City-Scale Decarbonization of Residential Heating under Transformer Constraints

Fabian Mkocheko
University of Massachusetts Amherst
Amherst, MA, USA

Walid A. Hanafy
University of Massachusetts Amherst
Amherst, MA, USA

Adam Lechowicz
University of Massachusetts Amherst
Amherst, MA, USA

David Irwin
University of Massachusetts Amherst
Amherst, MA, USA

Prashant Shenoy
University of Massachusetts Amherst
Amherst, MA, USA

Abstract

Space heating is the largest energy end-use in the residential sector and remains heavily reliant on natural gas infrastructure. To address the carbon emissions of residential heating, one approach is to transition residential heating from gas furnaces to electric heat pumps, which are more energy efficient and can be powered by increasingly greener and less carbon-intensive electric grids. One key challenge of this large-scale transition is that the distribution network (e.g., transformers) is often capacity-constrained, and distribution network upgrades typically span decades due to numerous supply chain issues. In this paper, we propose a transformer-level decarbonization approach that selects houses for electric heat pump retrofits based on their existing natural gas consumption and transformer capacity. We hypothesize that selecting houses with heterogeneous usage patterns can maximize displaced gas while respecting transformer thermal and overload constraints. Our city-scale evaluation show that our proposed approach can implement city-scale decarbonization without exceeding transformer ratings.

CCS Concepts

• **Social and professional topics** → *Sustainability*.

Keywords

Decarbonization, Residential Heating

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1 Introduction

Addressing climate change requires a significant reduction in greenhouse gas (GHG) emissions, a substantial portion of which originates from the residential sector. Worldwide, residential buildings account for approximately 21% of total energy consumption and 17%-18% of global energy-related emissions, a good portion of which is due to fossil fuel combustion for space and water heating [11, 12] . For instance, in New Jersey, 82.6% of housing units rely on fossil-based heating sources, including natural gas, fuel oil, and propane [20]. Electrification of these thermal loads, particularly through the adoption of high-efficiency electric heat pumps, represents a critical pathway toward decarbonization [25]. Heat pumps operate by moving heat rather than generating it through combustion, enabling *coefficients of performance* (COP) that greatly exceed those of traditional (additive) heating systems.

However, this large-scale transition away from fuel-based residential heating presents infrastructural challenges. Widespread transition to electric heat pumps introduces *new* electrical loads, fundamentally altering energy consumption patterns. In some regions, this is projected to shift seasonal peak demand from summer (due to air-conditioning use) to winter within the next 10 years, driven by electric heating [10]. This underscores the magnitude of the shift and the strain it will place on electric infrastructure that is already often operating near capacity limits [16].

Traditional electric grids are hierarchically structured, with high-voltage transmission networks carrying power over long distances and lower-voltage distribution networks delivering it to end consumers. The final "node" in the network before power is delivered to a home is typically a *distribution transformer*, which steps down the voltage for use in a cluster of homes. These transformers are a critical bottleneck for electrification—they are expensive, have manufacturing lead times that can exceed two years [21], and failures lead to localized blackouts, dangerous fires, and costly repairs. A transformer is *overloaded* when the demand *significantly* exceeds its rated capacity (reported in kilo-volt-amps (kVA)) and prolonged overloads degrade the transformer's internal insulation, shortening its operational lifespan and increasing the risk of sudden failure [1].

From a decarbonization perspective, it is natural to consider how a transition could be *optimized*, e.g., by maximizing the achievable carbon reduction given a certain number of heat pump retrofits. Prior work that has explored variants of this question often adopted a *myopic*, home-by-home perspective that does not consider the impact of retrofits on the electric grid. For example, several studies use control and planning techniques to minimize a single household's energy costs or maximize its use of on-site solar generation [4, 9, 18]. While valuable for individual decision-making, these approaches inherently ignore the impacts on the grid. A few studies have adopted a utility- or city-scale perspective, examining the impact of electrification on the distribution grid. These studies conduct large-scale data analysis and formulate optimization problems that consider an entire city or utility's service area, e.g., to quantify the impact

