

Optimizing Energy Solutions for Equity in Disadvantaged Communities: A Multi-Scale Approach from Deterministic to Stochastic Models

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I dedicate this dissertation to my parents, especially my late father, whose recent passing left me devastated. I wish he were here to witness this milestone and celebrate this chapter of my life with me. His memory continues to inspire and guide me.

I also dedicate this work to my in-laws and my beloved wife, whose unwavering support and constant encouragement provided strength when I needed it most. Their faith in me has been an anchor throughout this journey.

To our yet-to-be-born child, your upcoming arrival has brought immeasurable joy and renewed inspiration to my path.

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Abstract

In the United States, many households, especially those in lower- and middle-income brackets, struggle with the ‘heat or eat’ dilemma, where essential energy needs compete with basic necessities. This dissertation investigates strategies to minimize energy burdens for disadvantaged communities using a multi-scale optimization framework.

The first chapter introduces a linear optimization model to determine optimal investments in weatherization, rooftop solar, community solar, and community wind interventions. A case study of 32,660 households in Tennessee identifies key parameters influencing energy burden reduction and highlights how targeted measures can improve quality of life.

In the second chapter, the study expands to include Florida, incorporating temporal granularity by comparing annual, seasonal, and monthly intervention strategies. The analysis explores varying budget constraints and examines fluctuations in energy burdens before and after adopting interventions. This comparative approach offers insights into how local conditions and granular consumption patterns affect the effectiveness of these strategies.

The third chapter introduces stochastic parameters to address uncertainties inherent in real-world applications. By incorporating fluctuating electricity prices, renewable energy variability, demographic changes, and increased electric vehicle adoption, the study assesses intervention robustness through 2030. This approach ensures adaptability and sustainability, capturing the complexity of future energy demands.

The findings demonstrate that a portfolio of tailored interventions can significantly reduce energy burdens, providing policymakers and practitioners with a scalable framework for promoting energy equity. This research advances the understanding of energy burden mitigation by integrating deterministic and stochastic models, offering practical solutions for disadvantaged communities in diverse regions and conditions.

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Chapter 1

An Optimization Framework for Minimizing Energy Burden: A Case Study for Tennessee, USA

1.1. Introduction

1.1.1 Motivation

The ‘heat or eat’ dilemma due to energy burden is getting increased attention worldwide, particularly in the USA. The energy burden, defined as the ratio of annual energy expenses to gross annual income, serves as a crucial metric for gauging the energy solvency of a household. According to the US Department of Energy’s (DOE) Low-Income Energy Affordability Data (LEAD) Tool [5], the average energy burden for low-income households (8.6%) is roughly three times that compared to higher-income households (3%) [6]. On average, people in Tennessee spend 8% more on electricity bills compared to the rest of the country [7]. Some families spend as high as 27% of their income on energy-related expenses [8]. Drastically cutting back energy usage may result in health issues such as asthma, heat stress, cold stress, and mental health problems [9].

The energy transition from fossil fuel-based energy production to carbon-neutral energy production methods is energized by initiatives like President Biden’s net-zero emission policy

that demands a 65% reduction of greenhouse gas emissions by 2030 [10]. Other initiatives like Justice40 [11] require that low-income disadvantaged communities (DACs) benefit directly from government investment in areas like clean energy and affordable and sustainable housing. However, informed decisions are necessary to ensure the best use of these investments. Our study will show an optimized approach that considers a portfolio of four interventions, namely, weatherization, rooftop solar, community solar, and community wind.

In the US, residential and commercial sectors account for 22% and 18% energy usage respectively resulting in 40% combined use of total US energy usage [12]. Since significant energy is spent through buildings, it is necessary to ensure energy optimization by building efficient infrastructure. Weatherization helps in this regard by controlling sunlight, cold, and precipitation inside buildings by adopting a plethora of measures like mechanical, building shell, health, and safety, etc. [13] DOE offers weatherization assistance programs to eligible low-income households that results in lowering their energy burden significantly. According to an evaluation of this program, it is found that through this program a household may save at least \$372 annually [14].

Roof-top solar is another intervention that is gaining popularity. According to an analysis [15] from the National Renewable Energy Laboratory (NREL) in 2016, there are about 8 billion square meters of rooftops in the US where solar panels could be installed. Apart from energy contribution for a particular household, federal tax credits [16] and net metering policies [17] are acting as driving factors for its increasing popularity. Yet lower and moderate-income (LMI) households are less likely to adopt rooftop PVs due to a lack of LMI-targeted financial incentives, system leasing, and property-assessed clean energy financing [18].

Community solar and community wind are key interventions for net-zero emissions, offering shared renewable energy at lower costs without the need for individual rooftop space [19]. These approaches help tackle both the ‘heat or eat’ dilemma for DACs and low-to-middle-income households and play a crucial part in achieving carbon neutrality [20, 21]. However, Tennessee’s engagement in wind energy, primarily through the Buffalo Mountain wind project, is minimal compared to leaders like Texas and Iowa [22], despite the project’s significance as the first wind farm in the Southeastern United States [23]. Through investing in these interventions it is possible to decrease the energy burden for DACs and keep LMIs

out of the ‘heat or eat’ dilemma. Incorporating an optimization framework can mitigate the energy burden for DACs and improve energy utilization efficacy through a comprehensive intervention portfolio, thus enhancing energy equity and advancing toward net-zero emission goals.

1.1.2 Literature Review

Previous studies have covered energy equity-related research from different perspectives. Some of the perspectives include but are not limited to, distributed energy resources (DER) adoption trend and disparity, grid hosting capacity limitations, developing energy equity metrics, qualitative and quantitative research at the intersection of energy equity and policy, and policy-making based on certain initiatives.

DERs, like roof-top PV, play a very important role in the transition to clean energy. There are some critical determinants for the success of DER adoption. According to [24, 25], the critical determinants include financial support, general problem awareness, diffusion of innovations theory, the technical aspects of solar PV like energy performance, the effectiveness of renewable energy options, and peer influences. Although there are some excellent points in favor of adopting PVs, it has not happened equally across all portions of the US. There are many explanations for this unequal adoption rate. Few studies [26, 27] examine the adoption rate through the lens of socioeconomic factors and demographic information. They identified various factors including education level, racial disparity, low and medium-income households’ home ownership, and the availability of installers for a particular region.

Demographic or socioeconomic factors are not the only things that impact roof-top PV adoption disparity. The hosting capacity of the grid can hinder adoption. One of the studies [28] related to hosting capacity showed the effect of this phenomenon under two utilities from California that together serve about 30 million people. Their study found that for about half of the households, the utilities cannot support the size of the PV required to fully offset the households’ average annual electricity consumption.

The significance of energy burden as a pivotal energy equity metric is underscored in [29]. This metric sheds light on disparities by examining the proportion of household income spent on energy-related expenses. The authors delve into the detailed roles of stakeholders working

towards improving energy-burdened situations, emphasizing the need for close engagement from various parties. They argue that understanding the factors influencing energy burden and their consistency across different geographic granularity is crucial. A related study [30] sought to identify key predictors of energy burden at the urban scale. This research revealed that socioeconomic variables, particularly income-related factors, emerged as strong predictors. Spatial models demonstrated a better fit compared to non-spatial models, showcasing the complexity of these dynamics. Notably, variables like median household income and poverty proved to be general predictors, while physical variables such as building age were more accurate in some specific scenarios.

The traditional metric for assessing energy burden, which emphasizes the compromises households make to meet their energy needs, may not fully capture those who restrict their energy consumption to prioritize other necessities. Addressing this deficiency, [31] proposed a new metric termed as the ‘energy equity gap.’ This metric evaluates the disparity in inflection temperatures—the point at which households start using air conditioning—between low- and high-income groups, providing a nuanced view of income-related energy poverty. Their findings revealed an energy equity gap ranging from 2.6 to 4.2 degrees Celsius across different income levels, based on a dataset of 4,577 households. Complementing this, [32] identified variances in both cooling and heating energy equity gaps in a colder climate in northern Illinois, with gaps of approximately 3 and 6 degrees Fahrenheit between low and high-income groups. Further research by [33] introduced the ‘cooling slope gap,’ defined as the variation in energy consumption throughout the cooling season. The study indicated that households earning below \$15,000 annually reduce their energy usage by approximately 1.03 kWh for each degree Fahrenheit increase in outdoor temperature.

Some studies target mitigating energy burden by taking qualitative approaches like replacing existing setups with their suggested renewable alternatives. [34] identified DACs with high energy potential for the deployment of renewable energy. They also identified trends across DACs and renewable energy potential from county-level correlations using energy burden, environmental hazard, and socio-demographic data, technical generation potential, and levelized cost of energy. Some of their suggested deployment outcomes are to replace

mining, quarrying, and oil & gas extraction with wind power, and increase commercial and residential rooftop PV in counties with large populations of minority individuals.

Few other studies took a quantitative optimized approach with a portfolio of interventions to combat the energy-burdened situation of DACs. Heleno et al. [35] calculated the optimal portfolio for energy intervention involving a large number of energy-insecure households in Wayne County, Detroit, USA taking several interventions into account. Their findings showed that community solar investments played the most critical part. Another important factor to keep in mind is cost-effectiveness. In [36], researchers showed both cost-optimal and regionally equitable approaches of decentralized renewable electricity generation allocation for Switzerland considering generation costs, investment needs, and capacity requirements. Along with hot-humid or hot-dry regions, it is imperative to see how cold weather reacts to different intervention types. Such an instance was shown in [37] where the researchers suggested a sustainable energy system for Sachs Harbour, the northernmost community in the Northwest Territories of Canada by suggesting an intervention portfolio containing PV, wind turbine, battery, diesel, and converters through optimization techniques. Very recently another study dealt with energy burden reduction in terms of direct monetary savings with a set of different alternatives. Kerby et al. [38] showed a comparison among energy storage, rooftop solar, weatherization, and energy efficiency appliance upgrades. While energy storage showed the least variation in providing savings across different regions, weatherization provided the most savings in many regions.

Effective policy-making is crucial in developing infrastructure that yields long-term benefits. Wilson et al. [39] demonstrated that tailored energy efficiency packages for single-family households earning less than 200% of the federal poverty level can result in average annual savings of \$670. This finding highlights the potential of such initiatives in supporting economically DACs. In contrast, current aid programs, such as the Low Income Home Energy Assistance Program (LIHEAP), predominantly focus on immediate bill payment assistance. This approach, while providing short-term relief, lacks a sustainable mechanism for offering recurrent benefits to these communities. Redirecting resources towards more sustainable solutions could, therefore, have a more impactful and enduring effect [40].

1.1.3 Research Gaps

Despite the extensive exploration of energy burden issues within the existing literature, primarily through data analytics and machine learning, there remains a significant gap in employing quantitative optimization frameworks specifically tailored for energy burden reduction for DACs. This oversight suggests potential opportunities for devising more targeted and efficient intervention strategies.

Moreover, the literature lacks in-depth mapping of proposed interventions, a critical component for effective implementation planning across diverse geographic contexts. Such detailed mapping is essential for customizing solutions to the unique needs of different communities, thereby optimizing the impact of energy burden alleviation efforts.

Additionally, the granularity of sensitivity analysis concerning contributing parameters at the county level is notably absent. This level of detail is crucial for identifying regional variations in energy burden determinants, enabling the formulation of more precise and impactful mitigation strategies.

Addressing these gaps through a comprehensive, optimization-focused research approach can significantly enhance our understanding and mitigation of energy burdens. Incorporating detailed intervention mapping and localized sensitivity analyses would both bridge the current literature gap and provide a robust foundation for developing scalable, adaptable, and efficient energy burden reduction strategies.

1.1.4 Contribution

Our research makes a distinctive contribution to the field of energy equity by presenting the first-ever quantitative analysis specifically aimed at reducing the energy burden in selected Disadvantaged Communities (DACs) within Tennessee. This study stands out from previous model [35] in several critical ways:

Tailored Approach: We customize our framework to align with the specific socio-economic and environmental characteristics of the region. This results in a model that is finely tuned to address the unique challenges faced by 32,660 households across targeted

census tracts. Unlike broader models, our approach ensures that the proposed solutions are directly applicable and highly relevant to the communities in question.

Integration of Technological Interventions: Our model uniquely integrates multiple interventions, including weatherization, rooftop solar, community solar, and community wind. This combination is selected not only for its effectiveness in reducing energy costs but also for its potential to enhance sustainable energy practices within these communities.

Additionally, we also introduce a significant methodological enhancement:

Sensitivity Analysis: We incorporate a sensitivity analysis of key parameters affecting the energy burden. This novel addition allows us to:

- Assess the robustness of our interventions under varying conditions.
- Understand the differential impacts of each intervention, providing insights that are critical for policy formulation and adjustment.
- Rank the parameters by their influence on outcomes, guiding stakeholders in focusing efforts on the most impactful factors.

Furthermore, the practical implications of our research are substantial, enhancing its value to both academic and policy-making spheres:

Real-World Application: Our approach maps the proposed interventions directly onto real-world settings, which facilitates the practical implementation of solutions. This direct mapping ensures that our findings are not just theoretical but serve as a practical guide for community-based energy planning and policy development.

Policy Implementation and Adjustment: By providing a detailed analysis of intervention outcomes and parameter sensitivities, our study supports dynamic policy making. It allows policymakers to adjust strategies in real time, based on empirical evidence of what works best in specific community contexts.

Overall, our research not only contributes to academic knowledge but also provides a tangible, actionable framework for reducing energy insecurity in disadvantaged communities. By focusing on localized solutions, sensitivity analysis, and practical applications, this study sets a new standard for research in energy equity and community-focused energy policy.

1.1.5 Organization of the Paper

The rest of the paper is organized in the following manner. The methodology portion is described in section 1.2 which contains model information (for example, sets, variables, objective function, etc.), data acquisition and preprocessing, and different parameter calibration. Section 1.3 portrays the findings (proposed intervention counts and their mapping when applicable) from twelve different counties alone as well as a combined model (all 12). At the same time, it also exhibits the impact of sensitive parameters on energy burden reduction and provides a comprehensive ranking of those parameters. A summary of key findings and broader implications of this study are also discussed in this section. Section 1.4 contains possible future works to extend the current work. We conclude our paper with section 1.5 which summarizes the overall procedure followed to perform this study at a very high level and explores various policy implications. Additionally, appendix A and B contain additional tables and figures related to dataset features, highlighted portion of selected census tracts within Tennessee state, intervention mapping, and sensitivity plots for different counties.

1.2. Methods

This section begins with the selection procedure for DACs, utilizing a combination of qualification criteria. An overview of the dataset is provided, followed by a detailed description of the data preprocessing steps. We also elaborate on the derivation and rationale of various parameter values used throughout the study. Furthermore, the details of the model are discussed, including sets, variables, constraints, and the objective function. Steps involved in the methodology section are shown at a very high level as a flowchart in **Fig. 1**.

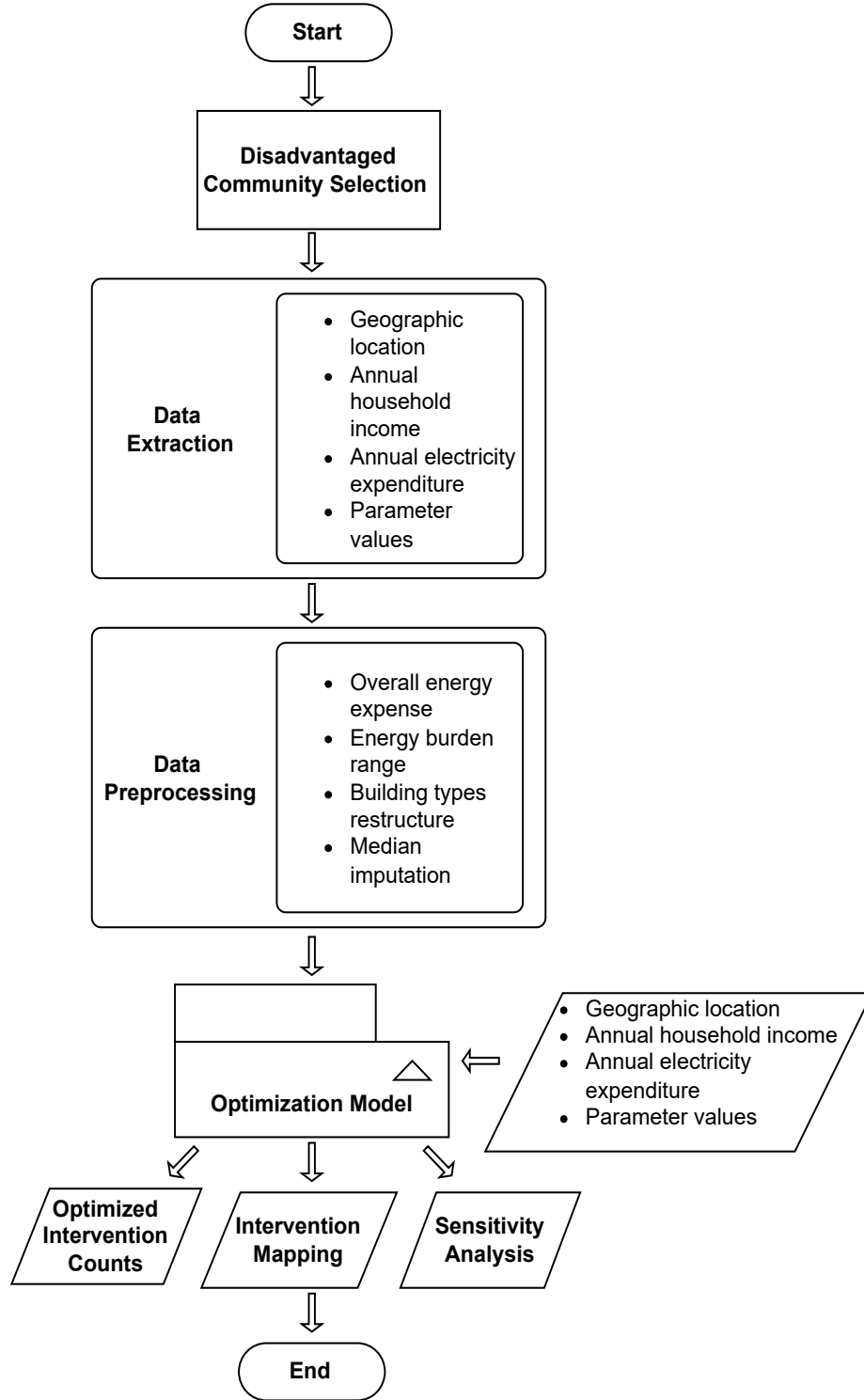


Figure 1: Flowchart shows the overview of different tasks involved throughout the whole study.

