Evaluating Power Control Strategies for Avoiding Residential Panel Upgrades in Cold Climates

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ABSTRACT

Residential electrification is increasing household electricity demand through adoption of heat pumps, electric water heaters, and electric vehicle chargers. Many homes still rely on 100–200 A service panels, which can be inadequate for simultaneous operation of electrical loads, making panel upgrades costly and a barrier to electrification. This work develops a residential simulation framework that integrates simplified thermal, HVAC, water heating, EV charging, and miscellaneous load models to evaluate the impact of different electrification scenarios as well as the success of power control system strategies.

Simulation results show that unmanaged operation frequently exceeds a 100 A panel limit especially when space heating is electrified. HVAC-only control can keep current below the limit but often cause unsatisfactory indoor conditions during the coldest days. In contrast, coordinated multi-device control reduces peak current by up to 70% with respect to the no-control baseline simulation, while maintaining indoor temperatures within comfortable bounds for nearly all scenarios. These findings demonstrate that intelligent load coordination can substantially defer or eliminate the need for panel upgrades in electrified homes.

Introduction

Many households use fossil-fueled technologies for driving, space heating, water heating, cooking, and clothes drying. Electrifying these end uses through technologies such as heat pumps (HPs) for heating, ventilation, and air conditioning (HVAC), electric resistance water heaters (ERWHs), and electric vehicles (EVs) offers a major opportunity to reduce greenhouse gas emissions and improve air quality (Delmastro and Chen 2023). However, widespread building electrification substantially increases electricity demand and can introduce new stresses on both building-level electrical infrastructure and upstream distribution systems.

At the residential level, the coincident operation of multiple high-power loads can exceed the capacity of existing service equipment, including the service panel, feeders, and branch-circuit conductors. Under the National Electrical Code (NEC), these components must be sized to safely accommodate the new electrical loads, described in NEC Article 220 National Fire Protection Association (2023). As a result, electrification often necessitates upgrades to service equipment to remain within these ratings.

This capacity limit is particularly pronounced in older housing stock. A substantial portion of homes were constructed when electric end-use adoption was limited, and many have service panels rated at 100 A or less. These panels may be insufficient to support simultaneous operation of electrified space heating, water heating, and EV charging (National Fire Protection Association 2023). Recent estimates suggest that more than 20 million homes in the United States may require electrical panel upgrades to accommodate full electrification under more traditional panel sizing methods, as in NEC Article 220.82 (National Fire Protection Association 2023), and without coordinated load control (Lindsey 2023). Without such upgrades, electrified homes may experience nuisance tripping of overcurrent protection devices (e.g., branch circuit breakers) or, in more severe cases, conductor overheating. However, upgrading electrical infrastructure typically requires replacement of the service panel and associated equipment, with reported costs ranging from $2,000 to $10,000 per household (Flores et al. 2024), making it a significant barrier to electrification.

An alternative to infrastructure upgrades is to coordinate the operation of major electrical loads so that total household current remains within the service rating by NEC Article 750.30 (National Fire Protection Association 2023). Power control systems can regulate device operation to limit coincident demand and maintain compliance with electrical constraints. Prior work has demonstrated the feasibility of such approaches using advanced model-based controllers that coordinate loads including HVAC systems, EV charging, and electric water heating (Pergantis et al. 2025a,b). While effective, these approaches often require detailed system models, forecasts, and centralized optimization, which may limit their practicality for widespread residential deployment.

The applicability of simpler, market-ready power control strategies across diverse appliance combinations and household configurations has not been systematically evaluated. In particular, heuristic or rule-based control strategies – commonly used in commercially available devices – remain underexplored in the context of whole-home current limiting. This study addresses this gap by developing a residential electrification simulation testbed to systematically evaluate power control strategies under a wide range of scenarios. The analysis focuses on cold-climate conditions, where electrification places the greatest stress on electrical infrastructure due to high space-heating demand. In these regions, many homes continue to rely on gas heating and therefore often have lower service capacities, further increasing the likelihood of electrical constraints during electrification.

Related Work

Recent work has examined how residential electrification may strain existing electrical infrastructure. Murphy et al. (2026) analyzed service panel capacities across U.S. single-family homes and found that while many residences have 200 A panels, roughly one-third retain 100 A or less. Lower-capacity panels are especially common in older and lower-income homes, and in colder regions such as the Northeast and Great Lakes. Although some homes have modest headroom, many lack sufficient breaker space or wiring capacity to support additional high-power loads.

Similarly, Less and Walker (2026) emphasized that electrical panel constraints can impede electrification retrofits even when nameplate capacity appears adequate. In particular, limited breaker slots or insufficient wiring often prevent installation of EV chargers or electric water heaters, indicating that panel-related barriers may become increasingly widespread as electrification accelerates. The authors further highlighted several potential pathways to mitigate these constraints, including higher-efficiency equipment, circuit-sharing devices, and control strategies that limit whole-home current below service ratings. However, the effectiveness of such control-based approaches across a wide range of residential electrification scenarios remains largely unexplored.

The present study thereby evaluates a range of practical power control system strategies within a residential electrification simulation testbed. The framework enables systematic analysis across multiple appliance combinations and household configurations. Particular emphasis is placed on cold-climate scenarios, where heating loads are high and electrification poses the greatest challenge to existing electrical infrastructure. To this end, a set of representative single-family detached buildings is modeled in the Northern U.S., in the IECC climate zone 5A.

The remainder of the paper is organized as follows. First, the simulation test bed is introduced. The main models used for space heating (building envelope and equipment), water heating (tank and heater), EV operation (battery and commute), and other household electrical loads are then described. Subsequently, the power control system formulations are presented. Lastly, a series of simulations is performed by generating different possible home-equipment configurations, such as electrifying only space conditioning or jointly electrifying space conditioning and water heating, under both uncontrolled and intervention scenarios. The paper concludes with directions for future research.