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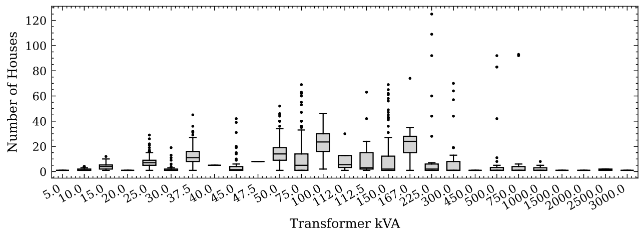


Figure 1: Number of houses per transformer by rated capacity

of heat pumps on the grid [2, 23, 24], optimize transition strategies [15], or optimize incentive strategies [19]. These "top-down" approaches give valuable insights into which types of homes have a large impact on decarbonization, but their approaches are computationally intractable for large cities, and they typically consider simple binary models of transformer overloading (i.e., a transformer is either overloaded or not) that ignore the temporal components of transformer wear.

On the other hand, other works have investigated control and demand response strategies for "peak shaving" that mitigate the impact of heat pumps on the distribution grid [5, 13]—these do consider the temporal dynamics of heat pump loads and how they impact grid health, but they are typically "post-hoc"—i.e., they are focused on changing load patterns after heat pumps have already been installed in certain houses, rather than optimizing a transition by selecting specific houses that are good candidates for retrofit.

In this work, we bridge these perspectives by developing a data-driven optimization framework to maximize decarbonization by coordinating heat pump retrofits at the distribution transformer scale. Our model assumes that no transformer upgrades are performed. Instead, given a fixed service capacity, our formulation distinguishes itself from prior work by capturing the temporal dynamics of the heat pump transition, including *when and where* the electric load will increase at a granular level. Our data-driven city-scale evaluation uses data from a New England city with 16,398 houses and 6,162 gas meters connected to 1,617 transformers.

(1) Our analysis highlights opportunities in implementing a city-scale decarbonization solution, such as the latent capacity of transformers and "what-if" scenarios where operating above the nameplate rating might be permissible based on e.g., outdoor temperature. Our results show that without exceeding the capacity, our approach can reduce carbon emissions by 31.6% (retrofitting 44.9% of homes). Allowing transformers to operate at 1.25× their rated capacity for short periods (an assumption justified by the cold weather in New England) [1, 6], can further increase the carbon savings (resp. retrofitted houses) to 41.7% (resp. 62.1%) compared to strict capacity constraints.

(2) Our results also show that further improvements can be achieved by identifying households with complementary load patterns (e.g., see Fig. 2) that can be retrofitted simultaneously without increasing coincident demand peaks. Through this more efficient allocation of a transformer's rated capacity, our results show that we can reduce heating carbon emissions by 41.7% compared to the status quo and by up to 10.0% and 9.1% compared to largest-load-first and smallest-load-first selection.

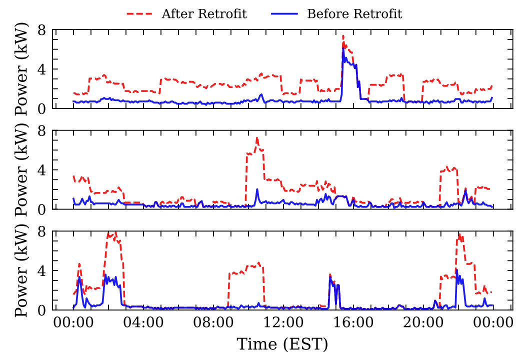


Figure 2: Three households' electric power usage before and after a heat pump retrofit on January 13th, 2024.

2 Analysis and Motivation

In this section, we present a city-scale analysis of distribution transformers and highlight opportunities to decarbonize residential heating without requiring distribution transformer upgrades. Our analysis relies on a dataset for a city in a cold-climate region (New England, USA), comprising 16,398 houses, 6,162 gas meters, and 1,617 transformers. See Section 4 for more details about the dataset and preprocessing steps. Fig. 1 highlights the number of houses (i.e., electric meters) per transformer across different transformer sizes. As shown, there is a substantial variation in the number of houses per transformer. For instance, amongst transformers with a 75 kVA capacity, the number of connected houses varies from 1 to 69, with a mean of 11. Importantly, the figure highlights that there is no direct correlation between the number of houses and the size of the transformer serving them, i.e., large transformers may serve a small number of houses. *A key insight from such variation is that many transformers are underutilized and can accommodate increases in load from retrofitting heating with electric heat pumps.*