1.2.1 Location Selection for Energy Burden Minimization

DOE launched programs like LEAP to help DACs by lowering both utility costs and high energy burdens [41]. The selection criteria include average energy burden, percent low income, historic fossil energy communities, and EPA Environmental Justice Screening Index Scores. The detailed qualification criteria for communities LEAP are as follows:

1. Tract must have a low-income population $\geq 30\%$
2. Median household energy burden $\geq 6\%$
3. Plus, one of the following criteria must be fulfilled
 - (a) Community has historical economic dependence on fossil fuel industrial facilities including extraction, processing, or refining
 - (b) Tract is classified as experiencing moderate or high susceptibility on the US Environment Protection Agency’s environmental justice screening tool

In our study, we used the above criteria to select the census tracts from different counties within Tennessee. These qualification criteria provided us with selective census tracts from 12 different counties in Tennessee. Those counties were Knox, Davidson, Gibson, Hamblen, Hardeman, Haywood, Lauderdale, Weakley, Sevier, Hamilton, Madison, and Shelby. Using specific FIPs of the selected census tracts (accordingly counties) from the ‘LEAD’ dataset, we extracted data involving five features, namely, ‘BLD’, ‘HINCP’, ‘ELEP’, ‘GASP’, and ‘FULP.’ The demographic and socio-economic factors of selected census tracts concerning different geographies like county, state, and country are shown in **Fig. 2**.

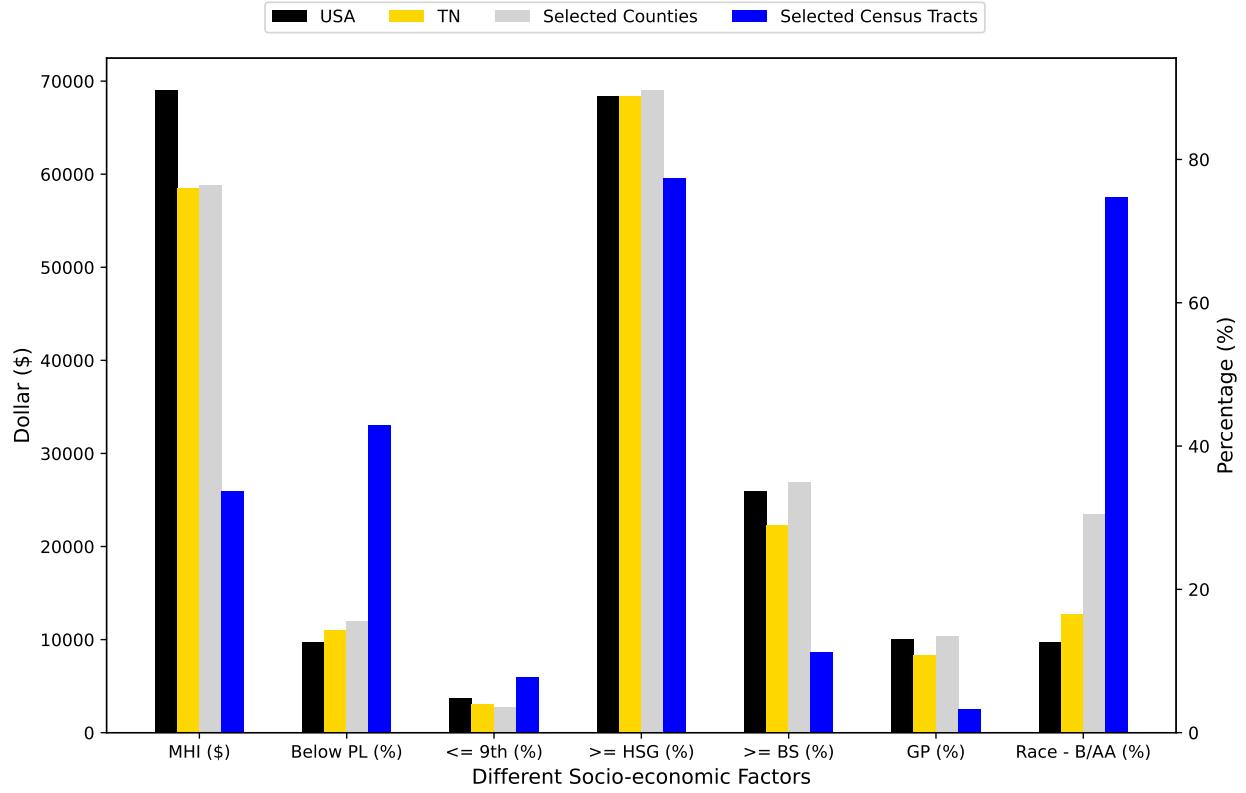


Figure 2: Demographic and Socio-economic factors of selected census tracts concerning county, state, and country based on 5-year American Community Survey data [1, 2, 3, 4]. The weighted average value was shown for both census tract and county. MHI, Below PL, <= 9th, >= HSG, >= BS, GP, and Race- B/AA stand for median household income, percentage of people below the poverty line, below 9th grade, high school graduate or higher, with a bachelor degree or higher, with graduate or professional degree, and from Black or African American race.

As we can see in **Fig. 2**, the median household income, and educational attainment (specifically the percentages of bachelor’s and graduate degree holders), in the selected census tracts, are notably lower in comparison to other geographical entities. Conversely, these tracts exhibit significantly higher percentages in factors such as the proportion of residents living below the poverty line and the prevalence of Black/African-American individuals. Detailed values are provided in **Table 15** and **Table 16**.

1.2.2 Data Acquisition and Pre-processing

One of the datasets used for this study was Low-Income Energy Affordability Data (LEAD) [5]. LEAD was built by Better Building’s Clean Energy for Low-Income Communities Accelerator (CELICA) [42] to provide insight into LMIs housing and energy behavior. It consists of data on income, energy expense, fuel type, housing type, and geography in the form of 24 columns for 50 states including Puerto Rico and Washington D.C. Data is available in different granularities like state, city, census tracts, etc. Our study uses data related to Tennessee with census tract-level granularity. **Table 13** in appendix A shows a detailed description of the different features.

Another dataset we used here is the one associated with DOE’s Local Energy Action Program (LEAP) pilot [43]. This program partners with low-income, energy-burdened DACs to support them during their transition from fossil fuel-based energy systems to clean energy. This dataset contains information about the average energy burden, historic fossil fuel energy communities, percent low income, and EPA environmental justice screening index score for all census tracts of 50 U.S. states including the District of Columbia (D.C.) and Puerto Rico. **Table 14** in appendix A shows a detailed description of features from this dataset.

There were some missing values in the LEAD dataset. One common technique to replace these missing values is to use mean/median imputation. Since our dataset was skewed, those empty values were replaced by the corresponding columns’ median values.

We also reformed one of the columns related to ‘housing type’ to match cost data available for weatherization across different housing types. Originally there were ten different categories. We aggregated them and regrouped them into four main categories. For example, ‘1 UNIT

DETACHED’ and ‘1 UNIT ATTACHED’ were bundled into one category as ‘single-family.’ The other three categories are ‘small multi-family’, ‘large multi-family’, and ‘mobile homes.’

The number of households in each housing type varies from county to county. Since we categorized them mainly into four categories in the preprocessing stage, the numbers are essentially the counts for each housing type in a particular County. The number of households in each housing type from selected census tracts in Tennessee is provided in **Table 1**. Housing type counts were shown at a granularity of county for illustration purposes.

The energy burden for each household is calculated by first determining the total energy expenditure. As energy consumption can come from multiple sources, the annual energy spending for a household is computed by summing expenditures from electricity, gas, and other fuels. Subsequently, the energy burden is ascertained by dividing the total energy expenditure by the household’s gross annual income.

1.2.3 Parameter Calibration

In this section, we showed how different parameter values critical to the model were obtained from various sources.

Table 1: Number of households in each housing type from selected counties in Tennessee. SF, SMF, LMF, and MH stand for single-family, small multi-family, large multi-family, and mobile homes respectively.

S/N	Housing Type County	SF	SMF	LMF	MH
1	Knox	1,010	960	300	20
2	Davidson	890	1,450	250	60
3	Gibson	450	300	0	75
4	Hamblen	120	195	40	25
5	Hardeman	350	60	20	160
6	Haywood	430	0	0	255
7	Lauderdale	270	295	20	55
8	Weakley	20	220	40	0
9	Sevier	655	810	190	140
10	Hamilton	870	880	210	30
11	Madison	1,215	1,110	190	65
12	Shelby	9,465	6,735	1,330	425
13	All Twelve (combined)	15,745	13,015	2,590	1,310

Total Budget

In this section, we showed how the fund of interventions for each county was determined. Various considerations were made keeping the current proposed budget, previously adopted budget, and similar past energy projects in mind. In some cases, the appropriate inflation rate was taken into consideration.

Previously, projects like Knoxville Extreme Energy Makeover (KEEM) received funds of around \$15 million for two years of project life [44] in Knox County. This year's proposed budget for Knox County includes \$8 million allocation for energy management projects [45]. We consider the same amount of budget as our fund for Knox County. Budget amounts for other counties were also chosen similarly. The selected budgets for eleven other counties were \$3.57 million for Davidson, \$1.27 million for Gibson, \$200,000 for Hamblen, \$500,000 for Hardeman, \$500,000 for Haywood, \$500,000 for Lauderdale, \$200,000 for Weakley, \$1 million for Sevier, \$1.5 million for Hamilton, \$2 million for Madison, and \$20 million for Shelby county. In the comprehensive analysis encompassing all twelve counties, the total budget allocation amounted to \$31.24 million. This figure aggregates the individual budgets specified for each county as previously detailed.

Electricity Price

The electricity prices vary across both county and utility providers. Due to the unavailability of data regarding which census tract is served by which utility provider, we used the utility providers for a particular county. We identified all the utility providers for a given county and collected their utility rate data. In the case of multiple utility providers, the average electricity rate was taken into consideration. In our case, the electricity average price ranges from \$0.0833-0.11497/kWh.

Intervention Parameters

The amount of peak sun hour is another important parameter while adopting PV panels. We advanced with the average sun hour value of 4.41 [46] throughout the year. The weatherization cost, savings, and lifetime per housing type were collected from different reports from Oak

Ridge National Laboratory (ORNL) [47, 48, 49, 50]. Costs were converted to 2023 dollar values (the original one was provided in 2008 value). The detailed values were provided in **Table 2**.

A rooftop solar system with a capacity of 6 kW was selected for this study. The approximate minimum roof space required was calculated to be 264 square feet, ensuring sufficient area for panel installation. The installation angle of the panels was assumed to match the latitude of the home, which typically ranges between 30 and 45 degrees, as recommended for optimal energy generation [51]. The residential photovoltaic (PV) installation cost was estimated at \$3.8/W, derived from the values reported in [52]. Consequently, the total cost for a 6 kW PV system amounts to \$15,960. Based on this configuration, a single rooftop PV system is expected to generate approximately 8,692.11 kWh of electricity annually. The average operational lifetime of this intervention is considered to be 20 years, aligning with industry standards.

For community solar interventions, several parameters, such as inverter efficiency and peak sunlight hours, were assumed to be similar to those used for rooftop solar systems. However, community solar systems differ in scale and are modeled with two distinct capacities: 1 MW and 0.5 MW. According to a report from the Lawrence Berkeley National Laboratory (LBNL) [52], the per-watt cost for non-residential PV systems is estimated at \$2/W. Using this cost metric, the total installation cost for a 1 MW community solar system is calculated to be \$2 million. This system is projected to generate approximately 1,448,685 kWh of electricity annually. For smaller systems with a capacity of 0.5 MW, both the cost and annual energy generation are proportionally halved, yielding a total cost of \$1 million and an annual energy output of 724,342.5 kWh. The average lifetime for community solar interventions is also considered to be 20 years, consistent with the rooftop solar systems.

Table 2: Weatherization costs, savings, and lifetime for each housing type collected through various reports from ORNL.

S/N	Housing Type	Cost (\$/household)	Savings (%)	Lifetime (Years)
1	Single-family	3671.34	12.4	35
2	Small multi-family	3412.05	13.9	35
3	Large multi-family	2785.11	12.3	35
4	Mobile homes	3510.09	8.2	35

Community wind interventions were designed using turbine capacities of 1 MW and 0.5 MW. The capacity factor, an essential parameter for wind energy generation, was set at 0.35 for Tennessee, based on data for turbines installed at an 80-meter tower height. The cost per kilowatt for wind turbines was approximated to be \$1,500, as indicated by a report from LBNL [53]. Using this cost estimate, the total installation cost for a 1 MW community wind system is \$1.5 million, with an expected annual electricity generation of 3,066,000 kWh. For the smaller 0.5 MW capacity turbines, the costs and energy generation values are reduced proportionally, resulting in a total cost of \$750,000 and an annual electricity generation of 1,533,000 kWh. The operational lifetime for community wind interventions is shorter compared to solar interventions, with an average lifetime of 15 years.

The detailed calculations and assumptions underlying these estimates provide a robust framework for understanding the costs and energy outputs associated with these renewable energy interventions. This information is critical for designing and implementing targeted energy equity programs in disadvantaged communities.

For convenience, the key specifications of the interventions considered in this study, including rooftop solar, community wind, and community solar, are summarized in **Table 3**. These specifications include intervention names, capacities, installation costs, annual energy generation, and the available lifetimes of the respective interventions. These details are critical for understanding the feasibility and comparative benefits of each intervention within the broader context of energy equity and sustainability. By consolidating this information into a table, it allows for a clearer comparison across interventions, enabling informed decision-making for policymakers and stakeholders.

Furthermore, the calibration values for various parameters used in the optimization models are summarized in **Table 4**. These values are essential inputs to ensure the accuracy and reliability of the models. They have been carefully compiled from a diverse range of credible sources, including peer-reviewed research articles, government and industry reports, and reputable online databases. Such calibration ensures that the models reflect real-world conditions as closely as possible. The tabulated format provides easy access to these values, facilitating quick reference during model development and analysis.

Table 3: Capacities, costs, annual energy generation, and lifetimes of rooftop solar, community solar, and community wind interventions.

S/N	Intervention	Capacity	Cost (\$)	Generated Energy (kWh)	Lifetime (Years)
1	Roof-top solar	6 kW	15,960	8692.11	20
2	Community solar	1 MW	2 million	1,448,685	20
		0.5 MW	1 million	724,342.5	
3	Community wind	1 MW	1.5 million	3,066,000	15
		0.5 MW	0.75 million	1,533,000	

Table 4: Different parameter values collected from various kinds of literature like research papers, scientific reports, websites, etc. K, D, G, Hb, Hd, Hw, L, W, Se, Hm, M, and Sb denote Knox, Davidson, Gibson, Hamblen, Hardeman, Haywood, Sevier, Hamilton, Madison, and Shelby County respectively. For illustration purposes, the parameter values were shown county-wise.

S/N	Parameter	Counties												All 12	Source
		K	D	G	Hb	Hd	Hw	L	W	Se	Hm	M	Sb		
1	Budget (\$M)	8	3.57	1.27	0.2	0.5	0.5	0.5	0.2	1	1.5	2	20	31.24	[45]
2	Electricity price (\$/kWh)	0.10	0.11	0.10	0.11	0.12	0.10	0.11	0.10	0.11	0.10	0.11	0.08	0.10	[54]
3	Household count	shown in Table 1												-	
4	Discount rate (%)	3												[55]	
5	Inverter efficiency (%)	90												[56]	
6	Capacity factor (%)	35												[57]	
7	Intervention capacity, cost, energy and lifetime	Table 2 and Table 3												[47]-[53]	
8	PV cost (\$/W)	3.8 (Residential) and 2 (Non-residential)												[52]	
9	Federal tax credit (%)	30												[58]	
10	Average peak sun hour (hrs)	4.41												[46]	
11	Cost of wind turbine (\$/kW)	1500												[53]	
12	Deviation from optimum roof angle (degree)	10												[59]	
13	Solar cell efficiency (%)	47.6												[60]	

1.2.4 Model

The necessary sets, parameters, decision variables, constraints, and objective function are provided in this section. For ease of access, all these are summarized in **Table 5**.

Objective Function

We seek to minimize the overall energy burden of all households. Let e^j denote the energy burden for household $j \in H$, then we write the objective function as:

$$\min \sum_{j \in H} e^j$$

The average household energy burden is calculated by dividing the total energy burden by the number of households considered. Another important thing to note is that we assume that the energy burden can not be greater than 100% for any household. In other words, a household can not spend more than what they earn for energy-related activities.

Constraints

Budget Each county has a given budget for its interventions. Since some interventions have a large up-front cost (community solar and community wind), we amortize the cost over their estimated lifetimes.