Simulation Methodology

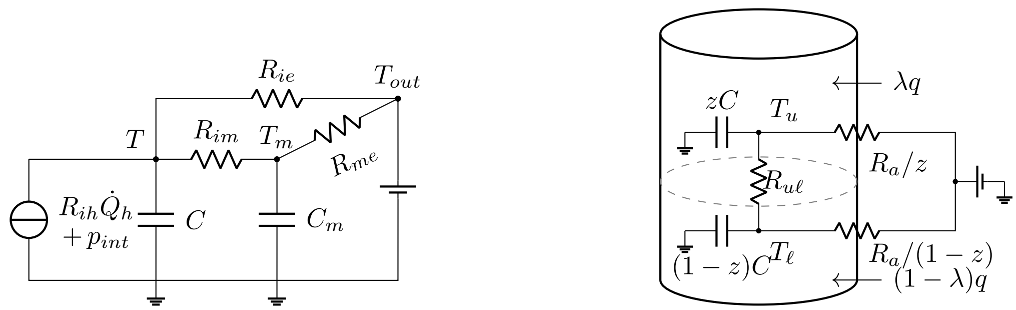
Simulation Testbed

The simulation testbed, implemented in MATLAB, represents a residential household with multiple electrified end uses. Its goal is to capture the coupled electrical and thermal behavior of major household loads under realistic conditions while remaining computationally efficient for multi-day simulations. The household model includes four subsystems: the building thermal envelope and heating system, a water heater (WH), an EV, and miscellaneous electrical loads. Household characteristics scale with occupancy, which determines building size, heating capacity, tank volume, EV usage, and background loads. Two representative household sizes are modeled: a three-occupant home (1000–1500 ft^2 / 93–139 m^2) and a five-occupant home (1800–2000 ft^2 / 167–186 m^2).

Thermal dynamics of the building and WH use resistance–capacitance (RC) models. The EV is represented with a battery energy balance, and other loads follow stochastic or time-of-day profiles. All dynamics are advanced using a forward Euler scheme with a five-minute time step, capturing short-term variations while keeping simulations tractable. At each time step, device-level electrical demand is then computed from their models.

Building Envelope and Heating Equipment

Space heating demand is modeled using a two-state RC representation of the building envelope, coupled with simplified heating equipment models. The RC network captures heat transfer between indoor air, the effective building thermal mass, and the outdoor environment (Figure 1).



(a) Building thermal RC model

(b) Two-node water heater model

Figure 1: Building envelope model (4R2C) and hot water tank model (3R2C) used in this study. The model's parameters were tuned on real-building run-time data as described in (Reyes Premer et al. 2026; Pergantis et al. 2024a,b).

The RC parameters for the building envelope and heating equipment are fitted using data from cold-climate detached homes. The two-node thermal mass representation captures indoor air and effective building mass temperatures, while resistances represent conductive and convective heat transfer. The RC values were obtained via regression against measured hourly temperature and heating energy data. Resistances R_{im}, R_{ie}, R_{me} represent interior–mass, interior–exterior, and mass–exterior pathways, while C and C_m are thermal capacitances of the air and effective building mass.

Furnace ratings were obtained based on standard square footage correlations. Subsequently, the simulated equipment configurations were: a) gas furnace, b) single-stage strip heat ("electric furnace") that matched the output capacity of the gas furnace, c) two-stage strip heat, with each stage delivering half of the total capacity d) a single-stage HP, with two stages of strip backup heat, with the backup heat being sized as described before to meet the full building design load in the case when the HP is going through a defrost cycle or not operational, a widely applied practice especially for non-cold climate HPs. The HP maximum operating power and coefficient of performance (COP) are adapted from (Pergantis et al. 2024b).

In the case of heat pump (HP) operation, defrost cycles are modeled as demand-based events with a fixed minimum delay between cycles. A Gaussian–logistic function represents the likelihood of defrost as a function of ambient temperature, capturing that defrost cycles do not occur above a threshold temperature and are most frequent under freezing conditions with high moisture availability. At lower ambient temperatures, the frequency of defrost cycles decreases due to reduced moisture availability in the air. This offers a simple non-mechanistic model for defrost cycles. Then, during defrost, two possible policies are considered: an aggressive comfort-based policy that always requires the maximum amount of backup heat to be in place to avoid cold blow, and a conservative policy that only uses the first stage of strip heat during defrost cycles. For the translation to electrical loads, resistive loads are considered to have a power factor of one, while for motor-based equipment (compressor, fan), the power factor is assumed to be 0.8.

In all scenarios, the thermostat controls were simulated, with hysteresis in place for the single- and two-stage equipment, while for the HP, a Proportional-Integral controller manages strip heat usage based on the real-time temperature tracking error, with appropriate staging and delays. In terms of the indoor setpoints, two possible cases are considered: a constant hold of 21 °C at all times and a nighttime setback setpoint between 11 PM and 3 AM of 18 °C, with the same hold as before the rest of the time. Setbacks were incorporated to evaluate the effect of coinciding events by reducing the heat demand overnight, thereby reducing the run-time of HVAC equipment overnight.

Domestic Hot Water Model

The domestic hot water supply is modeled using a two-node thermal representation of the tank (Fig. 1), which captures the stratification between upper and lower water layers. Four types of WHs are considered: gas-based, ERWH, 240 V hybrid heat pump water heaters (HPWH) and 120 V HPWHs. The 240 V hybrid HPWH includes both a heat pump and electric resistance elements for backup heating. The resistance elements are modeled with the same capacity as the ERWH, consistent with common configurations of 240 V hybrid HPWHs in the market Rheem (2024). The 120 V HPWH is modeled as a heat pump–only configuration without resistance elements, using the same compressor capacity as the 240 V unit Rheem (2024). Temperature control is implemented via a simple heuristic logic. Temperature control is implemented using simple heuristic logic. For systems with a single heating source, a deadband controller activates heating when the upper-node temperature drops 10 °F (5.5 °C) below the setpoint. For the 240 V hybrid HPWH, the heat pump operates using the same deadband as single-source WHs, while a secondary deadband at 20 °F (11 °C) below the setpoint activates the electric resistance elements. HP operation is characterized using a manufacturer-provided COP map as a function of ambient temperature and lower-node tank temperature (i.e., the condenser location). Electric resistance heating is assumed to be 95% efficient. The model accepts user draws in L/min and outputs upper- and lower-node temperatures, heat delivered, and electrical power demand.

