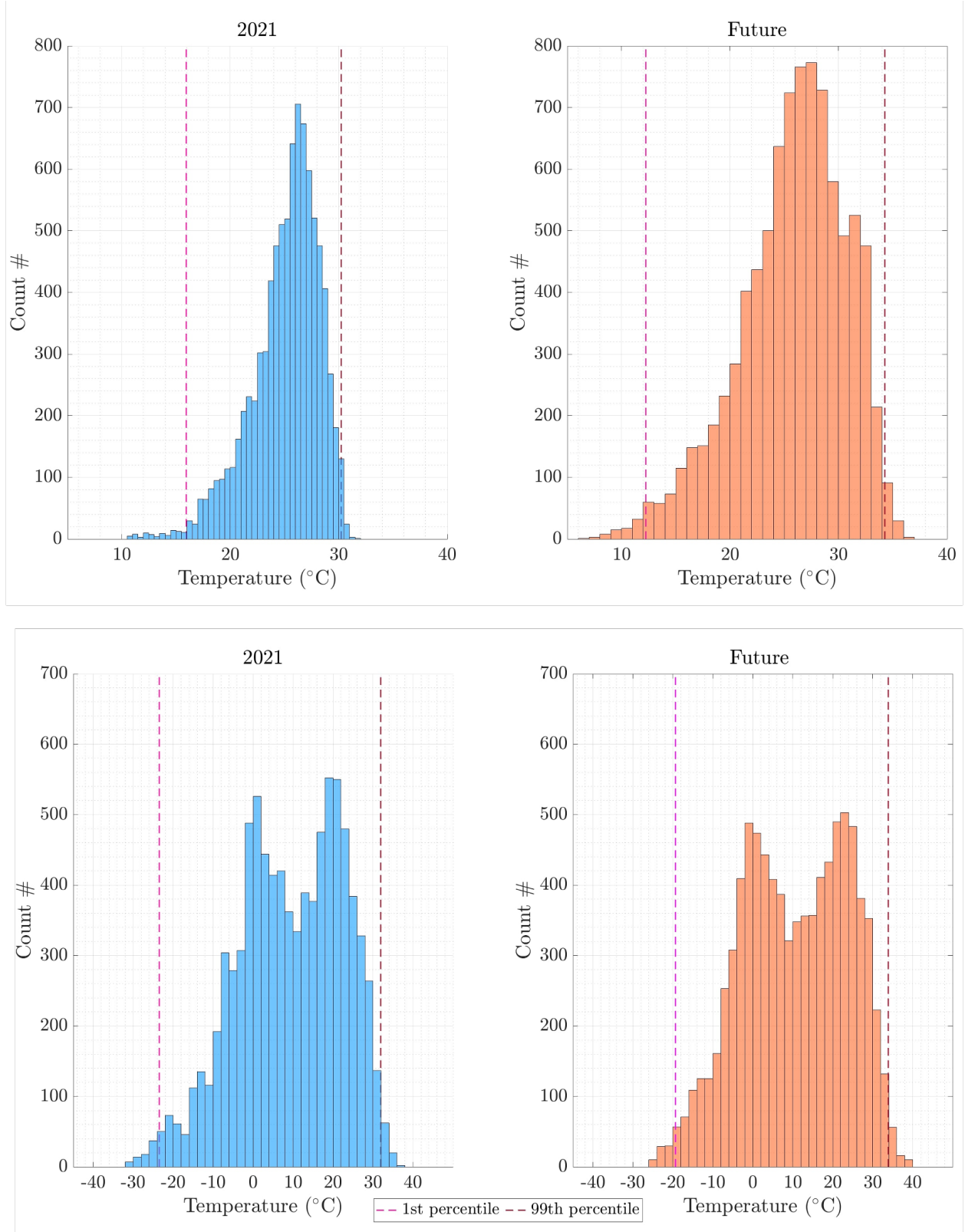


Figure S13: Historical and possible future outdoor temperature histograms in Miami, Florida (top row)(hot and humid with design heating temperature: 9 °C; design cooling temperature: 34 °C) and Minneapolis, Minnesota (bottom row)(cold with design heating temperature: -23 °C; design cooling temperature: 31 °C). The dashed magenta lines are the first and 99th percentiles.

efficient heat pumps’ sensitivity case, COPs at -15°C range from 1.1 to 1.5 for climate zones 1-4, and from 1.5 and 1.8 in climate zones 5-7. In all cases and climate zones, each heat pump’s COP is modeled as an affine function of the outside temperature.

Heat pumps sized for cooling. In the central case, heat pumps are sized to the larger of the design heating load or the design cooling load. In the ‘heat pumps sized for cooling’ sensitivity study, all heat pumps are sized to the design cooling load.

Lower temperatures overnight. In the central case, users maintain time-invariant indoor temperature setpoints. In the sensitivity case where users adjust space heating temperature setpoints overnight, they lower setpoints between 10 and 11 PM and raise them between 7 and 9 AM. Setpoint adjustment magnitudes vary from 1 to 3°C .

Future weather. When simulating the central case, we used historical weather data from 2021. In the sensitivity study, we used SSP2-RCP4.5 weather files from¹⁹ for the 2040–2059 epoch. Fig. S13 shows the outdoor temperature distributions in the historical (left) and future (right) weather data in Miami, Florida (top; hot and humid) and Minneapolis, Minnesota (bottom; cold). In Miami, future temperatures rise significantly, with a 99th percentile of 34°C (4°C higher than in the historical data). The future temperature distribution also has a heavier right-hand tail, suggesting an increased likelihood of extreme heat and a higher peak demand from air conditioning. For Minneapolis, the 99th percentile rises 32 to 34°C , a milder increase than in Miami. The 1st percentile rises from -24 to -20°C , suggesting a decreased likelihood of extreme cold and a lower peak demand from space heating. Other future weather scenarios could be simulated to deepen understanding of how climate change may influence grid reinforcement requirements.

Time steps. In the central case, all simulations use a one-hour time step. In a sensitivity study with 15-minute time steps, the peak aggregate demand from a 1,000-home neighborhood rose less than 1% relative to the peak aggregate demand under the same boundary conditions with a one-hour time step.

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