To further highlight this point, Fig. 4 shows peak utilization in January 2024 for each of the 1,617 transformers, which highlights the potential for decarbonization (the "Before Retrofitting" line corresponds to the existing conditions in the data). For instance, ~40% of transformers never exceeded 50% of their capacity rating even at their peak, indicating headroom for electrification while staying within capacity. Moreover, comparing peak and average utilization indicates that extreme loading is episodic rather than persistent. Such events generally coincide with extreme weather. However, transformer capacity ratings are specified under an ambient temperature of 30°C [6] and depend on cooling performance, while IEEE guidance allows roughly a 1% increase in permissible loading per °C below 30°C [1]. Thus, many *overload* events occur precisely when the allowable utilization is higher. In the city under study, the average temperature in January ranges from −8° C to 1° C [17], allowing a safe operating utilization of up to 138%.

Another key aspect is the selection of houses for retrofitting. For instance, while earlier work [23] advocated for prioritizing houses with higher gas consumption or efficiency, we argue that considering houses with complementary load patterns can increase the number of retrofitted houses and decarbonization without introducing overloading events. Fig. 2 shows an example of the load profiles of three houses connected to the same distribution transformer between midnight on Jan. 13th and midnight on Jan. 14th. The blue line shows the observed electric load before retrofitting. The dashed red line shows the modeled electric load after retrofit, computed by adding the projected heat-pump electricity demand to the observed electric load. As shown, different houses often have different peak times, for example, due to variations in working hours and daily routines. In this case, selecting houses with complementary load (non-coinciding peaks) can allow for higher decarbonization without increasing the peak load.

3 Design

In this section, we present a transformer-scale optimization model that can consider multiple objectives, subject to constraints accounting for the temporal dynamics of transformer overloading and the power demand of each household before/after a heat pump retrofit. Considering a distribution transformer with a rated operating limit of C, we let $\mathcal{H}$ denote the set of gas-using households connected to this transformer that are candidates for heat pump retrofits. We let $x_j \in \{0, 1\}$ be a binary decision variable that indicates whether or not house $j \in \mathcal{H}$ is retrofitted. Formally:

$$x_j = \begin{cases} 1 & \text{if household } j \text{ transitions to electric heating} \\ 0 & \text{otherwise} \end{cases}, \quad \forall j \in \mathcal{H} \tag{1}$$

We consider a time horizon of T (e.g., a year), and index 5-minute intervals by t. If the j^{th} house is retrofitted with a heat pump (i.e., $x_j = 1$), an additional load is placed on the transformer; we represent this as follows. First, let $p_j(t)$ denote the heating power required for the j^{th} house at time t – this varies over time based on the j^{th} house's gas usage profile. Then, we let c_j denote the effective coefficient of performance (COP) of a heat pump in the j^{th} house. We use fixed effective COP scenarios of 1.5, 2.0, and 2.5; within each scenario, the COP is constant across houses and time steps. COP indicates the efficiency of the heat pump – for instance, a COP of 2 means that a heat pump can move 2 watt-hours of heat indoors for every watt-hour of energy consumed.

Finally, we let $p^{\texttt{fixed}}(t)$ denote the transformer's existing load (i.e., before any retrofits). Taken together, we have the following variable $P(t)$ to capture the total transformer load at each time t:

$$P(t) = p^{\texttt{fixed}}(t) + \sum_{j \in \mathcal{H}} x_j \cdot \frac{p_j(t)}{c_j}, \quad \forall t \in T. \tag{2}$$

The transformer's capacity varies with temperature and is limited by a maximum utilization factor. Let C denote the rated capacity of the transformer, and $\overline{C}$ denote the allowed upper bound, which acts as a safety threshold, and is computed using a static utilization factor. Then, the transformer's maximum safe capacity at time t is:

$$C_{\max}(t) = \min\left(C \cdot \left[1 + 0.01 \cdot (30 - \theta_t)\right], \overline{C}\right), \quad \forall t \in T, \tag{3}$$

where θ_t is the ambient temperature at time t. The transformer then must satisfy the strict capacity constraint at every time step:

$$P(t) \leq C_{\max}(t), \quad \forall t \in T. \tag{4}$$

Objectives. We consider two different objectives for the optimization problem, both subject to the constraints discussed above.