The thermal and operational parameters of the WH models are summarized in Table 1. Tank sizing is correlated with occupancy, and element capacities reflect typical residential equipment ratings. The specific tank model parameters (insulation etc.) can be obtained in (Reyes Premer et al. 2026). Unlike space heating, for water heating, the tank size is scaled but not the total capacity, effectively increasing equipment run-times. For the five occupant home, an 80 gallon (303 L) tank is used. The target water setpoint is 49 °C (120 °F) for gas, ERWH, and 240 V hybrid HPWH systems. For the 120 V HPWH, the setpoint is increased to 60 °C (140 °F), reflecting common practice to maintain sufficient thermal capacitance in the absence of electric resistance backup.

Table 1: Water heater tank and equipment characteristics for representative configurations.

Type	Occupants	Water Volume (gal / L)	Upper Node Fraction z	Elec. Res. Capacity (kW)	HP Capacity (kW)
GAS	3 | 5	45 / 169 | 72 / 272	0.5	-	-
ERWH	3 | 5	45 / 169 | 72 / 272	0.5	4.5	-
120V HPWH	3 | 5	45 / 169 | 72 / 272	0.5	-	0.45
240V hybrid HPWH	3 | 5	45 / 169 | 72 / 272	0.5	4.5	0.45

Hot water draw profiles were obtained from the Building America Analysis Spreadsheets, which provide event-level residential water-use data including fixture draw timing, duration, and flow rates (U.S. Department of Energy 2011). Only the hot-water component was used, with representative profiles selected for 3- and 5-bedroom homes. The event data were converted to a continuous 5-minute time series by aggregating draw volumes within each interval and expressed as average draw rates (L/min) for model input.

Electric Vehicle Model

Apart from space and water heating, the other major electrical load is at-home vehicle charging. In these simulations, one vehicle (or none) is assumed to be in place per home. In future work, this will be extended to two vehicles per home. In all the simulations, charging is assumed to be available only at home, a scenario that increases the challenge of the power control system. Three scenarios of EV charging are considered: no charging (no EVs), level-I charging (1.9 kW, 120 V), and level-II fast charging (10 kW, 240 V).

The EV charging behavior is modeled using a simple battery energy balance, incorporating self-dissipation, charging efficiency, and driving consumption (Paterakis et al. 2015; Priyadarshan et al. 2024). The full set of EV parameters is provided on Table 2 (U.S. Census Bureau 2024; Priyadarshan et al. 2024).

Table 2: Key EV fleet parameters used in simulations

Parameter	Symbol / Units	Typical Value / Range
Battery energy capacity	$\overline{E}$ [kWh]	70
Minimum state-of-charge	E_{min} [%]	15
Initial state-of-charge	E_0 [%]	40–70
Level I charging power	P_{L1} [kW]	1.9 (120 V)
Level II charging power	P_{L2} [kW]	10 (240 V)
Charging efficiency	η [-]	0.9–0.95
Self-dissipation rate	r [1/h]	$8{\cdot}10^{-4}$
One-way commute time	t_{commute} [min]	25–60
Average speed	v [mph]	20–25
Energy consumed per leg	E_{leg} [kWh]	4–8

Rest-of-home Loads

The methodology presented thus far establishes models for the three primary residential electrical loads considered in this study: HVAC, WHs, and EV charging. Other household devices – including plug-in appliances, dishwashers, dryers, cooktops, and washing machines – are aggregated into a single category referred to as “rest-of-home” loads. Although these devices can potentially provide load-shifting flexibility (Salpakari and Lund 2016), accurately modeling their controllability would require a detailed representation of appliance scheduling and associated occupant comfort constraints. Furthermore, their peak current magnitudes and durations are typically smaller than those actively controlled in this study. As a result, these loads are treated as exogenous inputs to the simulation framework.

The “rest-of-home” load profiles were obtained from the Pecan Street sub-metered residential dataset for homes located in New York (Pecan Street Inc.). The raw dataset provides 1-minute time-stamped, circuit-level power measurements (kW) for each home, along with split-phase voltage measurements from the two service legs. Circuits associated with space conditioning (air-conditioning, furnaces, and electric heaters), EV charging, and WH were excluded to isolate “rest-of-home” consumption. The aggregate “rest-of-home” power profile was then resampled to 5-minute.

Representative ”rest-of-home” load profiles were selected using summary metrics of daily energy use and peak demand as a proxy for occupancy. Following screening to exclude atypical loads, one profile each was chosen to represent the 3- and 5-occupant cases, corresponding to lower- and higher-demand households. From each profile, a representative week with both high energy use and peak demand was selected. This conservative approach assumes that these peak load conditions coincide with the coldest weather week used in the simulation, resulting in a more challenging control scenario.

Control Algorithms

This section describes the power control strategies used to prevent violations of a prescribed service panel current limit. Since residential panels are rated in amperes, the controller operates on total household current. Assuming balanced 120 V loads across the split-phase system, total current is inferred from the aggregate real power measured at the main service by dividing by 240 V. The objective of all control strategies is to ensure that total household current does not exceed a safety threshold, I_{limit}, while minimizing occupant discomfort and disruption to end uses.

At each simulation timestep, the controller evaluates the non-controllable base load I_{rest} and the requested currents from each controllable device: HVAC $I_{\text{HP,req}}$, EV charging $I_{\text{EV,req}}$, and water heating $I_{\text{WH,req}}$. The total requested current is given by

$$I_{\text{total,req}} = I_{\text{rest}} + I_{\text{HP,req}} + I_{\text{EV,req}} + I_{\text{WH,req}} \tag{1}$$

If $I_{\text{total,req}} \leq I_{\text{limit}}$, all devices are permitted to operate. Otherwise, device-level lockout decisions are applied based on the selected control strategy.

The implemented strategies range from single-device, threshold-based lockout to coordinated multi-device priority allocation. The single-device approaches are intended to emulate decentralized current-limiting strategies that could be implemented by equipment manufacturers or by a third party. Both would require using measurements of total household current. Coordinated, centralized control is also evaluated as a progression from single-device control in scenarios with limited electrical capacity, where maintaining occupant comfort becomes more challenging.