Let S_{int} denote a binary variable for the selection of each community intervention, I_c^{int} represent the intervention cost for each community intervention, and L_{int} indicate the lifetime of each intervention. Furthermore, B_{int}^j is a binary variable for each household regarding the selection of community solar or wind projects, I_c^{tsk} is the intervention cost for rooftop solar, r is the discount rate, and T_b is the designated county budget for a specific county. Then, we can describe the budget constraint with Equation 1.1, which asserts that the total spending on these interventions should not exceed the allotted or proposed budget for each county.

$$\begin{aligned} \sum_{int \in \{cs, cw\}} S_{int} \cdot I_c^{int} \cdot \frac{r}{1 - (1 + r)^{-L_{int}}} + \sum_{int \in w} B_{int}^j \cdot I_c^{wk} \cdot \frac{r}{1 - (1 + r)^{-L_{int}}} \\ + \sum_{int \in rts} B_{int}^j \cdot I_c^{tsk} \cdot \frac{r}{1 - (1 + r)^{-L_{int}}} \leq T_b \end{aligned} \quad (1.1)$$

Table 5: Description of sets, parameters, and variables used in the optimization model.

Nomenclature	
Sets	
H_t	Set of Household with different housing type, it could be of four types. $t \in \{single - family, small\ multi - family, large\ multi - family, mobile\ homes\}$
I	Interventions including weatherization (w), roof-top solar (rts), community solar (cs), and community wind (cw)
H	Set of all households
Parameters	
T_b	Total budget (\$)
r	Discount rate (%)
E_p	Electricity price (\$/kWh)
η	Inverter efficiency (%)
c_f	Capacity factor (%)
ϕ	Deviation from optimum roof angle for roof-top solar (degree)
η_{PV}	Solar panel efficiency (%)
n_{H_t}	Number of households for each housing type, $t \in \{single-family, small\ multi-family, large\ multi-family, mobile\ homes\}$
L_i	Lifetime of interventions where $i \in I$
w_t	Weatherization savings for different housing type
I_c^{int}	Intervention cost for each intervention, $int \in \{cs, cw\}$
I_c^{wk}	Intervention cost for weatherization for different household types, $k \in H_t$
I_c^{rtsk}	Intervention cost for rooftop solar, $k \in H_t$
a_e^j	Annual energy expenses, $j \in H$
En_{int}	Energy generation from different interventions, $int \in \{rts, cs, cw\}$
A_j	Annual income for each household $j \in H$
Variables	
e^j	Energy burden for each household after optimization, $j \in H$
B_w^j	Binary variable for each household regarding weatherization, $j \in H$, $B_w^j \in \{0, 1\}$
B_{rts}^j	Binary variable for each household regarding rooftop-solar, $j \in H$, $B_{rts}^j \in \{0, 1\}$
S_{int}	Binary variable for each community intervention selection at the county level, $int \in \{cs, cw\}$, $S_{int} \in \{0, 1\}$
B_{int}^j	Binary variable for each household regarding community solar and community wind, $j \in H$, $int \in \{cs, cw\}$, $B_{int}^j \in \{0, 1\}$

Optimized Energy Burden After adopting the proposed interventions, a household's energy usage is reduced by the amount of rooftop solar produced, the impact of weatherization on energy usage, and the household's share of the energy produced by the community assets (solar and wind). At the same time, equivalent annual costs of the different interventions with varying lifetimes were obtained using similar methodologies described in [61].

Let A_j represent the annual income for each household $j \in H$, and a_e^j denote the annual energy expense for each household $j \in H$. Additionally, let w_t indicate the weatherization savings for different housing types, and B_w^j be a binary variable for each household for weatherization. The variable E_p represents the electricity price, while B_{rts}^j is a binary variable for each household regarding rooftop solar. The term En_{int} corresponds to the energy generation from different interventions, and S_{int} is a binary variable indicating the selection of each intervention at the county level. Finally, $\mathbf{card}(\mathbf{H})$ denotes the cardinality of the set of all households. Given these definitions, the revised energy burden (e^j) can be described by Equation 1.2.

$$e^j = \frac{1}{A_j} \cdot (a_e^j - w_t \cdot a_e^j \cdot B_w^j - En_{rts} \cdot E_p \cdot B_{rts}^j - \sum_{int \in \{cs, cw\}} En_{int} \cdot E_p \cdot S_{int} \cdot \frac{1}{\mathbf{card}(\mathbf{H})} \cdot B_{int}^j) \quad \forall j \in H \quad (1.2)$$

The methodology section started with DACs selection following LEAP criteria. Then the necessary data were extracted from the LEAD dataset and preprocessed for the intended purpose. After that, household data and parameter values were provided as input to the optimization model and then we obtained threefold results. The optimized intervention counts provided the necessary interventions needed for the proposed energy burden reduction. The intervention mapping was done to connect those interventions to specific census tracts.

Sensitivity analysis was performed to show how energy burden and intervention counts change as a result of changing selective parameter values. Through sensitivity analysis, we also provided a relative sensitivity score in a Likert scale from 1-8 for different parameters where 1 denotes the most sensitive and 8 denotes the least sensitive. Since the unit of different parameters was different, our approach was to observe the % change in energy burden for % change in a particular parameter. That score was obtained for both individual counties

and combined (all 12). We finally prepared an overall ranking of these parameters based on the mode value. In the case of a tie-in mode value among the parameters, we went for the overall score that is prepared by summing the individual and combined (all 12) scores. The parameter with the lower score keeps the original rank, shifts other parameters to the next available rank, and so on.

1.3. Results and Discussion

This section discusses the optimized interventions that will achieve energy burden reductions. We show the census tract-wise mapping of these interventions (weatherization and rooftop solar), discuss how sensitive these investments are to the parameter values, and provide a ranking among parameters.

1.3.1 Numerical Results

The average energy burden for the selected counties before and after applying the optimization model and the optimized interventions are shown in **Table 6**. In all cases, the proposed interventions decreased the energy burden by a significant margin (below the 6% threshold). For three of the counties, the initial average energy burden was less than 6%, the proposed technique showed equal effectiveness for these counties too by decreasing the energy burden value even further. In two of the counties (Hamblen and Weakley), the adoption of community solar intervention was not needed. This is because both of these counties contain a very low number of households (380 and 280 respectively). The model was able to significantly decrease the average energy burden using smaller investments. Another interesting fact is that the number of weatherization interventions is larger than the number of roof-top solar interventions in all of the cases. This is because weatherization provides greater energy savings at a cheaper rate than roof-top solar. Factors that contribute to determining these intervention selections include but are not limited to peak sun hour, capacity factor, inverter efficiency, electricity price, discount rate, deviation from optimum roof angle, and solar cell efficiency.

Table 6: The energy burden situation for different counties before and after applying optimization techniques along with intervention counts. CI, W, RTS, CS, and CW stand for community intervention (both CS and CW), weatherization, roof-top solar, community solar, and community wind.

S/N	Counties	CI (MW)	Avg. Energy Burden (%)		Intervention Counts			
			Before	After	W	RTS	CS	CW
1	Knox	1	5.97	1.45	2,152	2,066	1	1
		0.5	5.97	1.77	2,184	2,066	1	1
2	Davidson	1	5.29	1.23	2,552	2,504	1	1
		0.5	5.29	1.50	2,561	2,504	1	1
3	Gibson	1	8.28	1.60	778	778	1	1
		0.5	8.28	2.58	800	808	1	1
4	Hamblen	1	6.77	1.95	304	25	0	1
		0.5	6.77	2.58	236	27	1	1
5	Hardeman	1	9.78	3.79	482	138	1	1
		0.5	9.78	4.7	496	252	1	1
6	Haywood	1	9.58	4.8	599	118	1	1
		0.5	9.58	5.52	613	232	1	1
7	Lauderdale	1	8.75	3.47	553	128	1	1
		0.5	8.75	4.27	562	243	1	1
8	Weakley	1	9.52	1.34	260	19	0	1
		0.5	9.52	2.7	258	24	1	1
9	Sevier	1	8.10	5.20	1,696	401	1	1
		0.5	8.10	5.44	1,698	517	1	1
10	Hamilton	1	5.56	2.52	1,694	847	1	1
		0.5	5.56	2.75	1,716	960	1	1
11	Madison	1	9.43	5.1	2,257	1,205	1	1
		0.5	9.43	5.34	2,279	1,318	1	1
12	Shelby	1	8.03	4.33	17,030	14,998	1	1
		0.5	8.03	4.36	17,058	15,110	1	1
13	All 12	1	7.59	3.78	28,425	23,290	1	1
		0.5	7.59	3.79	28,534	23,389	1	1

In all counties—except Hamblen and Weakley—both individually and combined, the number of weatherized households and rooftop solar installations increased when the community intervention capacity decreased from 1 MW to 0.5 MW (**Table 6**). This occurred because the energy burden reduction strategy relied more on household-centric interventions. Notably, Hamblen and Weakley did not initially adopt community solar due to a low number of eligible households. However, with reduced community intervention capacities, both community solar and wind were adopted, enabling energy burden reduction with fewer weatherization interventions.

Fig. 3 shows a more detailed view of the households’ energy burden situation (before and after adopting interventions) with 1 MW community intervention capacity for the selected census tracts organized by counties. The overall shift of energy burden for households from right to left due to the implementation of interventions in twelve different counties both individually and then collectively (all 12) is significant.

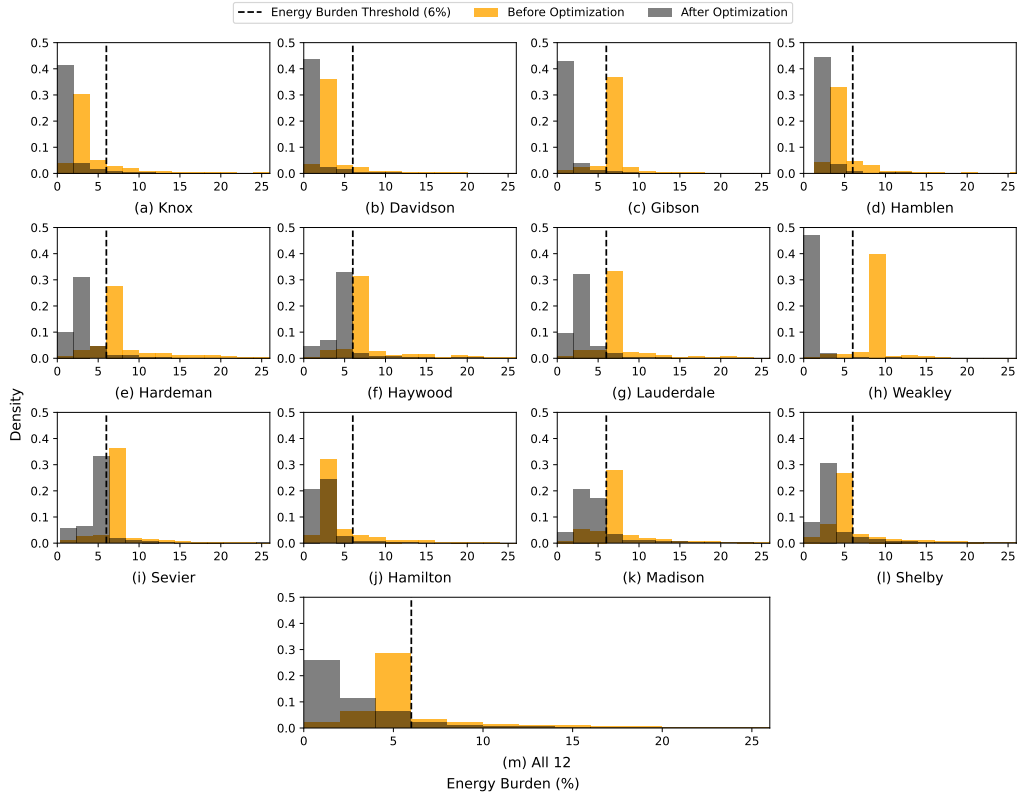


Figure 3: Energy burden scenario for DACs in selected Tennessee census tracts. The dotted line shows the 6% energy burden threshold, with a 1 MW community intervention capacity.

Reducing the energy burden beyond 6% was also achievable with lower community intervention capacities, as low as 0.5 MW as we can see from **Fig. 4**. A small community installation would produce a smaller amount of energy for the households in a tract to share and therefore not reduce the energy burden of the households in that tract as much as a larger installation. Therefore, the optimized portion of the histogram shifted a bit right, and additionally, the heights of the histogram bars were slightly reduced from their previous positions. This phenomenon is apparent in some of the histogram plots, especially in Gibson County, Hamblen County, Hardeman County, Haywood County, Lauderdale County, and Weakley County. The selected census tracts from these counties contain fewer households compared to others. Therefore, the reduction of community intervention capacity by 0.5 MW showed some significant differences in the histogram plot. Overall, the average energy burden value was under the target promoting that even as low as 0.5 MW of community intervention is sufficient for these studied households.

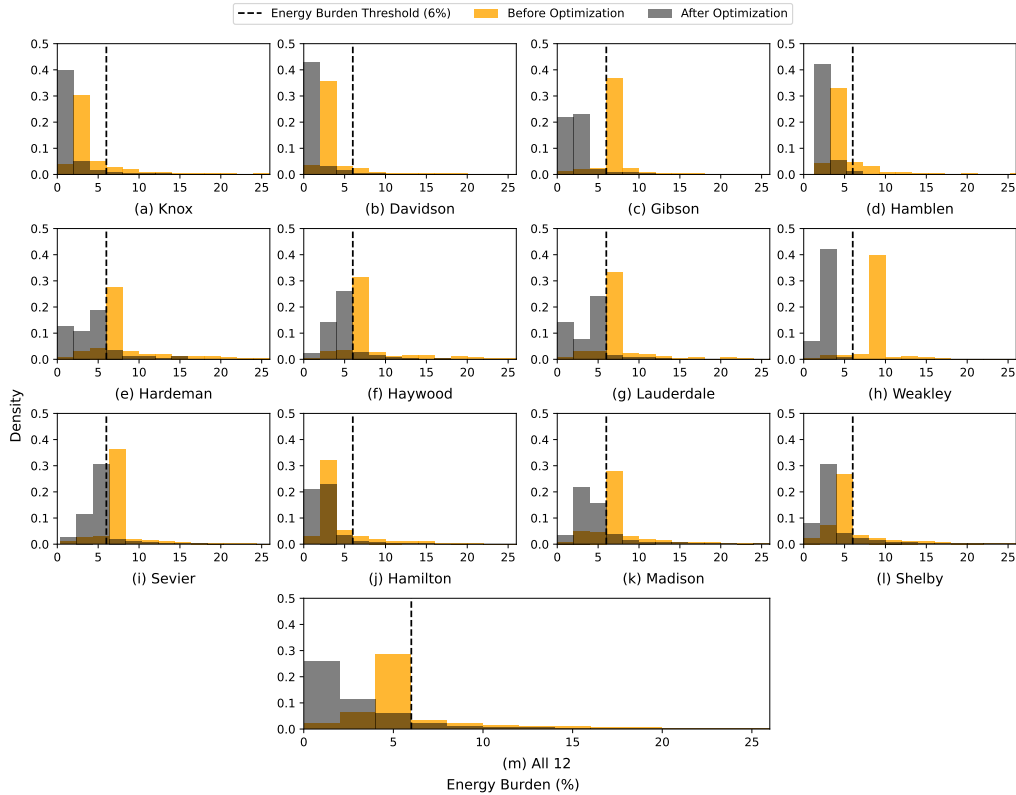


Figure 4: Energy burden scenario of DACs from selected census tracts in Tennessee, USA. The dotted vertical line portrays the energy burden threshold (6%) and is used for illustration purposes. The community intervention capacity of 0.5 MW was considered.

It is notable from both figures (**Fig. 3** and **Fig. 4**) that the adoption of proposed interventions could not reduce the energy burden for some households below the target whose initial energy burden was very high. In addition to the proposed interventions, we suggest taking advantage of more income-based energy assistance programs for those households to further reduce their high energy burden.

1.3.2 Mapping

We further identified the location of the proposed interventions at a granular level, mapping them to census tracts for six counties: Shelby, Davidson, Sevier, Madison, Knox, and Hamilton. These counties were selected based on the presence of multiple census tracts meeting the criteria for disadvantaged communities (DACs). For counties with only one census tract meeting the DAC criteria, mapping was not performed since the proposed interventions would inherently apply to the single eligible census tract in those cases. Therefore, the number of interventions proposed for such counties is directly associated with that specific census tract.

Table 7 presents a detailed breakdown of weatherized households and rooftop solar installations at the census tract level for Shelby County. This granular mapping allows stakeholders and policymakers to target interventions more effectively, tailoring resources to the areas of greatest need.

It is important to note that community solar and community wind interventions were not mapped to specific census tracts. Unlike weatherization and rooftop solar, which are tied to individual households, these community-based interventions serve broader populations and are not confined to particular locations. Instead, a county-wide allocation approach was used for community solar and community wind interventions. This strategy ensures that these interventions address the needs of the broader community while avoiding the limitations of household-specific targeting. Such an approach allows for flexibility in implementation and maximizes the impact of these shared resources.

This level of spatial granularity for weatherization and rooftop solar, coupled with the county-wide approach for community interventions, provides a comprehensive framework for addressing energy equity while balancing specificity and scalability.

Table 7: Optimized count of interventions for energy-burdened people of Shelby County, Tennessee within a limited allocated budget. The community intervention (both solar and wind) capacity of 1 MW was considered.