▷ *Minimize heating emissions (**ME**)*: This objective attempts to minimize the total emissions of houses in the set $\mathcal{H}$. To do so, we define the following quantities. First, let $I_j(t) : [T] \to \mathbb{R}_{\geq 0}$ denote a function that describes the GHG emissions due to electricity use at house j at time t. Note that since this is house-specific, it can capture the impact of any distributed energy resources, such as rooftop solar and/or battery storage. We further let $g_j(t) : [T] \to \mathbb{R}_{\geq 0}$ describe the gas usage of house j at time t (i.e., if it is not retrofitted with a heat pump). Finally, let η denote a conversion factor that captures the direct GHG emissions (e.g., due to combustion) from natural gas. We have the following optimization problem:

$$\min_{\{x_j\}_{j \in \mathcal{H}}} \sum_{j \in \mathcal{H}} \sum_{t \in [T]} x_j \cdot I_j(t) \cdot p_j(t) + (1 - x_j) \cdot \eta \cdot g_j(t), \quad \text{s.t. } (1, 2, 3).$$

▷ *Maximize household adoption (**MH**)*: This objective attempts to maximize the total number of households retrofitted with a heat pump. We have the following optimization problem:

$$\max_{\{x_j\}_{j \in \mathcal{H}}} \sum_{j \in \mathcal{H}} x_j, \quad \text{s.t. } (1, 2, 3).$$

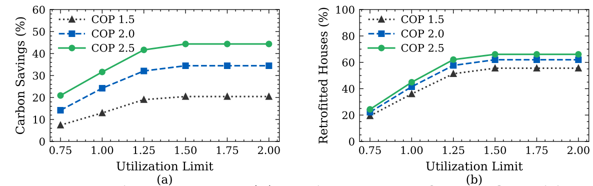


Figure 3: Carbon savings (a) and percent of retrofitted houses (b) across capacity limits and COP.

4 Evaluation

In this section, we evaluate the decarbonization potential of residential heating and show how our data-driven optimization framework can substantially reduce heating-related carbon emissions.

Datasets. In this study, we examine a dataset of residential buildings in a city in the New England region of the United States. We focus on January 2024, as it has the highest heating gas usage for the year. The dataset includes 16,398 houses, each represented by a residential electric meter; 6,162 of these houses also have gas meters. The houses are connected to 1,617 distribution transformers. Electricity demand is recorded at 5-minute granularity, whereas gas usage is recorded at 1-hour granularity. After converting gas usage to projected heat-pump electricity demand, we resample the resulting load to match the 5-minute electricity-demand granularity. To compute the retrofitted gas power consumption, we isolate heating energy in the gas usage profile by subtracting the summer hourly average gas usage from the hourly usage. We then convert the gas usage in CCF to retrofitted power usage, as highlighted in Section 3, using fixed COPs of 1.5, 2.0, and 2.5 [14], which capture sensitivity to different heat-pump efficiencies, weather, and house insulation levels [3]. Finally, to calculate the carbon emissions for heating, we use a natural gas conversion factor $\eta = 5,480$ gCO_2/CCF [22], where CCF (hundreds of cubic feet) is the unit of gas usage. For electricity usage, we utilize carbon intensity from Electricity Maps [7] for the New England ISO.

Solver Implementation. We implement the selection problem using Google OR-Tools' CP-SAT solver with binary decision variables to determine which houses should be retrofitted. We solve for two objectives: minimize total carbon emissions or maximize retrofitted households. Our constraints ensure that the total transformer load (base load plus projected heat pump load) does not exceed the dynamic capacity limit $C_{\max}(t)$ at 5-minute intervals. The limit $C_{\max}(t)$ is updated hourly based on the ambient temperature θ_t to reflect thermal dissipation and is bounded by a safety ceiling $\bar{C}$.