Electric vehicle control. In the EV-only control mode, the electric vehicle charger is treated as the sole controllable load. If total requested current exceeds the safety limit, $I_{\text{total,req}} > I_{\text{limit}}$, the EV charger is immediately locked out. All other devices continue operating without modification. This strategy implements a simple binary peak-shaving rule in which EV charging is treated as fully deferrable load where no modulation of the EV charging rate is available.

Electric heating. In the heating-only control mode, the HVAC system is treated as the controllable device. If the heating system is active and $I_{\text{total,req}} > I_{\text{limit}}$, the HVAC is temporarily locked out. If heating is inactive, or total current is below the threshold, no lockout is applied. For multi-stage systems, higher-power stages are curtailed first, allowing lower stages to operate when possible.

Water heater. In the WH control mode, electric water heating is treated as the only controllable load. When the heater is drawing power and total requested current exceeds the safety threshold, the WH is locked out. If no heating element is active, no action is taken. Although electric water heaters may include multiple heating stages, these are typically internally controlled and not easily accessible by a third party; therefore, the model assumes the water heater is either fully disconnected or allowed to operate.

Multi-device control. The multi-device controller represents a centralized controller in which there is any two or more combination of the EV, electric heating, or electric water heating. This controller implements a priority-based greedy allocation algorithm when multiple controllable devices are present. Rather than assigning fixed device precedence, the algorithm dynamically computes a priority score for each controllable load at every timestep. The multi-device controller assumes observability of key system states, such as the in-tank WH temperatures, the indoor temperature and setpoints as well as the EV SOC and departure times.

Each device is assigned a scalar priority score based on comfort and operational urgency:

- HVAC priority: Based on temperature deviation between the setpoint temperature in the home and the indoor temperature. Larger comfort violations increase priority.
- EV priority: Based on time-to-departure and state-of-charge ratio. Imminent departure with low SOC increases priority.
- WH priority: Assigned highest priority when hot water draw is detected.

A small persistence bonus is added to scenarios that have a heat pump and are currently operating to avoid short cycling. We then implement a greedy allocation logic as per Alg. 1. If no device fits within the available budget, only the highest-priority device is allowed to operate if feasible. In each configuration, priority scores are computed only for active controllable devices.

Results

The simulations were conducted over a seven-day period corresponding to the coldest week from the 2024–2025 winter in West Lafayette, Indiana. An electrical panel of 100 A is assumed to be in the house, there for per NEC Article 220.70 and 750.30(c) National Fire Protection Association (2023) the limit for the power control system must be 80% of the panel rating, thereby providing a limit to of 80 A. To first determine which electrification scenarios are susceptible to electrical panel upgrades, a baseline simulation was performed without any power control system. Figure 2 presents the resulting maximum current for the range of electrification scenarios considered. The scenario space includes combinations of HVAC electrification options, WH technologies, EV ownership levels, and household occupancy levels, which together produce a wide range of electrical demand profiles.

Algorithm 1 Priority-Based Current Allocation

Input: Current limit, rest-of-home current, current for each controllable device, and priority score for each controllable device
Initialize: Used current
Total current $\leftarrow$ rest-of-home current + current from all controllable devices
if total current is less than or equal to the current limit **then**
    Allow all controllable devices to operate
    return
end if
Available current budget $\leftarrow$ current limit $-$ rest-of-home current
Sort controllable devices from highest priority to lowest priority
for each controllable device, in order of priority **do**
    if device current is less than or equal to the remaining current budget **then**
        Allow the device to operate
        Used current^{+} $\leftarrow$ used current^{-} + device current
    else
        Lock out the device
    end if
end for
Output: Device operation and lockout decisions

The results indicate that the primary driver of maximum current draw is the electrification of space heating. Furthermore, when the design heating load is larger, as in the five-occupant household, the resulting maximum current increases substantially. Consequently, the analysis of power control strategies focuses primarily on scenarios in which the HVAC system is electrified.

Figure 3 presents the maximum current for the electrification scenarios under four different control strategies: water heater control only (Fig. 3a), EV control only (Fig. 3b), HVAC control only (Fig. 3c), and multi-device control (Fig. 3d). Each point represents the maximum current observed during the seven-day simulation for a single electrification scenario.

Figure 3a depicts how water-heater-only control provides limited reduction in maximum current. In a small number of scenarios—primarily those corresponding to the three-occupant household with a lower design heating load—panel upgrades can be avoided. However, the overall impact is minimal, and many scenarios still exceed the 100 A panel rating.

Figure 3b demonstrates how EV-only control provides somewhat greater mitigation. A larger number of scenarios for the three-occupant household can avoid panel upgrades compared to water-heater-only control. Nevertheless, this strategy remains insufficient for higher heating loads, and no panel upgrades for a 100 A panel can be avoided for the five-occupant household.

In contrast, Figure 3c highlights how HVAC-only control is able to maintain the maximum current below the panel rating across all scenarios. In a few cases the current slightly exceeds the NEC 80% continuous-load guideline, but these violations occur only for brief periods (less than 15 minutes). While this strategy effectively mitigates peak electrical demand, it does so by interrupting space heating, which can lead to reductions in indoor thermal comfort. This tradeoff is examined further in the subsequent analysis.