Census Tracts	W	RTS	Census Tracts	W	RTS
47157000200	403	335	47157000300	330	288
47157000400	415	346	47157000600	383	341
47157000700	452	400	47157000800	338	302
47157000900	395	379	47157001100	148	136
47157001300	397	355	47157001400	211	184
47157001900	270	243	47157002000	579	515
47157004500	276	225	47157005000	232	172
47157005300	470	418	47157005500	287	239
47157005600	329	300	47157005700	331	280
47157005800	478	427	47157005900	179	158
47157006000	225	192	47157006200	167	138
47157006500	472	441	47157006700	310	261
47157006800	308	263	47157006900	145	125
47157007500	141	119	47157007810	288	237
47157007821	213	169	47157007822	209	177
47157008110	501	446	47157008900	317	284
47157009100	207	189	47157009902	207	176
47157010110	254	225	47157010120	301	264
47157010300	226	193	47157010500	286	256
47157010610	337	291	47157010630	307	242
47157011020	286	260	47157011100	335	303
47157011200	308	265	47157011500	314	270
47157011600	553	507	47157011700	303	289
47157020512	524	486	47157020521	277	248
47157020523	458	422	47157022022	246	220
47157022023	312	285	47157022220	276	254
47157022310	287	254	47157022700	227	204

The spatial distribution of the proposed interventions for the selected census tracts in Shelby County, Tennessee, is illustrated in **Fig. 5**. This figure provides a visual representation of the allocation of weatherization and rooftop solar interventions across different census tracts. To enhance interpretability, the intervention counts are categorized into five ascending ranges, allowing readers to quickly assess the concentration of interventions across the region.

As discussed earlier, the counts for weatherization interventions are consistently higher than those for rooftop solar in each census tract. This disparity is driven by the broader applicability and lower cost of weatherization compared to rooftop solar, making it a more scalable solution for energy-burdened households. The central areas of Shelby County, marked with pentagon and plus signs, exhibit the highest concentration of proposed interventions. These central tracts correspond to areas with the greatest prevalence of energy-burdened communities, as identified in the preliminary analysis. This concentration underscores the need for targeted interventions in these high-priority zones to effectively alleviate energy burdens in disadvantaged communities (DACs).

To provide a comprehensive overview, the intervention details for other counties included in this study are summarized in **Table 17** in **Appendix A**. This table presents intervention counts for each selected census tract in these counties, offering a broader perspective on the geographical distribution of proposed solutions. The tabular representation complements the visual mapping in **Fig. 5** and serves as a valuable resource for policymakers and stakeholders who may need to reference specific data for their decision-making processes.

By combining visual and tabular formats, this study ensures that both granular details and broader trends in intervention distribution are accessible to a wide range of audiences. This approach facilitates effective communication of the results and highlights the importance of addressing energy equity at both the local and regional levels.

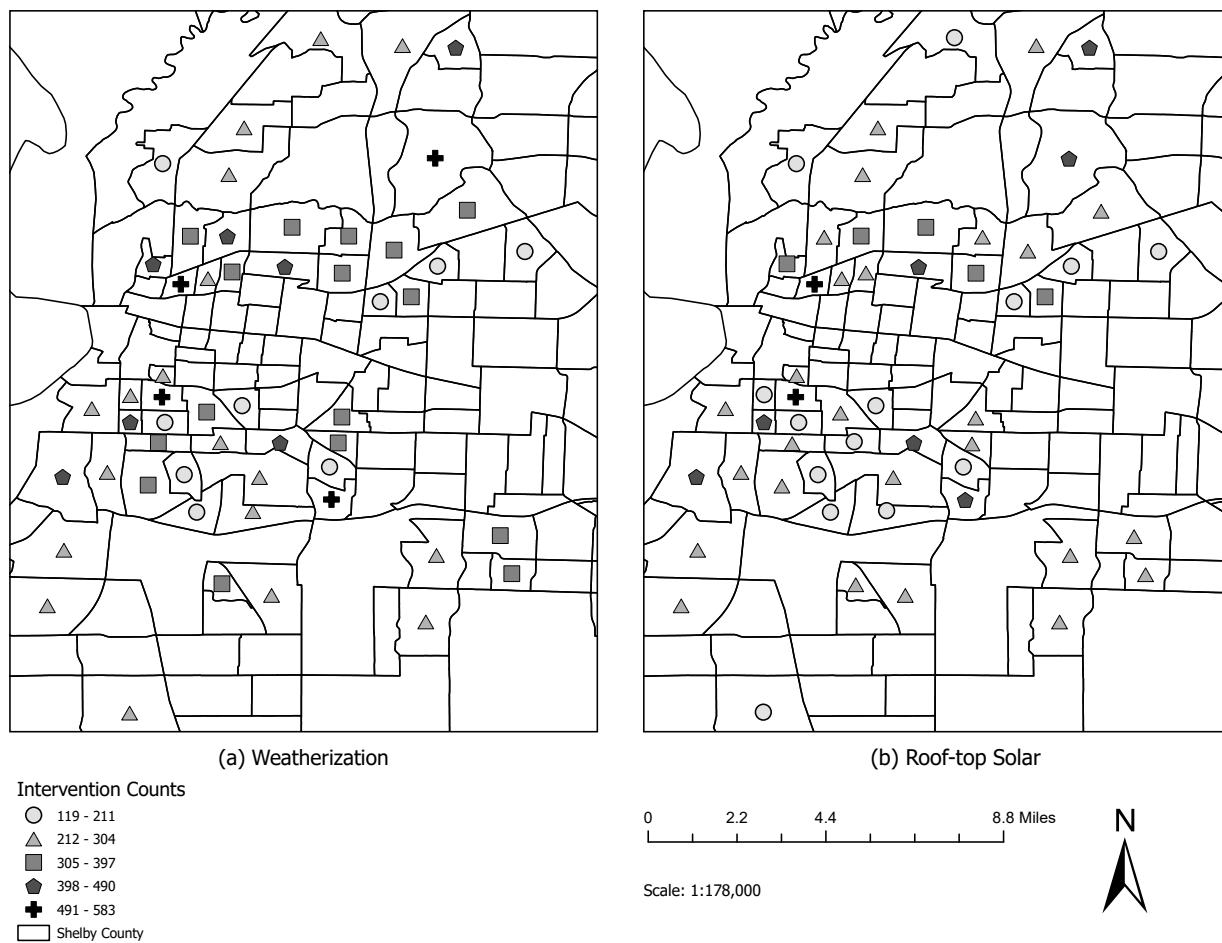


Figure 5: Mapping of interventions (weatherization and roof-top solar) to selective census tracts of Shelby County, Tennessee. The community intervention capacity of 1 MW was considered.

1.3.3 Sensitivity

This study explores the sensitivity of energy burden percentages to variations in eight key parameters, providing insights into how changes in these factors influence the outcomes of the proposed interventions. The selected parameters for sensitivity analysis include the wind capacity factor, inverter efficiency, discount rate, peak sunlight hours, budget, electricity price, deviation from the optimum roof angle, and solar cell efficiency. By controlling the counts of proposed interventions and systematically altering these parameter values, we highlight their respective impacts on energy burden reduction.

The sensitivity analysis for Shelby County, which considers a community intervention capacity of 1 MW, is illustrated in **Fig. 6**. This figure captures the dynamic relationship between parameter changes and the resulting energy burden percentage, offering a granular understanding of the intervention’s performance under varying conditions.

For a comprehensive perspective, additional sensitivity plots for other counties are provided in **Appendix B**, spanning from **Fig. 13** to **Fig. 24**. These plots offer similar analyses across different regions, emphasizing the broader applicability and variability of the findings.

In general, the sensitivity analysis reveals that an increase in the wind capacity factor, inverter efficiency, peak sunlight hours, budget, and solar cell efficiency leads to a decrease in the average energy burden percentage. This outcome reflects the enhanced efficiency and cost-effectiveness of the interventions under favorable conditions. Conversely, increases in the discount rate, electricity price, and deviation from the optimum roof angle result in higher average energy burdens, underscoring the detrimental effects of less favorable economic and technical conditions.

This sensitivity analysis serves as a critical tool for identifying the most impactful parameters and understanding their role in shaping the effectiveness of the interventions. The findings provide actionable insights for policymakers and stakeholders, enabling them to prioritize efforts and resources toward optimizing these key parameters. By tailoring intervention strategies to the most sensitive variables, the overall impact on energy equity can be maximized, ensuring sustainable and equitable outcomes for DACs.

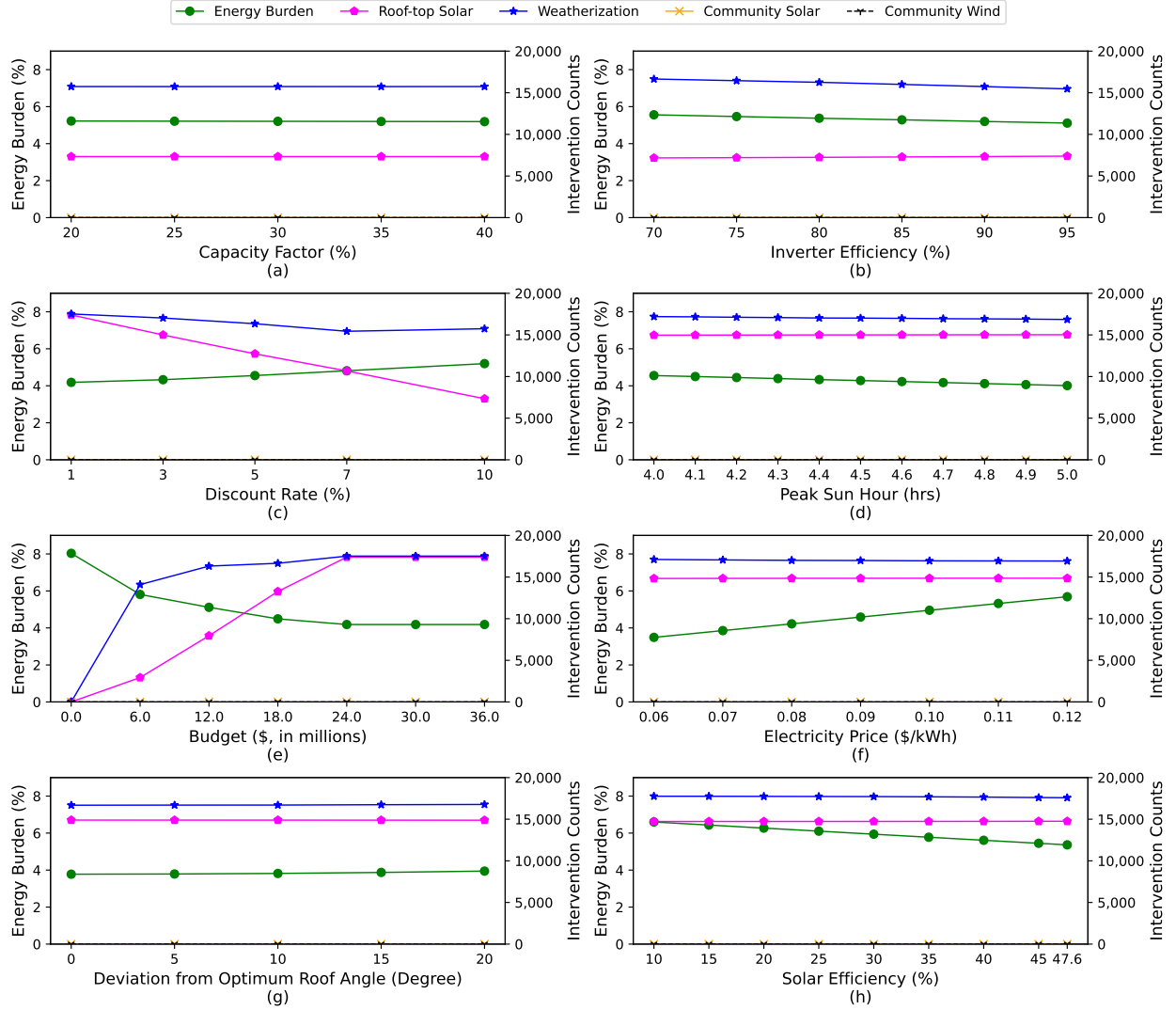


Figure 6: Change of energy burden and intervention counts in selected census tracts from Shelby County, Tennessee, USA with the change of different parameters. The community intervention capacity of 1 MW was considered. Since the counts of community interventions (either 0 or 1) are significantly lower compared to those for weatherization and rooftop solar installations, the yellow and black dotted lines representing these interventions are not easily visible on the graph. This holds for the rest of the sensitivity plots.

In our comprehensive analysis of eight critical parameters with varying units across 12 counties, both individually and in combination (all 12 counties aggregated), standardization techniques were employed to enable meaningful comparisons. This standardization ensured that differences in units and scales did not skew the results, allowing for a robust evaluation of parameter sensitivities across diverse geographic and socio-economic contexts.

The relative sensitivity of these parameters was assessed using a Likert scale ranging from 1 (most significant) to 8 (least significant). The results of this evaluation are summarized in **Table 8**, which presents the sensitivity rankings for each parameter across all analyzed counties as well as the combined dataset.

Our findings show that while most parameters varied in sensitivity across counties, the discount rate consistently ranked as the most sensitive, emphasizing the critical role of financial factors like cost of capital and time value of money. In contrast, the deviation from the optimum roof angle was the least sensitive, having minimal impact on energy burden reductions compared to economic and efficiency-related parameters.

Table 8: Relative score of parameters for each county individually and combinedly (all 12). Here 1 implies the most sensitive parameter whereas 8 implies the least sensitive. K, D, G, Hb, Hd, Hw, L, W, Se, Hm, M, Sb, and All 12 denote Knox, Davidson, Gibson, Hamblen, Hardeman, Haywood, Sevier, Hamilton, Madison, Shelby County, and all the 12 counties combined respectively. The last column (Rank) provides the overall ranking which was prepared using a combination of mode and $\sum$ score.

S/N	Parameter	Counties												All 12	∑ Score	Mode	Rank
		K	D	G	Hb	Hd	Hw	L	W	Se	Hm	M	Sb				
1	Capacity factor (%)	4	5	4	2	2	2	2	2	4	5	6	7	7	52	2	3
2	Inverter efficiency (%)	3	3	3	6	4	4	8	7	5	3	2	5	4	57	3	5
3	Discount rate (%)	1	1	1	1	1	1	1	1	1	1	1	1	1	13	1	1
4	Peak sun hour (hrs)	5	4	5	7	5	6	5	5	6	6	5	4	5	68	5	6
5	Budget (\$M)	7	7	7	5	7	7	6	4	7	7	7	6	6	83	7	7
6	Electricity price (\$/kWh)	6	6	6	3	6	5	4	3	3	4	4	3	3	56	3	4
7	Deviation from optimum roof angle (degree)	8	8	8	8	8	8	7	8	8	8	8	8	8	103	8	8
8	Solar cell efficiency (%)	2	2	2	4	3	3	3	6	2	2	3	2	2	36	2	2

Further analysis revealed that solar cell efficiency and capacity factor both achieved a mode value of 2, with solar cell efficiency scoring 2 in six counties and all 12 combined, while capacity factor did so in five counties. This distinction positioned solar cell efficiency as the second most sensitive parameter, followed by capacity factor in third. Electricity price and inverter efficiency ranked similarly. Overall, the sensitivity ranking from most to least is: discount rate, solar cell efficiency, capacity factor, electricity price, inverter efficiency, peak sun hours, budget, and deviation from the optimum roof angle (**Table 8**).

1.3.4 Managerial Insights

This section presents our study’s key findings and broader implications. The key findings offer a concise summary of our results, while the broader implications discuss considerations for adapting this model in other regions.

Key Findings

Our research presents a framework that comprehensively analyses energy burden mitigation techniques. We note the following insights gained from our case study:

- **Effective Burden Reduction:** Implementing the optimization model led to a substantial decrease in energy burdens across all studied counties, dipping below the critical 6% threshold, including those initially under this benchmark.
- **Selective Community Solar Adoption:** In counties with fewer households (Hamblen and Weakley), larger community solar interventions were deemed unnecessary, with smaller-scale investments sufficing for impactful energy burden reduction.
- **Preference for Weatherization:** Across the board, weatherization was favored over other interventions due to its cost-effectiveness and greater energy savings.
- **Scaled Community Interventions:** Reducing community intervention capacity to 0.5 MW resulted in a broader adoption of household-centric measures, proving even minimal community intervention can significantly impact energy burden reduction.

- **Challenges for High Energy Burdened Households:** Some households with initially high energy burdens remained above the target despite intervention adoption, indicating the need for additional income-based energy assistance programs.
- **Granular Intervention Mapping:** Detailed mapping of interventions at the census tract level for twelve different counties provided specific insights into the distribution and effectiveness of proposed measures.
- **Sensitivity Analysis:** The analysis determined the significance hierarchy of parameters for individual counties and collectively across all 12, providing a comprehensive ranking through mode and aggregate scores.

Broader Implications

The findings and methodologies of this study offer valuable insights for broader implications, suggesting several strategies for other regions considering similar energy burden reduction initiatives:

- **Adaptability of the Optimization Model:** The success of the optimization model in significantly reducing energy burdens below a critical threshold demonstrates its potential applicability in diverse geographical and socio-economic contexts. Other regions may consider the adaptability of this model to their specific conditions, including local energy costs, climate, housing characteristics, etc.
- **Customized Intervention Strategies:** Tailored intervention strategies based on the specific demographic, economic, and geographical characteristics of the region might be helpful. Small-scale, household-centric interventions (weatherization, rooftop solar) can be more effective and economical, especially in areas with fewer households.
- **Scalable Community Solutions:** Consideration for the scalability of community energy projects is crucial for ensuring that interventions can be effectively adjusted to meet the varying needs and resources of different regions. Smaller installations may offer a more flexible and equitable approach to energy distribution and burden reduction, particularly in less densely populated areas.

- **Data-Driven Approach:** The employment of a data-driven methodology is imperative to identify and prioritize interventions. Factors such as solar cell efficiency, electricity prices, and household energy consumption patterns should inform the selection and scale of interventions.
- **Policy and Program Support:** Support from local and state policies, including incentives for proposed interventions, can significantly enhance the feasibility and impact of these interventions. Additionally, promoting region or state-specific income-based energy assistance programs can address the needs of the most burdened households.
- **Sensitivity Analysis for Parameter Optimization:** Conducting sensitivity analyses to understand the impact of various factors on energy burden reduction outcomes might be beneficial. This approach helps in identifying the most influential parameters that should be considered in decision-making processes for a particular region or state.