4.1 Decarbonization Potential

We start by highlighting the decarbonization potential across different utilization limits and COP values to minimize carbon emissions

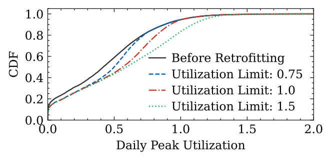
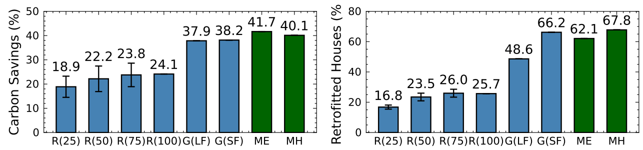


Figure 4: Daily Peak Utilization (COP=2.5).



(a) Carbon Savings (%) **(b) Retrofitted Houses (%)**

Figure 5: Comparing baselines across different objectives when considering a maximum utilization of 1.25× and COP = 2.5.

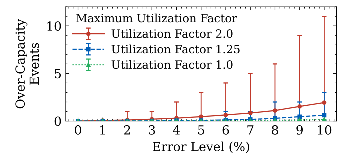


Figure 6: Over-Capacity Events (COP = 2.5).

from heating. Fig. 3 illustrates the carbon savings and the percentage of retrofitted houses across limits from 0.75× to 2.0× the rated transformer capacity. We also consider different COP values that represent the efficiency of heat pumps and house insulation. As shown, current utilization indicates that many houses can be retrofitted without exceeding transformer limits. For instance, at 75% of the rated capacity limit and COP = 2.5, emissions can be reduced by 20.9%, and 24.3% of the houses retrofitted. At the nameplate capacity (100%), emissions reduction increases to 31.6% with 44.9% of houses retrofitted. Allowing slightly higher utilization further increases potential savings: at 125% of rated capacity, carbon savings (resp. for retrofitted houses) increase by 31.9% (resp. 38.3%) compared to operating at rated capacity. However, beyond this point, the benefits saturate, as ambient temperature constraints limit the maximum achievable transformer utilization. Consequently, nominal utilization caps of 150–200% yield limited additional gains, with maximum improvements of 40.5% in carbon savings and 47.2% more retrofitted houses. The figure also shows the effect of lower COP values, which limit the efficiency of retrofitting the houses. As shown, while the trend remains unchanged across COPs, carbon savings increase significantly. For instance, at a utilization of 1.5, retrofitting reduces carbon emissions (resp. retrofit houses) by 34% (resp. 62%) and 20% (resp. 55%) for COPs of 2.0 and 1.5, respectively. Lastly, although the number of houses changes only slightly, the houses themselves differ significantly across COPs.

Another key aspect of our analysis is that heating retrofits primarily increase transformer utilization during moderate-load periods without impacting the extreme peak loads. Fig. 4 shows the daily transformer utilization before and after retrofits for capacity limits of 0.75×, 1×, and 1.5×. As shown, retrofits increase utilization for mid-level events while leaving peak utilization largely unchanged. For example, the average utilization rises by 9%, 19%, and 39% after retrofitting for capacity limits of 0.75×, 1×, and 1.5×, respectively. This demonstrates the utility of leveraging the latent capacity of transformers across the city to support substantial decarbonization, enabling the retrofitting of many houses while respecting the maximum allowed transformer capacity.

4.2 Comparing to Baselines

In this section, we compare against two baselines and report our optimization-driven framework, described as follows:

1) Random Assignment. This policy approximates the status quo of decarbonization, where a set of households randomly decide to upgrade their heating system (e.g., to leverage government or utility incentives [8]). In this case, we consider randomized selection, repeat it 30 times, across quotas **R(25)**, **R(50)**, **R(75)**, and **R(100)**, where **R(*p*)** retrofits *p*% of homes at random. However, to avoid overloading the transformer, we consider only cases in which the retrofitting adheres to the same constraints as our approach.

2) Greedy Assignment. This policy represents state-of-the-art approaches [23] that incrementally select the houses based on their size. We consider two variants: Largest First **G(LF)**, which aims to maximize decarbonization, and Smaller First **G(SF)**, which seeks to maximize the number of houses. Similarly, we follow the policy until we reach the thresholds.