In Figure 3d, multi-device control coordinates the operation of multiple flexible loads, such

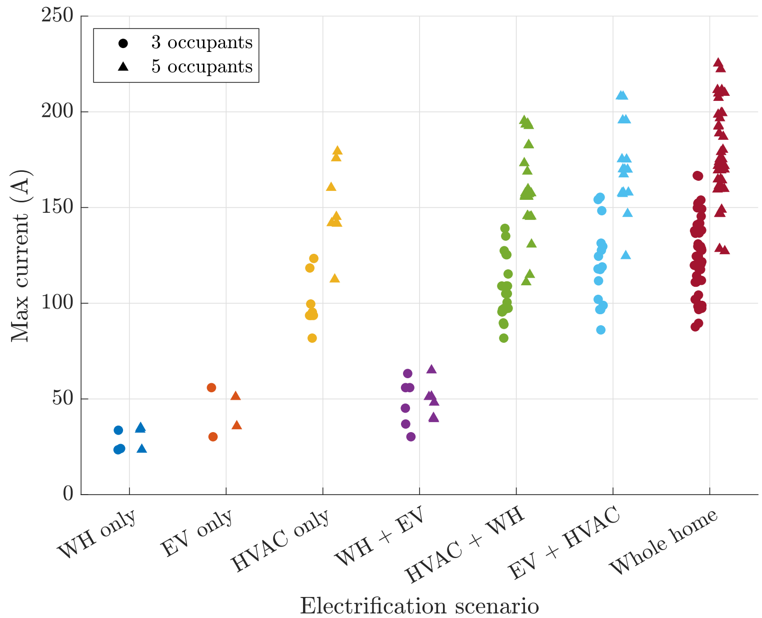


Figure 2: The maximum current for each scenario under various electrification levels. In each electrification scenario there is a combination of equipment types. In addition, for each electrification scenario, the points are categorized between circles and triangles for the 3 occupant and 5 occupant households respectively. Scenarios where the HVAC is electrified has the greatest impact on maximum current.

as the EV charger and HVAC system. By dynamically prioritizing loads, this strategy maintains the maximum current below the panel rating for both the three-occupant and five-occupant households. Compared with HVAC-only control, multi-device control also provides greater operational flexibility, enabling the system to reduce peak demand while improving occupant comfort in some scenarios.

Given that both HVAC-only control and multi-device control are capable of preventing panel upgrades, the remaining question is how these strategies affect occupant comfort. Across all simulated scenarios, domestic hot water temperatures remained within a comfortable range, and EV charging maintained a state of charge above 70% at 7:00 AM, ensuring adequate vehicle readiness for morning departures. Consequently, the primary source of potential discomfort arises from reductions in indoor air temperature due to interruptions in space heating during periods of high electrical demand. The following section therefore examines the indoor thermal comfort implications of HVAC-only and multi-device control.

Figure 4 evaluates the thermal comfort implications of the control strategies that were shown to mitigate electrical panel upgrades. The figure presents two cases: HVAC-only control (Figure 4a) and multi-device control (Figure 4b). Each subfigure is organized as a grid of electrification scenarios, where rows represent combinations of water heating technology and EV ownership level, and columns represent HVAC system type. Separate panels are shown for the three-occupant and five-occupant households.

In each grid cell, the color indicates the minimum indoor air temperature reached during the seven-day simulation period, while the number printed within the cell represents the maximum

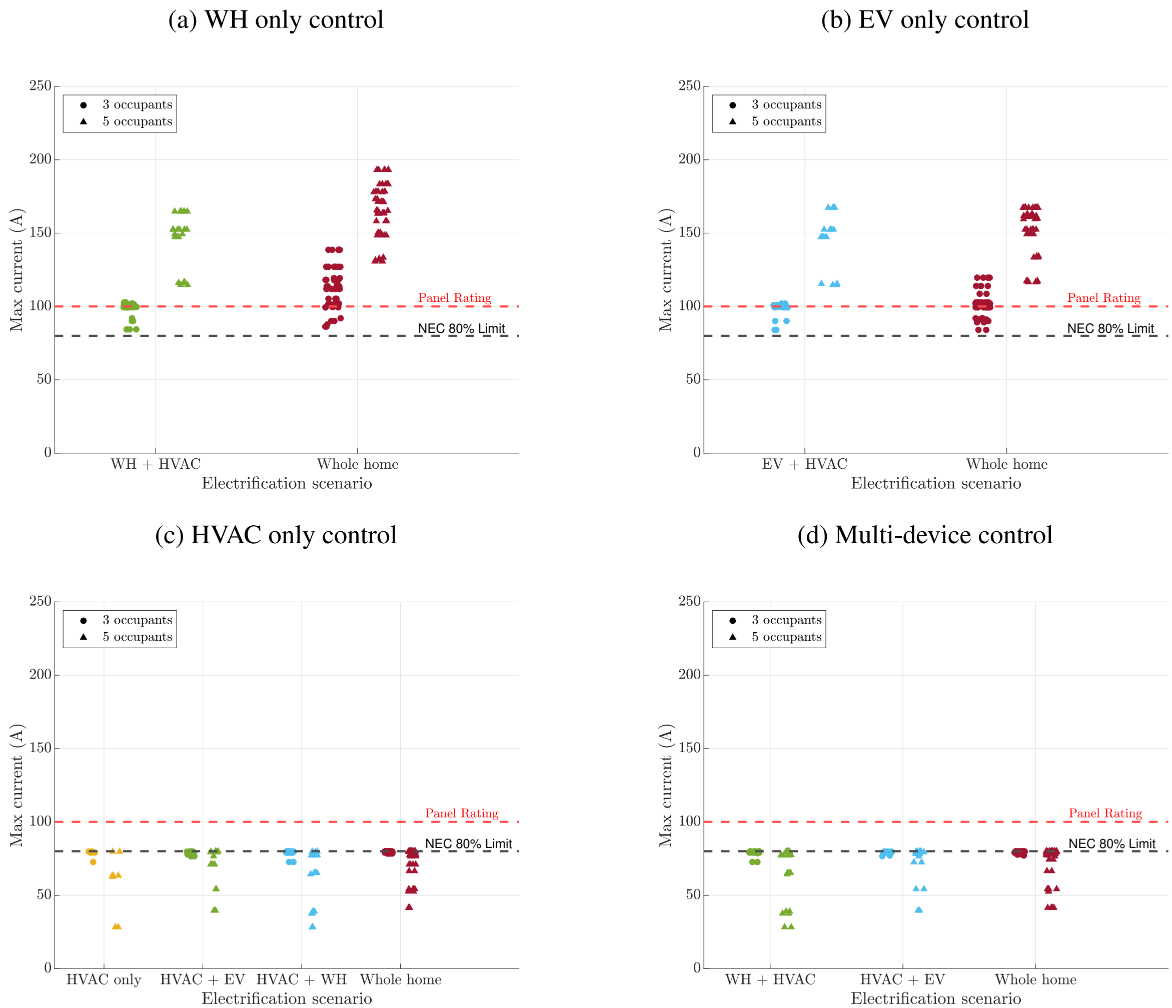


Figure 3: Maximum current for the various electrification scenarios under different control strategies.

current observed for that scenario. This visualization therefore simultaneously conveys both the electrical constraint satisfaction and the resulting thermal comfort performance.