1.4. Limitations

This study, while comprehensive in its current scope, acknowledges several limitations that could be addressed in future research. Firstly, the primary beneficiaries of the proposed interventions are households that rely exclusively on electricity for heating and cooling. The data predominantly covers tracts where electric-based systems are prevalent, thus providing equitable benefits across these regions. However, households utilizing gas and other fuel sources are less impacted by our current interventions. To align with national net-zero emission objectives, a transition to all-electric systems is necessary, necessitating substantial investments in both the electric grid and associated infrastructure. Future research could explore the economic implications of such transitions, including the costs associated with adopting technologies like heat pumps, induction stoves, and electrical panel upgrades.

Secondly, the regional focus of this study is Tennessee, characterized by its humid subtropical climate with warm, humid summers and mild winters. Extending this model to diverse climatic conditions could enhance its applicability and robustness. For instance, regions with long, harsh winters and heavy snowfall present different challenges for energy

consumption, particularly in heating. Similarly, areas experiencing hot, dry summers require strategies tailored to intensive cooling needs. Exploring regions with moderate temperatures and consistent precipitation throughout the year could further validate the model’s utility across different environmental contexts. Such expansions would allow for broader comparisons and more generalized insights applicable to a range of geographic settings.

Thirdly, the parameters employed in our analyses, such as peak sun hours and electricity prices, are assumed to be stable, which is more reflective of short-term scenarios. However, considering the long-term nature of the proposed interventions, a stochastic approach to these parameters might yield more precise and realistic outcomes. Future studies could incorporate stochastic modeling to account for the variability and uncertainty inherent in these parameters, enhancing the strategic planning of energy resources.

Lastly, this study does not account for potential self-limiting behaviors by households in response to energy costs or environmental concerns. Households may voluntarily reduce their energy usage to lower costs or minimize their carbon footprint, which could alter the effectiveness of the proposed interventions. Future research could benefit from integrating behavioral models to predict and incorporate consumer response to energy pricing and policy changes, thereby providing a more holistic understanding of the impacts of energy interventions.

These limitations notwithstanding, the current study lays a foundational framework for addressing energy equity through targeted interventions and provides a basis for expanded inquiry into sustainable energy solutions across diverse environments and long-term scenarios.

1.5. Conclusion and Policy Implications

Our study, centered around a quantitative approach using an optimization framework, addresses the critical dilemma of energy burden in disadvantaged communities (DACs) in Tennessee. By integrating interventions such as weatherization, rooftop solar, community solar, and community wind, we demonstrate substantial potential in reducing the financial strain associated with energy costs. The policy implications of our findings are both significant and actionable.

Firstly, our results underscore the effectiveness of targeted weatherization programs as a primary tool for immediate relief of energy expenditures across varied housing types. Policymakers should consider enhancing funding and accessibility to these programs, particularly in DACs where the energy burden is disproportionately high. Expansion of these initiatives can be supported by leveraging data-driven insights to optimize the allocation of resources, ensuring that the most vulnerable households receive timely and effective interventions.

Secondly, the implementation of distributed energy resources (DERs) like rooftop and community solar, as well as community wind projects, not only supports the reduction of the energy burden but also contributes to environmental sustainability goals. However, the adoption of such technologies is often hindered by upfront costs and lack of awareness. Policies aimed at subsidizing initial costs, coupled with community-focused educational programs, could accelerate the adoption rates and benefits derived from these technologies.

Moreover, our study highlights the need for policies that integrate energy efficiency interventions with broader socio-economic benefits. For instance, integrating energy efficiency improvements with housing development and rehabilitation projects could provide dual benefits of reduced energy burden and improved living conditions. Such integrative approaches are particularly crucial in low-income and economically marginalized communities.

As the world engages with the urgent need for a transition to clean energy, in light of the severe impacts of CO₂ emissions from fossil fuel consumption on climate change, our study gains even more relevance. It's crucial that this transition not only prioritizes environmental sustainability but also ensures social equity. Our findings underscore the necessity of a holistic approach to energy policy, one that equally addresses the needs of all households, including the DACs. This is vital in fostering a culture of energy equity, where the benefits of clean energy interventions are shared universally.

In conclusion, our research offers a framework to reduce energy burdens while supporting sustainable energy policies. By addressing economic, environmental, and social factors, policymakers can build resilient, equitable energy systems that eliminate the trade-off between energy needs and basic necessities, improving quality of life and advancing energy equity.

Chapter 2

Annual, Seasonal, and Monthly Analysis of Energy Intervention Strategies in Tennessee and Florida

In the second chapter, a comprehensive analysis of intervention adoption was conducted with enhanced granularity. This chapter expanded the scope of the study by incorporating the state of Florida, complementing the initial focus on Tennessee. The analysis compared the number of interventions adopted over a one-year period with those adopted across four distinct seasons (Winter, Spring, Summer, and Fall) and twelve individual months (January to December), while accounting for varying budget constraints in each state. Additionally, fluctuations in energy burden prior to any intervention were thoroughly examined, providing critical insights into the comparative effectiveness of monthly, seasonal, and annual intervention strategies in addressing energy equity.

2.1. Introduction

This chapter provides a comprehensive analysis of energy intervention strategies, focusing on how their timing and adoption can reduce energy burdens in disadvantaged communities. Through a detailed comparison of annual, seasonal, and monthly interventions across two states, Tennessee and Florida, this chapter seeks to advance the understanding of how local

conditions and energy consumption patterns influence the effectiveness of various energy equity measures.

2.1.1 Purpose and Objectives

This chapter delves into a detailed and comprehensive analysis of energy intervention strategies with increased granularity, focusing on the temporal distribution of interventions to alleviate energy burdens in disadvantaged communities. The primary goal of this chapter is to examine how energy interventions, such as weatherization, rooftop solar, and community-based renewables, perform when deployed over different timeframes—annually, seasonally, and monthly. By expanding the study to include Florida, in addition to the initial focus on Tennessee, this analysis aims to compare the effectiveness of these interventions across varied climatic conditions, socio-economic contexts, and energy consumption patterns.

The analysis is conducted by comparing the number of interventions adopted over a one-year period with those adopted across four distinct seasons (Winter, Spring, Summer, and Fall) and twelve individual months (January to December). The study also takes into account the varying budget constraints specific to each state, offering a deeper understanding of the optimal allocation of resources for energy equity.

This chapter seeks to answer several important research questions: Does the granularity of intervention timing (i.e., annual, seasonal, or monthly) significantly impact the effectiveness of these strategies in reducing energy burdens? How do variations in seasonal and monthly energy consumption influence the outcomes of interventions, and what lessons can be drawn for policymakers looking to optimize these strategies? By critically assessing fluctuations in energy burden prior to intervention adoption, this chapter provides essential insights into how the timing of interventions can address energy inequities more effectively.

The findings presented in this chapter are pivotal in advancing the overarching goals of this dissertation, which is to develop and evaluate intervention strategies that maximize energy equity for disadvantaged communities. By addressing energy inequities through both a temporal and regional lens, this chapter contributes to a broader understanding of how tailored interventions can be designed to meet the unique needs of different populations. Ultimately, the results of this analysis will guide future research and policy recommendations

that prioritize effective, equitable energy solutions for communities across varying geographies and climates.

2.1.2 Overview of the Study Area

The two states selected for this analysis—Tennessee and Florida—offer contrasting yet complementary perspectives on energy intervention strategies due to their distinct energy consumption patterns, climatic conditions, and socio-economic demographics. These differences make them ideal case studies for assessing how energy interventions perform under various circumstances.

Tennessee, located in the southeastern United States, experiences a temperate climate characterized by cold winters and hot, humid summers [62]. This seasonal variation in temperature leads to significant fluctuations in energy demand, with higher consumption in both summer (for cooling) and winter (for heating) [63]. Tennessee also has a notable percentage of energy-burdened households, particularly in rural areas, where income levels are lower, and access to energy-efficient technologies is more limited [64]. These characteristics make Tennessee a prime candidate for exploring how annual, seasonal, and monthly interventions can alleviate energy burdens across diverse population segments.

In contrast, Florida, located in the subtropical and tropical regions of the United States, has a markedly different energy consumption profile [65]. The state experiences warm temperatures year-round, with a particular emphasis on high cooling demands during the extended summer months [66]. Florida’s energy landscape is shaped by urban and rural divides, population density, and significant levels of energy-burdened communities [67]. Urban centers in Florida face high electricity demands for cooling, while rural communities often contend with energy poverty due to both socio-economic challenges and limited access to renewable energy infrastructure.

The choice of these two states allows for a comparative analysis of how interventions designed to reduce energy burdens perform across regions with differing climate demands and socio-economic conditions. Tennessee’s seasonal energy needs present a scenario where winter heating and summer cooling dominate, making it a model for examining how seasonally specific interventions—such as weatherization or heating system upgrades—can alleviate

energy burdens. Meanwhile, Florida’s consistent cooling requirements provide a contrasting scenario where renewable energy sources like community solar or energy-efficient cooling systems may offer more substantial long-term benefits.

By analyzing these two states, this chapter captures a wide range of challenges faced by disadvantaged communities in different climatic zones, enhancing the generalizability of the findings. The results from Tennessee and Florida can inform broader discussions on how intervention strategies must be adapted to local conditions to effectively reduce energy burdens and promote energy equity across the United States.

2.2. Literature Review

In the first chapter, we explored the broader landscape of energy equity by examining the critical determinants of Distributed Energy Resources (DERs) adoption, energy policy, and the implications of energy burden as a key metric. Building on the foundation laid in that chapter, the second chapter extends the inquiry by focusing on how the temporal adoption of energy interventions—whether conducted annually, seasonally, or monthly—affects the reduction of energy burden, particularly in disadvantaged communities in Tennessee and Florida. While the first chapter discussed various structural factors contributing to energy inequity, such as grid hosting limitations, socio-economic disparities, and the role of renewable energy adoption (e.g., rooftop solar), this chapter introduces time as a critical variable in optimizing energy burden reduction.

2.2.1 Temporal Energy Burden Dynamics

Studies have explored energy burden from multiple perspectives, yet the temporal dimension remains understudied. However, a deeper understanding of how seasonal and monthly fluctuations in energy consumption affect energy burdens is vital, particularly in regions where climatic extremes drive up heating and cooling costs.

A study by Forrester et al. [68] provides important insights into how rooftop solar adoption impacts energy burdens over time, focusing on yearly savings for households across the United States. The study found that 36% of low-to-moderate income (LMI) adopters

experienced a reduction in energy burden after solar adoption, but the degree of reduction was highly dependent on geographic and socio-economic factors. While solar energy consistently reduced the energy burden for LMI households, the magnitude of savings varied, with regions experiencing lower electricity costs showing less dramatic reductions in energy burden [68]. This finding underscores the importance of region-specific interventions and suggests that seasonal variations—such as Florida’s year-round cooling demands—must be considered when optimizing renewable energy strategies for energy burden reduction.

In a complementary study [69], the Pacific Northwest National Laboratory (PNNL) analyzed the comparative effectiveness of energy storage, weatherization, and energy efficiency upgrades in reducing energy burden. This study identified that energy storage plays a crucial role in mitigating energy burden, particularly in regions with seasonal spikes in energy demand, such as Tennessee’s cold winters and hot, humid summers. However, it was also noted that weatherization interventions had a more immediate and pronounced effect on energy burden reduction in colder regions, where heating costs dominate winter energy usage [69]. This suggests that a seasonal approach—where specific interventions are timed to align with seasonal energy needs—could yield better outcomes than interventions deployed annually or without regard for timing.

2.2.2 Seasonality and Energy Burden

As identified in Chapter 1, the disparities in DER adoption are often influenced by factors such as income level, racial inequities, and homeownership [26]. However, these factors intersect with seasonal and climatic variables to shape energy consumption patterns. A report [70] by Rocky Mountain Institute highlighted the particular vulnerability of low-income households in the southern United States, where cooling needs drive up energy burdens during the summer months. The report emphasizes that the energy burden for low-income households in states like Florida and Tennessee can be up to eight times higher than that of households earning above the median income [70]. These findings suggest that energy interventions must not only address socio-economic inequities but also be sensitive to seasonal demands to achieve a meaningful reduction in energy burden.

The research conducted by Shen et al. [71] further corroborates these findings, showing that energy burden is not static but varies significantly across different seasons. In colder climates, heating-related energy burden during the winter months disproportionately impacts low-income households, while in warmer climates, cooling-related burdens in the summer dominate [71]. This cyclical pattern suggests that an annualized approach to energy burden reduction may miss critical windows where targeted interventions, such as increased weatherization during winter or solar adoption in summer, could have the most impact.

2.2.3 Monthly Energy Consumption Patterns and Energy Burden

The inclusion of monthly intervention analysis in this chapter addresses a critical gap in the existing literature, which often overlooks how monthly fluctuations in energy consumption affect energy burdens. Studies that do explore monthly energy consumption patterns reveal that low-income households often respond to rising temperatures by reducing their energy usage more aggressively, exacerbating energy poverty during peak summer months. For instance, research indicates that increased cooling costs during summer disproportionately impact these households, making it difficult for them to maintain safe living conditions as they are forced to reduce energy use to manage costs [72].

Studies from the American Council for an Energy-Efficient Economy (ACEEE) support the idea that targeted interventions, such as weatherization programs timed for early summer, could alleviate this burden by reducing cooling costs before the peak demand period. Such interventions help low-income households maintain safe energy usage levels and prevent the dangerous reduction of energy consumption [73].

Similarly, findings from the Lawrence Berkeley National Laboratory [68] show that rooftop solar adoption results in the most significant reduction of energy burden during summer months, particularly in regions like Florida, where cooling needs dominate household energy consumption. This underscores the importance of considering monthly energy patterns when designing interventions, particularly in climates with extreme seasonal variations in energy costs.

2.2.4 Gaps and Contributions

While Chapter 1 explored energy burden reduction using a primarily annual perspective, it is clear that energy consumption patterns fluctuate throughout the year. Seasonal peaks in heating and cooling, particularly in states like Tennessee and Florida, highlight the need for more granular analysis to uncover the full impact of energy interventions. This chapter addresses gaps in the existing literature by analyzing how monthly and seasonal variations can provide more actionable insights for reducing energy burdens, especially for disadvantaged communities.

Key gaps addressed in this chapter include:

1. **Lack of Temporal Granularity:** The first chapter focused on annual energy burden reduction, which fails to capture the nuances of energy consumption driven by monthly and seasonal fluctuations. This chapter introduces finer temporal granularity to better align interventions with real-world energy usage patterns.
2. **Overlooking Peak Demand Periods:** Granular insights, such as the role of peak seasons in driving energy costs, are missing from the broader literature. Existing studies generalize energy interventions as single-event annual strategies, overlooking the potential for seasonal or monthly adjustments that could better target high-demand periods, such as winter heating in Tennessee or summer cooling in Florida.
3. **Neglect of Monthly Dynamics:** Previous research has largely neglected the detailed impacts of energy burden at a monthly scale. Few studies explore how interventions like weatherization or solar installations could be optimized if timed according to specific seasonal needs (e.g., cooling in summer or heating in winter). This chapter addresses this gap by demonstrating the effectiveness of monthly intervention strategies.
4. **Need for Time-Sensitive Strategies:** There is a lack of fine-tuned analysis integrating time-sensitive intervention strategies, which could provide a clearer path to energy equity, especially in regions with diverse climatic conditions like Tennessee and Florida. This chapter shows how adaptive strategies can more effectively reduce energy burdens during critical periods of energy demand.

5. **Energy Equity Considerations:** Existing studies often do not prioritize equity in the distribution of community interventions. This chapter ensures that households with higher energy burdens receive a proportionally greater share of energy contributions from community solar and wind interventions. This equity-focused approach prioritizes those most in need, effectively reducing disparities and promoting fairer outcomes.

In this chapter, we take a refined approach by analyzing energy burden across annual, seasonal, and monthly perspectives, focusing on the temporal dynamics of energy consumption. By incorporating monthly and seasonal variations, this chapter addresses the overlooked granularity in energy equity studies, offering a more comprehensive understanding of how time-sensitive interventions can improve energy outcomes for disadvantaged communities. The inclusion of both Tennessee and Florida in the analysis allows for a deeper exploration of how climatic differences shape the effectiveness of these interventions, setting the stage for more effective and targeted policy recommendations.

2.3. Methodology

This section outlines the criteria for selecting Disadvantaged Communities (DACs), details of the model (including sets, parameters, variables, objective function, and constraints), data sources, and parameter calibration.

Initially, DACs in Tennessee were selected as described in Chapter 1 (see Section 1.2.1). DACs from Florida were selected using the same criteria [41]. After applying these criteria, the details of selected households in Tennessee are presented in **Table 1**. Given the statewide approach in this chapter, housing types are aggregated, unlike the county-wise data in Chapter 1. For Florida, the counts for housing types are as follows: 12,243 for single-family, 7,725 for small multi-family, 3,123 for mobile homes, and 2,099 for large multi-family dwellings.

Following the selection of DACs, relevant data were collected, including Federal Information Processing (FIP) codes, housing types, annual expenditures on electricity, gas, and other fuels, and household income. Additional parameters, such as electricity prices, residential electricity consumption ratios, peak sun hours, and wind speeds at 80-meter hub heights, were also gathered for both Tennessee and Florida, spanning annual, seasonal, and monthly

intervals from July 2023 to June 2024. Peak sun hours and wind speed data were collected on an FIP-specific basis.