3) Optimization-driven Framework. Our contribution that considers the objective-driven formulations from Section 3 in minimizing heating emissions (**ME**) or maximizing adoption (**MH**).

Fig. 5 shows that our proposed approach, which can select houses with complementary demand, outperforms other baselines. For instance, random selection often misses opportunities by selecting non-compatible houses, houses with significant heating demand, or houses at overloaded transformers, resulting in infeasible solutions and a maximum of 24.1% carbon reductions (resp. 25.7% for retrofitted houses). In this case, our approach that considers these aspects can further reduce carbon emissions by 58.5% (resp. by 146.0% for more retrofitted houses). Moreover, greedy strategies that incrementally select the largest or smallest houses per transformer overlook opportunities to exploit complementary demand across households. Our **ME** objective achieves higher carbon reductions than **G(LF)** and **G(SF)**, improving carbon reductions by 10.0% and 9.1%, respectively, while our **MH** objective increases the share of retrofitted houses by 39.5% and 2.4%, providing a balance between carbon reductions and adoption. This highlights that, by accounting for both household demand profiles and transformer constraints, our optimization framework can more effectively identify feasible retrofits and maximize decarbonization potential.

4.3 Data Robustness

Houses' energy consumption can vary from year to year, introducing unanticipated overloads. To evaluate the robustness of our approach, we add random noise to each transformer's aggregate power consumption at every 5-minute interval, matching the time scale of our capacity constraints. The noise is sampled independently from a normal distribution with mean zero, and we vary its standard deviation to represent different error levels. Fig. 6 demonstrates the effect of errors on over-capacity events per distribution transformer, computed according to the allowed temperature-dependent transformer latent capacity. As shown, the introduced errors rarely affect the number of over-capacity events. At a 10% error level, the average number of over-capacity events is 4.4 for a utilization factor of 1.25 and 5.6 for a utilization factor of 2.0.

5 Conclusion

This paper proposes a data-driven approach that leverages the latent capacity of transformers and the complementary household heating demand profiles to minimize heating-related carbon emissions through heat pump retrofits. Our future work will integrate these transformer-level retrofits with transmission network capacity.

References

[1] 2025. IEEE Approved Draft Guide for Loading Mineral-Oil-Immersed Transformers and Step-Voltage Regulators. *IEEE PC57.91/D11, May 2025* (2025), 1–118.

[2] Muhammad Akmal, Brendan Fox, John David Morrow, and Tim Littler. 2014. Impact of heat pump load on distribution networks. *IET Generation, Transmission & Distribution* 8, 12 (Dec. 2014), 2065–2073. doi:10.1049/iet-gtd.2014.0056

[3] Daniel R. Bayer and Marco Pruckner. 2023. Modeling of Annual and Daily Electricity Demand of Retrofitted Heat Pumps Based on Gas Smart Meter Data. In *Proceedings of the 10th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation* (Istanbul, Turkey) *(BuildSys '23)*. Association for Computing Machinery, New York, NY, USA, 248–251. doi:10.1145/3600100.3623745

[4] Phuthipong Bovornkeeratiroj, Walid A Hanafy, David Irwin, and Prashant Shenoy. 2025. GreenThrift: Optimizing Carbon and Cost for Flexible Residential Loads. *ACM Journal on Computing and Sustainable Societies* 3, 2 (2025), 1–21.

[5] Jochen L. Cremer et al. 2017. Optimal Scheduling of Heat Pumps for Power Peak Shaving and Customers Thermal Comfort. In *Proceedings of the 6th International Conference on Smart Cities and Green ICT Systems*. SCITEPRESS - Science and Technology Publications, 23–34. doi:10.5220/0006305800230034

[6] Eaton Corporation. 2019. Dry-type distribution transformers—general purpose. Design Guide CA009001EN.

[7] Electricity Maps. 2024. Electricity Maps. https://www.electricitymap.org/map.

[8] Energize Connecticut. 2025. Residential Air Source Heat Pump Incentive Details. https://www.energizect.com/rebates-incentives/heating-cooling/heat-pumps/residential-air-source.