For the HVAC-only control case (Figure 4a), thermal comfort is generally maintained for many scenarios in the three-occupant household. However, several cases experience significant temperature reductions, particularly when a Level 1 EV charger is present together with single-stage electric resistance heating. In these scenarios, the control strategy frequently disables the heating system to maintain the electrical current below the panel limit, resulting in substantial indoor temperature drops and occupant discomfort.

The five-occupant household exhibits substantially worse comfort performance under HVAC-only control due to the larger design heating load. Nearly all scenarios experience uncomfortable indoor temperatures during the cold-weather period. The most severe cases occur for single-stage and two-stage electric resistance heating systems, where minimum indoor temperatures fall well below typical comfort thresholds. Heat pump systems with electric resistance backup perform somewhat better, particularly when using aggressive or conservative strip-heating control strategies, but still experience noticeable reductions in indoor temperature during periods when heating

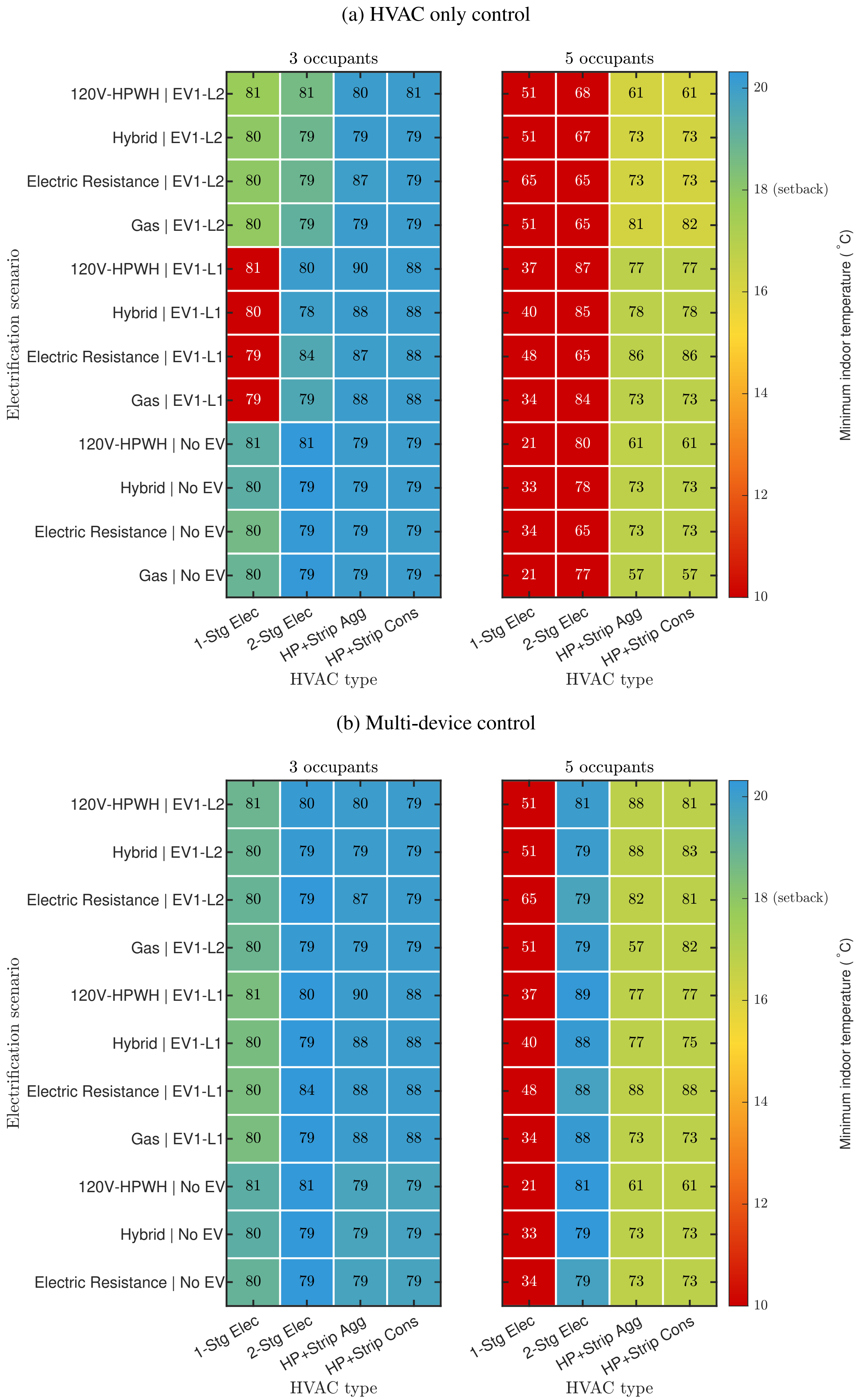


Figure 4: Thermal discomfort under HVAC only and multi-device control. Cell color indicates minimum indoor temperature, while the value inside each cell shows the maximum current for the scenario.