Subsequent data preprocessing involved median imputation and restructuring of housing types, as described in Section 1.2.2. Energy expenditure, energy burden, and energy generation per household were calculated using appropriate ratios, parameter values, and temporal selections (annual, seasonal, or monthly). The curated dataset, along with other parameter values, was then inputted into the temporal optimization model. The model produced a portfolio of interventions, detailing the number of interventions within each temporal scope and the resulting reduction in energy burden upon adoption. A flowchart summarizing these steps is provided in **Fig. 7**.

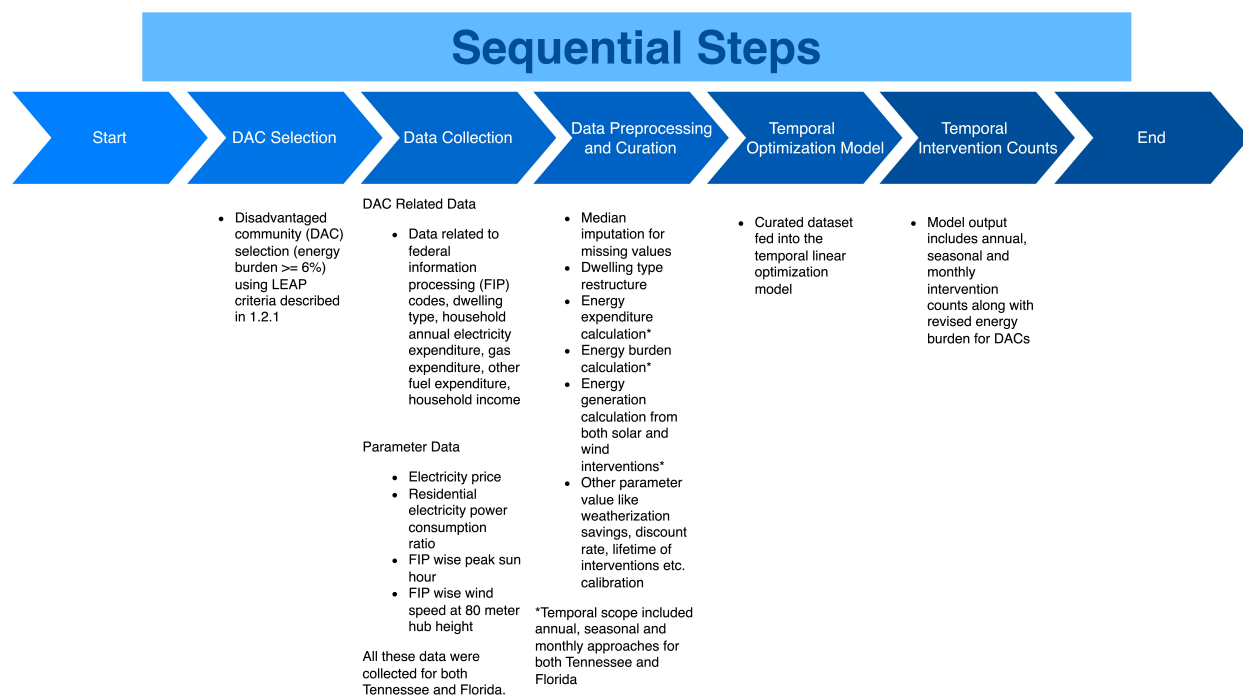


Figure 7: Sequential steps of the temporal model used in this study to reduce the energy burden for DACs in Tennessee and Florida.

2.3.1 Model

Different sets, parameters, constraints, and objective function are described in this section. For ease of access, all these are summarized in **Table 9**.

Objective Function

The objective function is constructed to minimize the energy burden for each household across various time periods t . Let $EB_{h,t}$ denote the revised energy burden for household $h \in \mathcal{H}$ at time period $t \in \mathcal{T}$. The objective function for the deterministic optimization model is presented in Equation 2.1.

$$\min \frac{1}{|\mathcal{H}| \cdot |\mathcal{T}|} \sum_{h \in \mathcal{H}} \sum_{t \in \mathcal{T}} EB_{h,t} \quad (2.1)$$

where:

- $|\mathcal{H}|$: Number of households,
- $|\mathcal{T}|$: Number of time periods (annual, seasonal, or monthly, depending on the model granularity).

Constraints

Budget

The total cost of interventions must not exceed the allocated budget (T_b) for each state (Tennessee and Florida). This ensures the feasibility of the optimization model within financial limitations. The set of time periods $\mathcal{T}$ is defined according to the model's granularity, encompassing annual, seasonal, or monthly intervals. The variables $\text{Count}_{i,t}$ represent the number of community interventions of type i (community solar or community wind) adopted in each time period t , with corresponding costs Cost_i and cost amortization factors CAF_i . Similarly, $W_{h,t}$ and $\text{RTS}_{h,t}$ are binary variables indicating whether household h adopts weatherization or rooftop solar interventions, respectively, during time period t .

Table 9: Description of sets, parameters, and variables used in the temporal optimization model.

Nomenclature	
Sets	
$\mathcal{H}$	Set of selected households using the criteria described 1.2.1, indexed by h
$\mathcal{T}$	Set of time periods, varying based on model granularity. • Annual: $\mathcal{T} = \{1\}$ • Seasonal: $\mathcal{T} = \{1, 2, 3, 4\}$ denoting winter, spring, summer and fall respectively • Monthly: $\mathcal{T} = \{1, 2, \dots, 12\}$ denoting January- December
$\mathcal{I}$	Set of four interventions: $\{w, rts, cs, cw\}$ denoting weatherization, rooftop solar, community solar and community wind respectively
$\mathcal{B}$	Set of housing types: $\{\text{single family, small multi-family, large multi-family, mobile homes}\}$
Parameters	
T_b	Total budget (\$)
r	Discount rate (%)
P_t	Price of electricity (\$/kWh) in time period $t \in \mathcal{T}$
L_i	Lifetime of interventions where $i \in \mathcal{I}$
S_b	Weatherization savings for different housing type $b \in \mathcal{B}$
$Cost_{w,b}$	Cost of weatherization for housing type $b \in \mathcal{B}$
$Cost_i$	Cost for each intervention $i \in \{rts, cs, cw\}$
CAF_i	Cost amortization factor for each intervention $i \in \mathcal{I}$
$HINCP_{h,t}$	Income of household $h \in \mathcal{H}$ in time period $t \in \mathcal{T}$
$Gen_{i,t}$	Energy generation from intervention $i \in \mathcal{I}$ in time period $t \in \mathcal{T}$
$Exp_{h,t}$	Energy expenditure of household $h \in \mathcal{H}$ in time period $t \in \mathcal{T}$
$Contrib_{h,i}$	Contribution of community intervention $i \in \{cs, cw\}$ for each household $h \in \mathcal{H}$ based on initial energy burden
Variables	
$W_{h,t}$	Binary variable indicating whether household $h \in \mathcal{H}$ adopts weatherization intervention in time period $t \in \mathcal{T}$
$RTS_{h,t}$	Binary variable indicating whether household $h \in \mathcal{H}$ adopts rooftop solar intervention in time period $t \in \mathcal{T}$
$Count_{i,t}$	Integer variable for the number of community interventions $i \in \{cs, cw\}$ adopted in time period $t \in \mathcal{T}$
$EB_{h,t}$	Revised energy burden for household $h \in \mathcal{H}$ in time period $t \in \mathcal{T}$ after adopting interventions

These interventions have associated costs ($\text{Cost}_{w,b}$ for weatherization specific to housing type b , and Cost_{rts} for rooftop solar), and cost amortization factors (CAF_w and CAF_{rts}). Given these definitions, the budget constraint is formalized as 2.2.

$$\sum_{i \in \{cs, cw\}} \sum_{t \in \mathcal{T}} \text{Count}_{i,t} \cdot \text{Cost}_i \cdot \text{CAF}_i + \sum_{h \in \mathcal{H}} W_{h,t} \cdot \text{Cost}_{w,b} \cdot \text{CAF}_w + \sum_{h \in \mathcal{H}} \text{RTS}_{h,t} \cdot \text{Cost}_{rts} \cdot \text{CAF}_{rts} \leq T_b \quad (2.2)$$

This constraint ensures that the total expenditure on interventions does not exceed the budget allocated by state authorities, thus maintaining the project's economic viability.

Temporal Consistency of Interventions

Interventions selected at the beginning of the year or the specified start of the period should be carried forward into subsequent time periods. This applies to all categories of interventions: weatherization, rooftop solar, community solar, and community wind. Let t denote the starting time period (e.g., Winter for seasonal models or January for monthly models), and $t + 1$ the subsequent time period. The continuity of interventions across periods ensures consistent implementation and effectiveness. The following equations formalize this concept:

For community solar and community wind interventions, the number of interventions selected in the starting time period t is maintained in the following time period $t + 1$, as shown in Equation 2.3.

$$\text{Count}_{i,t+1} = \text{Count}_{i,t} \quad \forall t \in \mathcal{T}, i \in \{cs, cw\} \quad (2.3)$$

Similarly, the adoption status of weatherization interventions by households is carried over from one time period to the next, as illustrated in Equation 2.4.

$$W_{h,t+1} = W_{h,t} \quad \forall t \in \mathcal{T} \quad (2.4)$$

The same principle applies to rooftop solar interventions, ensuring that once a household adopts this intervention in a given time period t , it remains adopted in $t + 1$, as indicated in

Equation 2.5.

$$\text{RTS}_{h,t+1} = \text{RTS}_{h,t} \quad \forall t \in \mathcal{T} \quad (2.5)$$

These relationships ensure that the effects of interventions are consistent across the modeling periods, aligning with strategic energy management and sustainability goals.

Household Intervention Caps

The number of households receiving weatherization or rooftop solar interventions in any given time period should not exceed the total number of households $|\mathcal{H}|$ included in the set of all selected households $\mathcal{H}$. This constraint ensures that the implementation of interventions is limited to the actual number of available households, reflecting a realistic and feasible application of resources. The following equations enforce these limits:

For weatherization, the total number of households that can receive the intervention during any time period t is capped by the total count of households in the set $\mathcal{H}$, as defined by Equation 2.6.

$$\sum_{h \in \mathcal{H}} W_{h,t} \leq |\mathcal{H}| \quad (2.6)$$

Similarly, for rooftop solar, the total number of installations in any time period t is also limited to the number of households in $\mathcal{H}$, as stipulated in Equation 2.7.

$$\sum_{h \in \mathcal{H}} \text{RTS}_{h,t} \leq |\mathcal{H}| \quad (2.7)$$

These constraints serve to maintain the scale of interventions within the bounds of available resources, ensuring that the projected benefits of weatherization and rooftop solar are achievable and sustainable over time.

Non-Negativity and Binary Constraints

The decision variables in our model must adhere to non-negativity and appropriate type restrictions to reflect their operational definitions and practical constraints. Specifically, the binary nature of the household-specific interventions for weatherization (W_h) and rooftop solar (RTS_h) implies that these variables can only take the values of 0 or 1, indicating whether an intervention is not adopted or adopted, respectively, by household h . Additionally, the

number of community interventions ($\text{Count}_{i,t}$) is an integer variable, representing the count of interventions implemented, which must be a non-negative whole number. These constraints are formally represented in Equation 2.8.

$$W_h, \text{RTS}_h \in \{0, 1\}, \quad \text{Count}_{i,t} \in \mathbb{Z}^+ \quad (2.8)$$

This formulation ensures that the variables are consistent with the physical realities of intervention deployment and accounting within the optimization model.

Revised Energy Burden

The revised energy burden for each household after adopting necessary interventions is quantified by Equation 2.9. This formula adjusts the initial energy expenditures $\text{Exp}_{h,t}$ of household h in time period t by accounting for energy savings from weatherization, energy generated from rooftop solar, and contributions from community solar and wind interventions. Specifically, savings from weatherization are calculated based on the applicable percentage S_b , which is multiplied by the energy expenditure $\text{Exp}_{h,t}$ and the binary variable $W_{h,t}$ indicating adoption. Energy generation from rooftop solar for each household is computed by multiplying the generation $\text{Gen}_{rts,t}$, the price of electricity P_t , and the binary variable $\text{RTS}_{h,t}$. For community interventions (solar and wind), the generation from each intervention type i is considered along with the total number of these interventions $\text{Count}_{i,t}$ and their specific contribution to each household $\text{Contrib}_{h,i}$. All these components are then normalized by the household's income $\text{HINCP}_{h,t}$, providing a proportionate measure of the energy burden. Considering all the aforementioned discussion, we get Equation 2.9.

$$\text{EB}_{h,t} \geq \frac{\text{Exp}_{h,t} - S_b \cdot \text{Exp}_{h,t} \cdot W_{h,t} - \text{Gen}_{rts,t} \cdot P_t \cdot \text{RTS}_{h,t}}{\text{HINCP}_{h,t}} - \frac{\sum_{i \in \{cs, cw\}} \text{Gen}_{i,t} \cdot P_t \cdot \text{Count}_{i,t} \cdot \text{Contrib}_{h,i}}{\text{HINCP}_{h,t}} \quad (2.9)$$

This comprehensive approach ensures an accurate depiction of the financial impact of energy interventions on households, thereby allowing for more informed decision-making regarding energy management and policy implementation.

2.3.2 Data

Data collection and preprocessing were conducted as described in Section 1.2.2. In addition to these steps, granular data on electricity prices, wind speed at an 80-meter hub height, peak sun hours, and residential electricity consumption were collected for both Tennessee and Florida.

Electricity price data for both states was sourced from the U.S. Energy Information Administration (EIA), provided as monthly time series data spanning from 2001 to 2024. Data specific to Tennessee was accessed through this link, while Florida’s data was obtained via this link.

To accurately assess peak sun hours across different locations, census tracts were matched to zip codes using the HUD-USPS ZIP Crosswalk Files. Using these zip codes, peak sun hour data was then obtained from NREL’s solar data-based calculator. The resulting data is included in Appendix **Table 18** and **Table 19**.

Wind speed data, considered at an 80-meter hub height to align with specifications for a 1 MW wind turbine (with an 80-meter rotor diameter and 40-meter blade radius), was gathered from the National Renewable Energy Laboratory’s (NREL) Wind Resource Database. Detailed values are presented in Appendix **Table 20** and **Table 21**.

Annual energy expenditure data for households was drawn from the LEAD dataset [5], as previously discussed in Section 1.2.2. Since this dataset provides annual values, additional seasonal and monthly residential energy expenditure ratios were derived from EIA data for both states, using ratios provided by the EIA’s electricity consumption data for seasonal adjustments, accessible through this link. **Table 10** shows the detailed ratios for both Tennessee and Florida.

Table 10: Expenditure ratios for Tennessee and Florida (seasonal and monthly).

Expenditure Ratios	Seasonal				Monthly											
	Win	Spr	Sum	Fal	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Tennessee	0.28	0.20	0.29	0.23	0.101	0.090	0.072	0.068	0.065	0.080	0.101	0.108	0.097	0.070	0.067	0.084
Florida	0.23	0.19	0.31	0.27	0.074	0.065	0.071	0.074	0.080	0.092	0.110	0.115	0.102	0.082	0.067	0.067

2.3.3 Parameter Calibration

This section details the calculation of various parameter values, including the energy expenditure ($Exp_{h,t}$), energy generation ($Gen_{i,t}$), contributions from community interventions ($Contrib_{i,t}$), the cost amortization factor (CAF_i), and the total budget (T_b). Additional parameter values, such as the discount rate, intervention capacity, cost, and photovoltaic (PV) cost, are provided in section 1.2.3.

Energy Expenditure

If **ELEP**, **GASP**, and **FULP** represent the expenditures on electricity, gas, and other fuels, respectively, and $ratio_{t,heating\ fuel}$ denotes the ratio associated with temporal heating fuel usage, then Equation 2.10 illustrates the overall energy-related expenses for time period $t \in \mathcal{T}$. Here, $heating\ fuel \in \{\text{electricity, gas, other fuel}\}$.

$$Exp_{h,t} = ratio_{t,electricity} \cdot \text{ELEP} + ratio_{t,gas} \cdot \text{GASP} + ratio_{t,other\ fuel} \cdot \text{FULP} \quad (2.10)$$

Energy Generation

Energy generation from interventions such as rooftop solar, community solar, and wind turbines plays a crucial role in reducing the energy burden for individual households. The energy produced by these interventions primarily derives from wind and solar sources. This section presents the equations and values used for calculating these two types of energy generation.