[9] Avik Ghosh et al. 2024. Advanced Predictive Rule-based Control for HVAC Cost Reduction Under Dynamic Electricity Pricing in Residential Buildings. Purdue University, International High Performance Buildings Conference.

[10] NECPUC Retail Demand Load Flexibility Working Group. 2024. Effects of Future Peak Loads: Ten-Year Forecast and Longer-Term Outlook.

[11] International Energy Agency. 2025. Energy system - Buildings. https://www.iea.org/energy-system/buildings

[12] IPCC. 2022. Chapter 9: Buildings. In *Climate Change 2022: Mitigation of Climate Change*. Cambridge University Press. https://www.ipcc.ch/report/ar6/wg3/chapter/chapter-9/

[13] Kamran Jalilpoor et al. 2024. Optimizing Grid Integration of Heat Pumps for Balancing Hosting Capacity and Customer Satisfaction. In *2024 International Conference on Smart Energy Systems and Technologies (SEST)*. IEEE, 1–6.

[14] N.J. Kelly and J. Cockroft. 2011. Analysis of retrofit air source heat pump performance: Results from detailed simulations and comparison to field trial data. *Energy and Buildings* 43 (01 2011), 239–245. doi:10.1016/j.enbuild.2010.09.018

[15] Adam Lechowicz et al. 2023. Equitable Network-Aware Decarbonization of Residential Heating at City Scale. In *Proceedings of the 14th ACM International Conference on Future Energy Systems* (Orlando, FL, USA) *(e-Energy '23)*. Association for Computing Machinery, New York, NY, USA, 1–13. doi:10.1145/3575813.3576870

[16] Yanning Li and A. Jenn. 2024. Impact of electric vehicle charging demand on power distribution grid congestion. *Proceedings of the National Academy of Sciences of the United States of America* 121 (2024). doi:10.1073/pnas.2317599121

[17] Meteostat Contributors. 2026. Historical Weather Data from Meteostat, 1 January 2016 – 31 January 2025. https://meteostat.net. Accessed: 12 January 2026. Data aggregated by Meteostat under CC BY 4.0; original observations from NOAA, Deutscher Wetterdienst, Environment Canada.

[18] Maria Pinamonti, Alessandro Prada, and Paolo Baggio. 2020. Rule-Based Control Strategy to Increase Photovoltaic Self-Consumption of a Modulating Heat Pump Using Water Storages and Building Mass Activation. *Energies* 13, 23 (Nov. 2020), 6282. doi:10.3390/en13236282

[19] Anupama Sitaraman et al. 2025. Dynamic Incentive Allocation for City-Scale Deep Decarbonization. *ACM J. Comput. Sustain. Soc.* 3, 3, Article 22 (July 2025), 25 pages. doi:10.1145/3736650

[20] U.S. Census Bureau. 2023. American Community Survey 1-Year Estimates: Table B25040 / DP04 — House Heating Fuel (New Jersey). Variables: DP04_0063PE (utility gas), DP04_0066PE (fuel oil/kerosene), DP04_0065PE (electricity).

[21] U.S. Department of Energy. 2024. DOE and Industry Team Up to Keep the Lights On for America.

[22] U.S. Environmental Protection Agency. 2025. Greenhouse Gas Equivalencies Calculator: Calculations and References. https://www.epa.gov/energy/greenhouse-gas-equivalencies-calculator-calculations-and-references Accessed: 2025-09-18.

[23] John Wamburu et al. 2023. Analyzing the Impact of Decarbonizing Residential Heating on the Electric Distribution Grid. *SIGENERGY Energy Inform. Rev.* 3, 2 (June 2023), 47–60. doi:10.1145/3607114.3607119

[24] John Wamburu et al. 2023. Equity-Aware Decarbonization of Residential Heating Systems. *SIGENERGY Energy Inform. Rev.* 2, 4 (Feb. 2023), 18–27. doi:10.1145/3584024.3584027

[25] Agnieszka Żelazna and Artur Pawłowski. 2025. Review of the Role of Heat Pumps in Decarbonization of the Building Sector. *Energies* 18, 13 (2025), 3255.

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