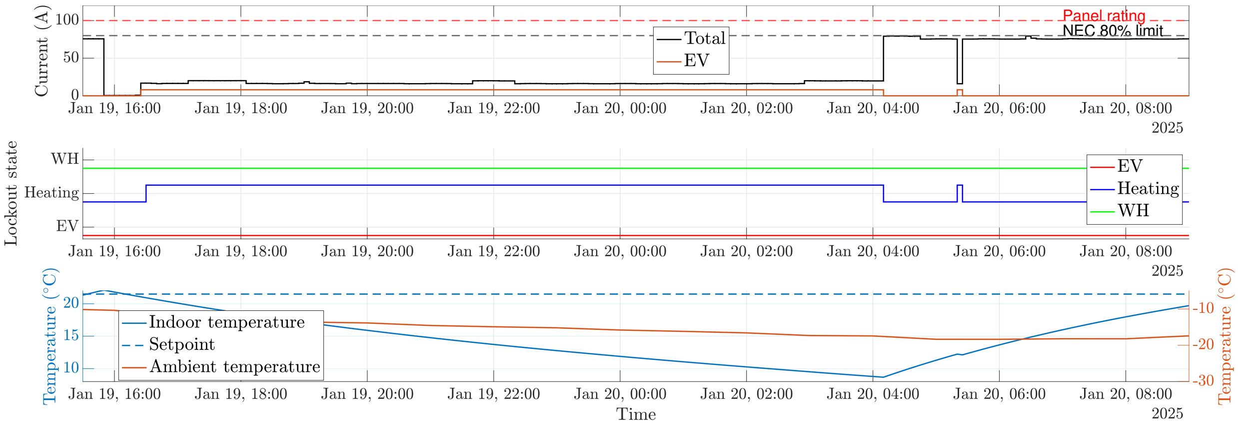


Figure 5: Time series figure of HVAC only control.

must be curtailed to maintain the electrical constraint.

Multi-device control (Figure 4b) improves thermal comfort by providing additional flexibility to manage electrical demand. For the three-occupant household, all scenarios maintain indoor temperatures within a comfortable range. In particular, scenarios that previously experienced discomfort under HVAC-only control—such as those with Level 1 EV charging and single-stage electric resistance heating—are now able to maintain acceptable indoor temperatures.

For the five-occupant household, multi-device control also provides substantial improvements. Two-stage electric resistance heating systems now maintain indoor temperatures within a comfortable range, whereas these scenarios previously experienced large temperature reductions under HVAC-only control. However, some scenarios remain challenging. In particular, homes with single-stage electric resistance heating still experience severe comfort degradation due to the limited heating capacity and the inability to modulate operation during constrained electrical periods. Heat pump systems with electric strip backup show moderate improvement under multi-device control, although some scenarios still experience mild discomfort, with minimum indoor temperatures approaching approximately 17 °C during portions of the seven-day simulation.

Overall, these results demonstrate that while HVAC-only control can effectively maintain electrical demand below the panel rating, it does so at the expense of thermal comfort in many scenarios. Coordinated multi-device control substantially improves comfort outcomes while still maintaining compliance with electrical constraints.

To further illustrate the operational behavior that leads to the comfort outcomes observed in Figure 4a, time-series examples are shown in Figure 5 and Figure 6. These figures correspond to a representative scenario with a hybrid heat pump water heater, one EV with a Level 1 charger, and single-stage electric resistance space heating in the three-occupant household.

Figure 5 shows the time-series behavior under HVAC-only control. The top panel shows the total household current draw, with the panel rating and the NEC 80% limit indicated for reference. The middle panel shows the lockout state of each flexible load, including the water heater, space heating system, and EV charger. When a device's line is elevated, that device is locked out by the control system. The bottom panel shows the indoor air temperature relative to the thermostat setpoint. The time window shown corresponds to the overnight period from approximately 5:00 PM to 9:00 AM the following morning.

In this scenario, the Level 1 EV charger operates for an extended duration overnight due to

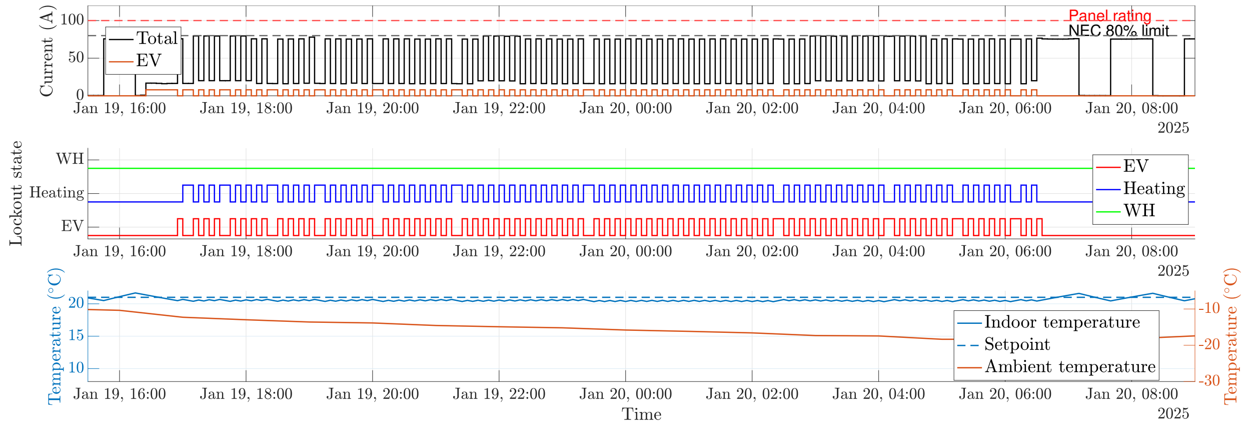


Figure 6: Time series figure of multi-device control.

its relatively low charging power. As a result, the available electrical capacity for space heating is limited for several hours. To maintain the household current below the panel constraint, the control system locks out the space heating system during this period. Consequently, the indoor temperature steadily decreases and falls below 15 °C, producing the significant comfort degradation observed in the heatmap results.

Figure 6 shows the same scenario under multi-device control. The structure of the figure is identical, but the coordinated control strategy allows the controller to dynamically prioritize loads by selectively locking out both the EV charger and the heating system when necessary. Rather than maintaining continuous EV charging, the controller alternates between EV charging and space heating operation. This coordinated scheduling maintains the total current below the panel constraint while allowing the heating system to periodically operate. As a result, the indoor temperature remains close to the thermostat setpoint throughout the overnight period, avoiding the large temperature drops observed under HVAC-only control.

One important operational consideration is that the improved comfort under multi-device control is partially enabled by increased cycling of flexible loads. While this behavior is acceptable for certain devices, excessive cycling of HVAC equipment—particularly heat pump compressors—may lead to increased equipment wear. Therefore, practical implementations of such control strategies may incorporate additional constraints on cycling frequency to balance electrical demand management with equipment longevity.