Wind Energy

The generated energy from community wind in a given time period t , represented as $Gen_{cw,t}$, is calculated based on factors including air density (ρ), the swept area of the rotor (A), the power coefficient (C_p), wind speed (V), and the duration of the time period (T). The air density ρ is assumed to be 1.225 kg/m³, and the power coefficient C_p , which is dimensionless, is set to 0.20. The rotor diameter is 80 meters, giving a rotor radius of 40 meters, which is used to compute the swept area A with Equation 2.12. The generated power output for the 1 MW wind turbine is then determined by Equation 2.11 including extra 10%

loss.

$$Gen_{cw,t} = 0.9 \times 0.5 \times \rho \times A \times C_p \times V^3 \times T \quad (2.11)$$

where the swept area A of the rotor is calculated by:

$$A = \pi R^2 \quad (2.12)$$

Solar Energy

The energy output from solar panels, whether in rooftop or community installations, is calculated based on peak sun hours (PSH), the number of solar panels (N_{PV}), the rated power output per panel (P_{rated}), panel efficiency (η_{panel}), inverter efficiency ($\eta_{inverter}$), wiring efficiency (η_{wiring}), shading loss factor ($\eta_{shading}$), temperature-related efficiency ($\eta_{temperature}$), and tilt angle loss factor (L_{tilt}). Specifically, the value of N_{PV} is 17 for rooftop solar and 2,857 for community solar, and the rated power output per panel P_{rated} is set at 0.35 kW. The efficiency factors η_{panel} , $\eta_{inverter}$, η_{wiring} , $\eta_{shading}$, $\eta_{temperature}$, and L_{tilt} are assigned values of 0.75, 0.95, 0.97, 0.90, 0.98, and 0.95, respectively. The generated solar energy for each time period t is calculated using Equation 2.13.

$$Gen_{rts/cs,t} = PSH \times N_{PV} \times P_{rated} \times \eta_{panel} \times \eta_{inverter} \times \eta_{wiring} \times \eta_{shading} \times \eta_{temperature} \times L_{tilt} \quad (2.13)$$

Contribution from Community Interventions

To address energy burden disparities, we applied a need-based contribution model, where households with higher energy burdens receive a greater share of benefits from community interventions. The contribution from a community intervention i (where $i \in \{cs, cw\}$) for each household h is calculated based on the household's initial energy burden (EB_h) and the total energy burden across all households in the set $\mathcal{H}$. This proportional approach ensures that households with greater energy burdens receive a larger share of contributions. The contribution calculation is given by Equation 2.14.

$$Contrib_{h,i} = \frac{EB_h}{\sum_{h \in \mathcal{H}} EB_h} \quad (2.14)$$

Cost Amortization Factor

Since different interventions have varied lifetimes, as presented in **Table 2**, we introduced a cost amortization factor (CAF_i) to standardize costs over a one-year period, aligning with the study’s annual timeframe. The cost amortization factor is calculated based on the discount rate (r) and the lifetime (L_i) of each intervention. The discount rate r is set at 3%. This approach allows for the distribution of intervention costs over a consistent period, regardless of their original lifespans. The formula for the cost amortization factor is given by Equation 2.15.

$$CAF_i = \frac{r}{1 - (1 + r)^{-L_i}} \quad (2.15)$$

This formulation enables a realistic representation of intervention costs within the budget and time constraints of the study.

Total Budget

The budget selected for Florida follows the same procedure used for Tennessee. Based on Tennessee’s per capita budget, we allocated a budget of \$24.24 million for Florida to appropriately match the size of the DACs in the state.

2.4. Results and Discussion

This study investigates the impact of varying temporal granularity—annual, seasonal, and monthly—on energy burden reduction in disadvantaged communities across Tennessee and Florida. By analyzing intervention adoption rates and their resulting effects on energy burden over different temporal scopes, this research aims to provide actionable insights for enhancing targeted policies and intervention strategies. The analysis covers 32,457 households in Tennessee and 25,190 households in Florida with proposed portfolio of interventions.

2.4.1 Tennessee

In Tennessee, the adoption of interventions across different temporal resolutions reveals significant variations in both intervention counts and resulting energy burden levels. The

temporal granularity affects not only the distribution of interventions but also the overall effectiveness in reducing energy burdens.

Annual Approach

The annual approach offers a macroscopic view of intervention adoption, simplifying decision-making by treating the year as a single decision period. Under this approach, weatherization was adopted by 24,778 households, and rooftop solar by 3,150 households (**Fig. 8(a)**). These high adoption rates, especially for weatherization, reflect the cost-effectiveness and practicality of this intervention compared to other options. Notably, no community solar interventions were selected, while 195 community wind interventions were adopted.

Energy generated by community-based interventions was proportionally allocated to households based on their energy burden, ensuring that those with the highest burdens received the most significant support. This targeted distribution maximized the impact of community interventions, helping reduce the average energy burden from 7.6% to 2.61% (**Fig. 8(b)**). The annual approach provides a straightforward strategy for intervention planning, especially useful for long-term policy frameworks.

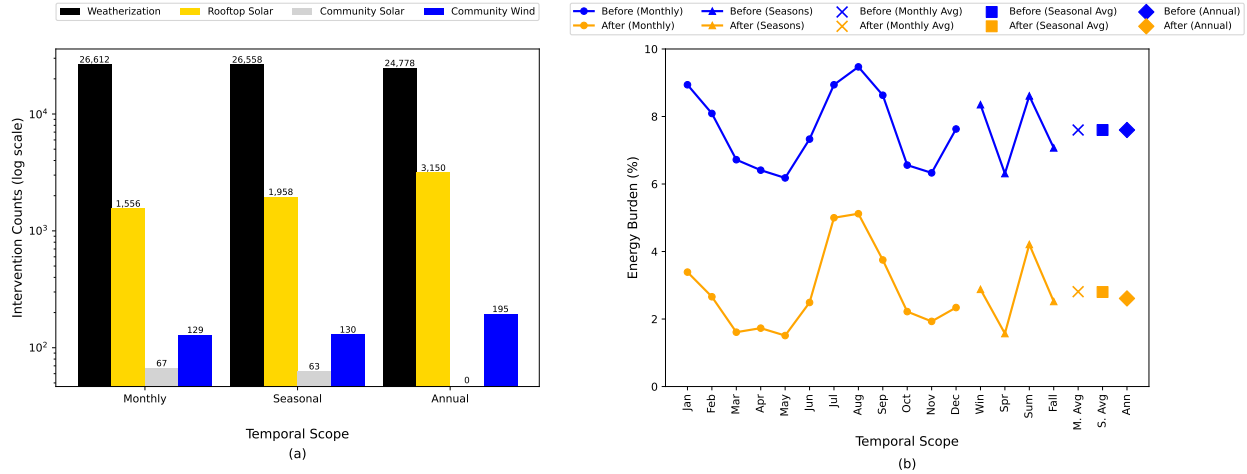


Figure 8: Energy burden reduction across varying temporal scopes (annual, seasonal, and monthly) in disadvantaged communities in Tennessee, showing the impact of intervention adoption.

Seasonal Approach

The seasonal approach introduces greater granularity by considering variations in energy usage across different seasons. This method resulted in a higher adoption of weatherization (26,558 households) compared to the annual approach, while rooftop solar adoption decreased to 1,958 households. Interestingly, 63 community solar interventions were adopted, and community wind interventions decreased to 130 (**Fig. 8(a)**).

This approach yielded a revised average energy burden of 2.80% (**Fig. 8(b)**), which, while higher than the annual approach, better captures the dynamic effects of seasonal energy needs. As shown in **Fig. 8(b)**, energy burdens peaked during winter and summer due to significant heating and cooling demands. The seasonal model effectively mitigated these peaks, keeping the energy burden below the critical 6% threshold during the most demanding seasons.

The seasonal approach highlights the importance of aligning interventions with seasonal energy consumption patterns, offering policymakers a more adaptive strategy to address fluctuating energy needs.

Monthly Approach

The monthly approach provides the highest level of granularity, allowing for detailed tracking of energy burden variations and intervention efficacy. In this model, weatherization adoption further increased to 26,612 households, while rooftop solar adoption decreased to 1,556 households. Community solar interventions saw their highest adoption (67), reflecting a greater reliance on solar energy when monthly data was considered. Conversely, community wind adoption dropped to its lowest level (129) but still higher than community solar (**Fig. 8(a)**).

Monthly energy burden trends (**Fig. 8(b)**) reveal high burdens in January, a steady decline to the lowest point in May, a peak in August, and a tapering off towards the year-end. This pattern mirrors seasonal trends but provides more precise insights for intervention timing. The monthly approach achieved an average energy burden of 2.81%, comparable to the annual and seasonal approaches but offering finer control over monthly fluctuations.

The monthly approach is particularly valuable for dynamic intervention strategies, ensuring that energy burdens remain below the 6% threshold even during high-demand months. This granularity enables more responsive policies tailored to real-world energy consumption patterns.

2.4.2 Florida

The analysis in Florida mirrors the approach used in Tennessee, allowing for cross-state comparison and revealing insights specific to Florida’s unique climatic and energy demand patterns.

Annual Approach

In Florida, the annual approach led to 6,924 households adopting weatherization, making it the most widely adopted intervention. Rooftop solar was adopted by 1,286 households, while number of community solar and community wind interventions were 0 and 180, respectively (**Fig. 9(a)**).

This intervention portfolio reduced the average energy burden from 6.37% to 1.53% (**Fig. 9(b)**), demonstrating the effectiveness of annual intervention strategies in managing year-round energy demands. The annual model provides a clear, simplified framework for policy implementation.

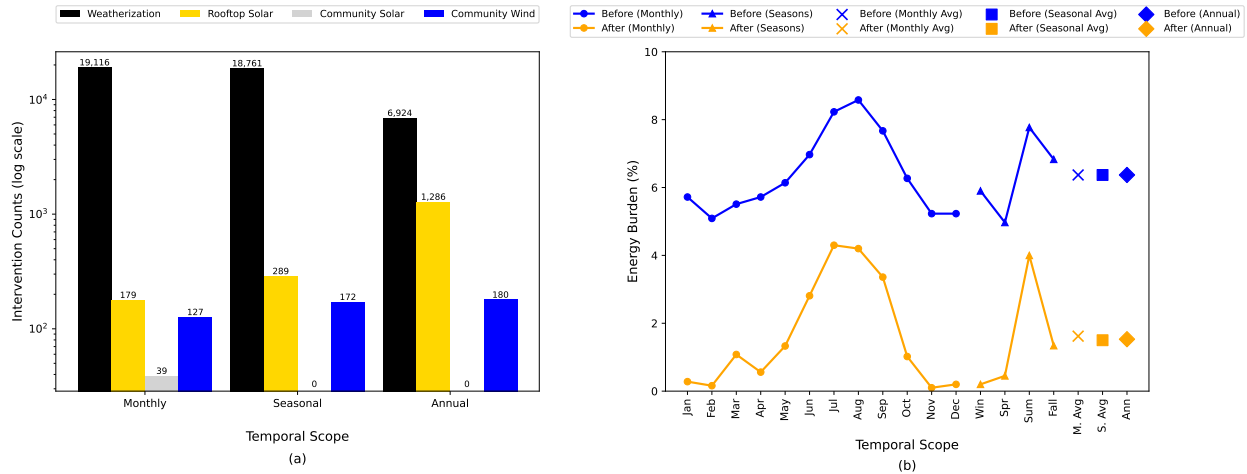


Figure 9: Energy burden reduction across annual, seasonal, and monthly scopes in Florida’s DACs, showing intervention impact.

Seasonal Approach

The seasonal approach revealed lower adoption rates for most interventions compared to the annual model, except for weatherization, which increased to 18,761 households. Rooftop solar adoption dropped to 289 households, and community wind interventions decreased slightly to 172, with no community solar intervention adoption (**Fig. 9(a)**).

Seasonal energy burden trends (**Fig. 9(b)**) highlight higher burdens during summer and early fall, driven by increased cooling demands. Despite fewer interventions compared to the annual approach (except weatherization), the seasonal model effectively maintained energy burdens below the 6% threshold across all seasons. This demonstrates the model's capacity to address season-specific energy needs, providing a tailored approach for Florida's warm climate.

Monthly Approach

In the monthly approach, weatherization adoption reached 19,116 households, while rooftop solar adoption further decreased to 179 households. Community solar interventions increased to 39, and community wind adoption further dropped to 127 (**Fig. 9(a)**).

Monthly energy burden trends (**Fig. 9(b)**) show high burdens in early months, followed by a subsequent decline, a peak in August, and a decrease towards the year-end. Even during peak summer months, the interventions successfully kept energy burdens below the 6% threshold, underscoring the efficacy of the monthly model in managing real-world fluctuations.

This study demonstrates the impact of temporal granularity on energy burden reduction in disadvantaged communities in Tennessee and Florida. The annual, seasonal, and monthly approaches each offer unique advantages, with annual models providing simplicity, seasonal models addressing seasonal demand fluctuations, and monthly models offering the most precise control over intervention timing. These insights can guide policymakers in designing targeted, adaptive energy intervention strategies that effectively reduce energy burdens and promote energy equity.

2.4.3 Comparative Analysis of Intervention Portfolios: Tennessee vs. Florida

For both Tennessee and Florida, weatherization and rooftop solar emerge as the preferred interventions within the portfolio due to their superior cost-benefit ratio. Simpler models, such as the annual models, did not consistently include community solar in their recommended portfolios. However, more granular approaches, specifically the seasonal and monthly models, incorporated all intervention types, with the exception of Florida’s seasonal model, which omitted community solar.

Notably, as the analysis transitioned from annual to more granular monthly models, a significant increase in community solar interventions was observed, accompanied by a proportional decrease in community wind. Although community wind continues to represent the majority of interventions, the inclusion of substantial community solar contributions in the monthly models reflects a diversification in the intervention portfolio. This diversification aligns with real-world variations in factors such as peak sun hours and wind speeds, making the monthly models more comprehensive.

The comparative analysis also highlights key trade-offs between different modeling approaches. The annual model demonstrates the highest overall reduction in energy burden for both states. However, this comes at the expense of capturing temporal variations that more granular models, such as seasonal and monthly models, effectively address. While the seasonal and monthly models achieve slightly lower overall reductions in energy burden, they offer critical insights into temporal variability, particularly during periods of peak energy demand, such as extreme summer heat or winter cold spells.

This granularity is essential for tailoring interventions to specific temporal needs. For instance, during the summer months, rooftop solar may yield higher benefits due to increased sun exposure, while weatherization interventions may be more impactful during winter to reduce heating costs. By accounting for these fluctuations, seasonal and monthly models allow for more precise allocation of resources, maximizing the effectiveness of interventions when and where they are most needed.

Furthermore, the observed increase in community solar in the monthly models suggests that solar-based solutions play a more significant role in granular approaches, even if community wind remains dominant. This finding can guide policymakers in making informed decisions regarding renewable energy investments. By adopting a dynamic, multi-intervention approach that blends weatherization, rooftop solar, community solar, and community wind, stakeholders can achieve more resilient and equitable energy solutions.

In conclusion, while annual models provide a high-level overview of potential energy burden reductions, the insights derived from seasonal and monthly models are invaluable for addressing the nuanced energy needs of disadvantaged communities. A diversified intervention strategy, informed by these granular models, ensures that interventions are both cost-effective and responsive to real-world conditions, ultimately fostering more sustainable and equitable energy outcomes in Tennessee and Florida.

2.5. Conclusion

This study presents a comprehensive analysis of energy intervention strategies across annual, seasonal, and monthly temporal granularities for disadvantaged communities in Tennessee and Florida. By incorporating enhanced granularity, we have demonstrated how the timing and type of interventions influence the reduction of energy burdens, addressing key gaps identified in the existing literature, particularly the need for more time-sensitive strategies and equity-focused interventions.

Key Findings and Insights

1. *Effectiveness of Weatherization and Rooftop Solar:*

Across all temporal models, weatherization and rooftop solar emerged as the most consistently effective interventions due to their superior cost-benefit ratio. Weatherization, in particular, exhibited significant adoption rates in both states, highlighting its immediate and tangible impact on energy burden reduction. This reflects the importance of low-cost, high-impact interventions that can be widely implemented across varying socio-economic and climatic conditions.

2. *Impact of Temporal Granularity:*

The annual models achieved the greatest overall reduction in energy burden, providing a simplified approach that effectively addresses long-term energy inequities. However, they fall short in capturing seasonal and monthly fluctuations in energy demand. In contrast, seasonal and monthly models offer finer insights into the dynamic nature of energy consumption, particularly during periods of peak heating and cooling demand. These granular models enable time-sensitive strategies that maximize effectiveness when and where it is most needed.

3. *Diversification of Intervention Portfolios:*

The analysis revealed a notable increase in community solar interventions in more granular models, even as community wind remained the majority intervention. This diversification reflects real-world conditions such as peak sun hours and wind speed variations, underscoring the need for a blended approach to renewable energy interventions. By adopting diversified portfolios, policymakers can enhance the resilience and adaptability of energy interventions.

4. *State-Specific Strategies:*

The comparison between Tennessee and Florida highlights the importance of context-specific strategies. Tennessee's energy burdens are driven by distinct winter heating and summer cooling demands, making weatherization and heating-focused interventions crucial. Conversely, Florida's year-round cooling needs necessitate interventions like rooftop and community solar. These differences emphasize the need for tailored policies that align with regional climatic and socio-economic conditions.

Policy and Practical Implications

1. *Adaptive Policy Frameworks:*

Policymakers should adopt flexible intervention strategies that consider annual, seasonal, and monthly variations in energy consumption. While annual models provide a straightforward approach for budgeting and planning, seasonal and monthly models

enable dynamic adjustments to optimize interventions during periods of peak energy burden.

2. *Resource Allocation:*

To maximize the effectiveness of energy burden reduction, resources should be allocated based on temporal patterns of energy demand. For example, increasing weatherization efforts before winter in Tennessee or promoting solar adoption before summer in Florida can help mitigate the highest energy burdens.

3. *Investment in Diverse Renewables:*

A combination of weatherization, rooftop solar, community solar, and community wind offers the most resilient strategy for energy equity. Investments should prioritize a diversified intervention portfolio to address the unique needs of disadvantaged communities, ensuring a balance between immediate impact and long-term sustainability.

4. *Equity-Focused Strategies:*

Ensuring that households with the highest energy burdens receive a proportionally greater share of community solar and wind interventions is critical for promoting energy equity. This study highlights the importance of equity-focused distribution, addressing disparities more effectively and providing fairer outcomes for disadvantaged communities.

5. *Granular Data Utilization:*

Incorporating monthly and seasonal energy consumption data into policy frameworks allows for more precise and effective interventions. This approach helps identify critical periods of energy burden and deploy resources accordingly, reducing inefficiencies and maximizing impact.

In conclusion, this study highlights the significance of temporal granularity in designing effective energy intervention strategies. While annual models offer simplicity and broad effectiveness, the nuanced insights provided by seasonal and monthly models are crucial for addressing the dynamic energy needs of disadvantaged communities. By embracing a diversified, adaptive, and equity-focused approach, policymakers can develop interventions

that are both cost-effective and responsive to real-world conditions, ultimately fostering sustainable and equitable energy outcomes in Tennessee, Florida, and beyond.