Discussion

This work demonstrates the limitations of existing single-device demand management approaches under certain electrification scenarios. Control strategies targeting only EV charging or water heating are generally insufficient to prevent electrical panel upgrades when space heating is electrified. While HVAC-only control can maintain current below the panel rating, it can do so at the expense of indoor thermal comfort when heating must be curtailed during periods of high electrical demand. These results highlight the importance of coordinated multi-device control strategies that dynamically allocate limited electrical capacity across multiple flexible loads.

The results also suggest opportunities for equipment-level design improvements that could mitigate electrical constraints. Many electric resistance heating systems operate with relatively large discrete heating stages, which can prevent operation when available electrical capacity is limited. Reducing the size of the first heating stage or segmenting electric resistance elements into smaller increments could allow partial heating operation under constrained conditions, improving both comfort and operational flexibility.

Future work should evaluate these control strategies across a broader range of electrical service ratings. Although a 100 A panel is common in many homes, existing residences frequently operate with 125 A, 150 A, or 200 A service. Assessing electrification scenarios across these panel ratings would provide a more comprehensive understanding of potential bottlenecks and the extent to which coordinated demand management can defer panel upgrades.

Conclusion

This study evaluated the ability of demand management strategies to mitigate electrical panel constraints in electrified residential buildings during cold-weather conditions. The results show that single-device control strategies are often insufficient to prevent panel upgrades when space heating is electrified, particularly in homes with higher heating loads. Coordinated multi-device control can substantially reduce peak electrical demand while maintaining acceptable levels of occupant comfort. These findings highlight the importance of integrated control strategies and equipment design considerations for enabling large-scale residential electrification without widespread electrical service upgrades.

References

C. Delmastro and O. Chen. Buildings. Technical report, International Energy Agency, July 2023.

Robert Flores, Sammy Houssainy, Weixi Wang, Khanh Nguyen Cu, Xiao Nie, Noah Woolfolk, Ben Polly, Ramin Faramarzi, Jim Maclay, Jaeho Lee, and Jack Brouwer. Addressing Building Related Energy Burden, Air Pollution, and Carbon Emissions of a Low-Income Community in Southern California. *Advances in Applied Energy*, 2024.

Brennan D. Less and Iain S. Walker. Characterizing peak electricity demand for u.s. households: an assessment of end-use loads and demand factors. *Applied Energy*, 410:127422, 2026. ISSN 0306-2619.

Douglas Lindsey. U.S. residential electrical panels: How many need to be upgraded. Technical report, EPRI, 2023.

Sean Murphy, Lixi Liu, Brennan Less, Yingli Lou, Jeff Deason, Iain Walker, and Xin Jin. Characterizing electrical panel capacity, breaker space, and loads in u.s. single-family homes. *Journal of Building Engineering*, 120:115576, 2026. ISSN 2352-7102.

National Fire Protection Association. National Electrical Code (NEC) 2023, Article 220: Branch-Circuit, Feeder, and Service Load Calculations, 2023.

Nikolaos G. Paterakis, Ozan Erdinç, Anastasios G. Bakirtzis, and João P. S. Catalão. Optimal Household Appliances Scheduling Under Day-Ahead Pricing and Load-Shaping Demand Response Strategies. *IEEE Transactions on Industrial Informatics*, 11(6):1509–1519, 2015.

Pecan Street Inc. Pecan Street Dataport: Residential Data. https://dataport.pecanstreet.org/academic.

Elias N. Pergantis, Jaewon Park, Priyadarshan Priyadarshan, Trevor J. Bird, Davide Ziviani, and Kevin J. Kircher. Open-source tool-box for identifying envelope dynamics of detached residential buildings. In *Proceedings of the International High Performance Buildings Conference*. School of Mechanical Engineering, Purdue University, 2024a. URL https://docs.lib.purdue.edu/ihpbc/434/. Paper No. 3139.

Elias N. Pergantis, Priyadarshan, Nadah Al Theeb, Parveen Dhillon, Jonathan P. Ore, Davide Ziviani, Eckhard A. Groll, and Kevin J. Kircher. Field Demonstration of Predictive Heating Control for an All-Electric House in a Cold Climate. *Applied Energy*, 360:122820, 2024b. ISSN 0306-2619.

Elias N Pergantis, Levi D Premer, Arash J Khabbazi, Feng Wu, Davide Ziviani, and Kevin J Kircher. Active current limiting control of residential appliances for breaker panel protection across the us: a preliminary study. *Journal of Physics: Conference Series*, 3140(5):052027, nov 2025a.

Elias N. Pergantis, Levi D. Reyes Premer, Alex H. Lee, Priyadarshan, Haotian Liu, Eckhard A. Groll, Davide Ziviani, and Kevin J. Kircher. Protecting residential electrical panels and service through model predictive control: A field study. *Applied Energy*, 386:125528, 2025b. ISSN 0306-2619.

Priyadarshan, Elias N. Pergantis, Constance Crozier, Kyri Baker, and Kevin J. Kircher. Edgie: A simulation test-bed for investigating the impacts of building and vehicle electrification on distribution grids. In *Proceedings of the 57th Hawaii International Conference on System Sciences*, 2024.

Levi D. Reyes Premer, Elias N. Pergantis, Leo Semmelmann, Davide Ziviani, and Kevin J. Kircher. Model predictive control lowers barriers to adoption of heat-pump water heaters: A field study. *Energy Conversion and Management*, 348:120723, 2026. ISSN 0196-8904.

Rheem. Heat pump water heaters, 2024. URL https://www.rheem.com/products/residential/water-heating/heat-pump-water-heaters/.

Jyri Salpakari and Peter Lund. Optimal and rule-based control strategies for energy flexibility in buildings with PV. *Applied Energy*, 161:425–436, 2016. ISSN 0306-2619.

U.S. Census Bureau. Why we ask questions about... commuting / journey to work. https://www.census.gov/acs/www/about/why-we-ask-each-question/commuting/, 2024. Accessed: 2024-05-27.

U.S. Department of Energy. Building america analysis spreadsheets, 2011. URL https://www.energy.gov/cmei/buildings/building-america-analysis-spreadsheets. Page lists BA Analysis workbooks updated 01/26/2011.