The findings underscore the need for continued research into the temporal dynamics of energy burden and the development of policies that reflect these complexities. By doing so, we can ensure that energy equity is not just an ideal but a tangible reality for all communities, regardless of geography or socio-economic status.

Chapter 3

Incorporating Stochastic Analysis for Uncertainty and Scenario Projections in Energy Burden Mitigation

In this chapter, we present a comprehensive analysis that incorporates stochastic parameters to address the uncertainties associated with energy burden reduction. By evaluating multiple scenarios for stochastic parameters, projecting future data trends, and examining the implications of increased electric vehicle market penetration, we aim to assess the effectiveness of various energy burden mitigation strategies. Furthermore, we investigate the impact of transitioning from deterministic to stochastic parameters on the model's outputs, providing a more nuanced understanding of potential outcomes. This methodological approach captures the inherent variability and complexity of real-world applications, resulting in a robust, realistic, and adaptive framework for energy burden reduction.

3.1. Introduction

In the preceding chapters, we assumed that critical parameters—such as electricity prices, peak sun hours, and wind speeds—were deterministic, implying their values remained constant throughout the study period. However, real-world conditions are inherently dynamic, and these parameter values frequently fluctuate due to environmental, economic, and societal

factors. This variability introduces uncertainty in energy generation outcomes, making it challenging to achieve the theoretical maximum energy generation consistently.

Renewable energy projects typically span significant lifetimes, necessitating solutions that are not only effective today but also sustainable for the foreseeable future [74][75]. For this study, we adopted a five-year timeframe, aiming to evaluate whether the selected interventions can effectively reduce energy burdens by 2030. This approach aligns with the broader goal of ensuring long-term energy equity in disadvantaged communities.

As we project into 2030, demographic changes such as population growth, migration patterns, birth rates, and mortality rates may alter the population distributions within our selected states and disadvantaged communities [76][77]. These demographic shifts will influence energy demand and the effectiveness of interventions. Therefore, our models account for potential population dynamics to ensure that the proposed solutions remain relevant under evolving conditions.

Another significant consideration is the anticipated increase in electric vehicle (EV) adoption as part of national and global net-zero emission goals [78]. By 2030, market penetration of electric vehicles is expected to rise, which will impose additional loads on existing electrical infrastructure [79]. This increased demand will likely impact disadvantaged communities, making it crucial to understand how EV adoption dynamics intersect with energy equity goals. Consequently, incorporating the potential growth in EV usage within these communities ensures a more comprehensive and resilient intervention strategy.

To address the uncertainties inherent in energy burden mitigation, this chapter employs stochastic optimization techniques. Stochastic optimization incorporates randomness or probabilistic elements into the modeling process to account for variability in key parameters — such as electricity prices, wind speeds, and peak sun hours [80]. Unlike deterministic approaches, which rely on fixed values, stochastic optimization considers multiple scenarios and potential outcomes, providing a more robust framework [81]. This method enhances the reliability of intervention strategies, particularly when dealing with dynamic factors like fluctuating renewable energy resources and electricity prices. By integrating stochastic optimization, we aim to develop energy solutions that adapt to real-world uncertainties, ensuring more resilient and equitable outcomes for disadvantaged communities.

Our study focuses on a portfolio of interventions, including weatherization, rooftop solar, community solar, and community wind, tailored for selected census tracts in Tennessee and Florida. We aim to determine whether these interventions can effectively mitigate energy burdens both in the present and over a significant future horizon. By considering the uncertainties inherent in parameter values and demographic trends, our approach provides a robust framework for sustainable energy solutions that adapt to real-world complexities.

This holistic analysis seeks to bridge the gap between theoretical models and practical outcomes, ensuring that disadvantaged communities benefit from reliable, equitable, and sustainable energy solutions. Our findings contribute to the ongoing discourse on energy justice and provide actionable insights for policymakers, energy providers, and community stakeholders aiming to achieve long-term energy equity.

3.2. Literature Review

Stochastic optimization has become an essential tool for addressing uncertainties in the design and operation of renewable energy systems. These uncertainties, stemming from factors such as energy prices, renewable resource availability, and fluctuating energy demands, challenge the reliability and efficiency of deterministic models. Mavromatidis et al. [82] developed a two-stage stochastic programming approach for distributed energy systems (DES) design, capturing uncertainties in energy prices, heating and electricity demands, and solar radiation patterns. Their findings underscore the limitations of deterministic approaches, which tend to underestimate costs and CO₂ emissions due to their inability to adapt to variable real-world conditions.

Expanding on the integration of renewable energy technologies, Tran and Smith [83] explored the application of stochastic optimization in district energy systems (DES). By employing Monte Carlo simulations, they demonstrated that accounting for uncertainties in solar photovoltaics (PV) and wind energy could lead to significant cost savings and improved operational efficiency. This research highlights the importance of incorporating multiple energy carriers—electricity, heating, and cooling—within a unified stochastic framework to achieve resilient and cost-effective energy solutions.

Hybrid renewable energy systems (HRES) present additional complexity due to the variability of renewable resources and energy loads. Sharafi and ElMekkawy [84] employed a dynamic multi-objective particle swarm optimization (DMOPSO) approach to address these uncertainties, focusing on wind speed, solar radiation, ambient temperature, and energy consumption. Their study aimed to minimize costs, maximize renewable energy use, and reduce emissions. The use of advanced optimization techniques like DMOPSO allows for the generation of Pareto-optimal solutions, offering decision-makers a balanced trade-off between conflicting objectives. However, these studies primarily employ deterministic frameworks for evaluating energy equity, which fail to capture the probabilistic nature of real-world energy dynamics.

Azizi et al. [85] advanced the field by proposing a stochastic optimization model for the daily operation of multi-energy systems. Their approach integrated neural network-based predictions for renewable energy generation, addressing uncertainties in wind speed and solar radiation. By combining machine learning with stochastic optimization, their model improved the reliability and efficiency of multi-energy systems. While this approach is robust, it does not specifically address the issue of energy equity or the distributional impacts of interventions across households with varying energy burdens.

The placement of renewable energy infrastructure also significantly affects system efficiency. Ramshani et al. [86] explored the joint placement of photovoltaic panels and green roofs under climate change uncertainty using a two-stage stochastic programming model. Their work demonstrated how strategic infrastructure placement could mitigate the adverse effects of climate variability. Similarly, Barah et al. [87] focused on optimizing green infrastructure (GI) placement under precipitation uncertainty, enhancing urban resilience to unpredictable weather patterns. While these studies optimize infrastructure placement under uncertainty, they do not specifically address the equity dimension of energy interventions.

Economic assessments of renewable energy systems often rely on levelized cost of electricity (LCOE) calculations. Lee and Ahn [88] applied stochastic modeling to estimate the LCOE for solar PV in South Korea, incorporating uncertainties in capacity factors, capital expenditures, and discount rates. Their work provides a more realistic cost assessment compared to

deterministic methods. However, the equity implications of these cost estimations, particularly for disadvantaged communities, remain unexplored.

Despite these advancements, several critical gaps persist in the literature. Most studies addressing energy equity rely on deterministic approaches, which fail to capture the probabilistic nature of real-world energy systems. This limitation is significant because uncertainties in resource availability, energy prices, and demographic changes directly affect the effectiveness of interventions. Furthermore, current models tend to assign equal importance to all energy-burdened households, potentially diluting the impact of interventions for the most severely burdened households. As a result, even after adopting interventions, some households may remain energy-burdened. Additionally, there is a lack of research that considers the dynamic changes in population for future scenarios, an important factor for ensuring the sustainability of energy equity solutions. Finally, the literature scarcely explores the impact of future electric vehicle (EV) adoption on energy-burdened households, particularly in the context of disadvantaged communities.

Research Gaps

1. **Deterministic Approaches in Energy Equity:** Previous studies addressing energy equity, such as those by [35], [36], [37], and [38], have made significant strides using deterministic frameworks. While these approaches offer valuable insights, they do not fully capture the inherent uncertainties in renewable energy generation (e.g., variations in peak sun hours, wind speed) and energy prices.
2. **Distributional Impact of Interventions:** Current models tend to treat all energy-burdened households equally, which can dilute the effectiveness of interventions. This approach often leaves the most severely burdened households with inadequate relief. There is a need for models that prioritize interventions based on the severity of energy burden to ensure equitable outcomes.
3. **Dynamic Population Changes:** The literature on energy equity does not consider the dynamic nature of population changes due to factors such as migration, birth rates,

and death rates. These demographic shifts can significantly impact the long-term effectiveness of energy equity interventions, yet they are largely ignored in existing models.

4. **Impact of Electric Vehicle Adoption:** With the increasing push toward net-zero emissions, the adoption of electric vehicles (EVs) is expected to rise. However, the literature lacks comprehensive studies on how future EV market penetration will affect energy systems in disadvantaged communities. This gap is crucial, as EV adoption can introduce additional loads that may strain existing energy infrastructure.

Proposed Contribution

This study aims to address these critical gaps by developing a two-stage stochastic optimization framework to promote energy equity in disadvantaged communities in Tennessee and Florida—making it the first study of its kind for these regions. The proposed framework will:

- **Incorporate Uncertainty:** By treating energy equity as a two-stage stochastic problem, the model will account for uncertainties in electricity prices, peak sun hour, and wind speeds, providing a more realistic and adaptable solution.
- **Prioritize Severely Burdened Households:** The framework will provide weighted contribution from community interventions for households with the highest energy burdens, ensuring that the most vulnerable populations receive the greatest benefit.
- **Account for Population Dynamics:** The model will integrate demographic projections to assess the impact of population changes on energy burden over time, ensuring that interventions remain effective in future scenarios.
- **Include EV Adoption Dynamics:** The study will evaluate the potential impacts of increased EV market penetration on energy systems in disadvantaged communities, addressing the additional loads introduced by EV charging.

By combining these elements, this research aims to provide a comprehensive, equitable, and forward-looking approach to reducing energy burdens. The findings will offer valuable

insights for policymakers, energy providers, and community stakeholders, contributing to the broader goal of energy justice and sustainability.

3.3. Methodology

This section outlines the selection criteria for Disadvantaged Communities (DACs), the two-stage stochastic model (including sets, parameters, variables, objective function, and constraints), data sources, parameter calibration, and scenario generation.

DACs in Tennessee and Florida were selected using LEAP criteria [41] (see Chapter 1, Section 1.2.1). Details of selected households in Tennessee are in **Table 1**, with Florida housing types aggregated as: 12,243 single-family, 7,725 small multi-family, 3,123 mobile homes, and 2,099 large multi-family dwellings.

Following the selection of DACs, household data were collected, including FIP codes, housing types, annual energy expenditures (electricity, gas, other fuels), and household income. Additional parameters such as electricity prices, zip code-specific peak sun hours, wind speeds at 80-meter hub heights, population growth, and electric vehicle data (kWh per mile, annual mileage) were gathered for Tennessee and Florida. Peak sun hours and wind speeds were collected on an FIP-specific basis.

Subsequent data preprocessing steps, as detailed in Section 1.2.2, included median imputation and restructuring of housing types. Energy burden was calculated using annual income and household energy expenses, while energy generation from rooftop solar, community solar, and community wind was estimated under appropriate scenarios. Preprocessed data, combined with scenario projections, population growth, and electric vehicle adoption rates, was integrated into a two-stage stochastic model over a 5-year horizon. The model determines the optimal number of interventions needed to reduce energy burden in disadvantaged communities (DACs) in Tennessee and Florida. A flowchart summarizing the methodology is shown in **Fig. 10**.

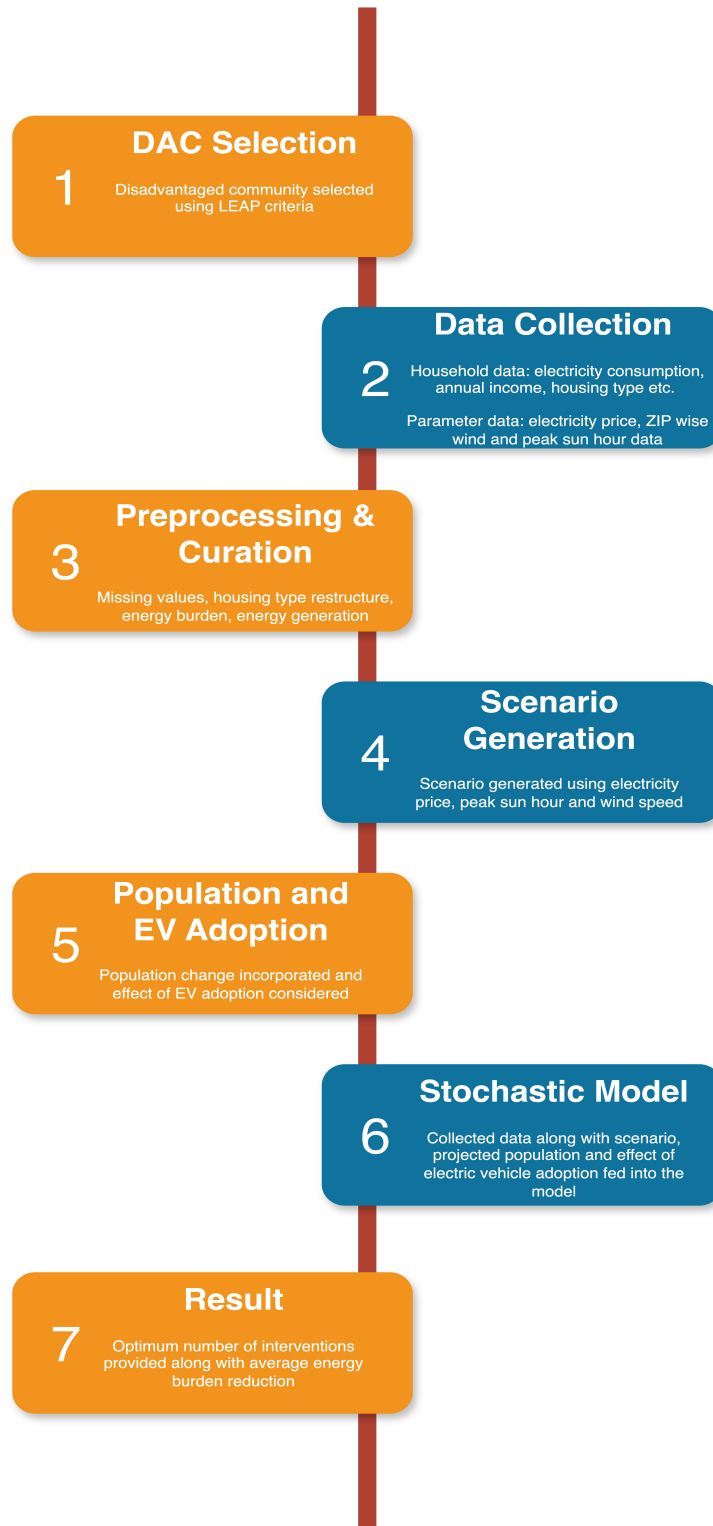


Figure 10: Sequential steps of the two-stage stochastic model used in this study to reduce the energy burden for DACs in Tennessee and Florida.

3.3.1 Model

Sets, parameters, objective function, and constraints of the stochastic optimization model are described in this section. **Table 11** contains the relevant details.

Objective Function

The objective function is constructed to minimize the expected energy burden for each household across all scenarios. Let $EB_{h,s}$ denote the revised energy burden for household $h \in \mathcal{H}$ under scenario $s \in \mathcal{S}$. The objective function for the stochastic optimization model is presented in Equation 3.1.

$$\min \frac{1}{|\mathcal{H}| \cdot |\mathcal{S}|} \sum_{h \in \mathcal{H}} \sum_{s \in \mathcal{S}} EB_{h,s} \quad (3.1)$$

where:

- $|\mathcal{H}|$: Number of households,
- $|\mathcal{S}|$: Number of scenarios.

Constraints

Budget

The total cost of interventions must not exceed the allocated budget (T_b) for the optimization model. This ensures that the interventions remain financially feasible. In the stochastic model, the variables W_h and RTS_h are binary, indicating whether household h adopts weatherization or rooftop solar interventions, respectively. Similarly, $Count_i$ represents the number of community interventions of type $i \in \{cs, cw\}$ (community solar or community wind).

Table 11: Description of sets, parameters, and variables used in the stochastic optimization model.

Nomenclature for Stochastic Model	
Sets	
$\mathcal{H}$	Set of households indexed by h
$\mathcal{Z}$	Set of zip codes indexed by z
$\mathcal{I}$	Set of interventions: $\{w, rts, cs, cw\}$ denoting weatherization, rooftop solar, community solar, and community wind respectively
$\mathcal{B}$	Set of housing types: $\{\text{single family, small multi-family, large multi-family, mobile homes}\}$
$\mathcal{S}$	Set of scenarios indexed by s
Deterministic Parameters	
T_b	Total budget (\$)
L_i	Lifetime of intervention $i \in \mathcal{I}$
S_b	Weatherization savings for different housing types $b \in \mathcal{B}$
$Cost_{w,b}$	Cost of weatherization for housing type $b \in \mathcal{B}$
$Cost_i$	Cost for each intervention $i \in \{rts, cs, cw\}$
CAF_i	Cost amortization factor for intervention $i \in \mathcal{I}$
$HINCP_h$	Income of household $h \in \mathcal{H}$
$Gen_{i,s}$	Energy generation from intervention $i \in \mathcal{I}$ under scenario $s \in \mathcal{S}$
Exp_h	Energy expenditure of household $h \in \mathcal{H}$
$Contrib_{h,i}$	Contribution from community intervention $i \in \{cs, cw\}$ for household $h \in \mathcal{H}$ based on initial energy burden
Stochastic Parameters	
$P_{z,s}$	Price of electricity (\$/kWh) for zip code $z \in \mathcal{Z}$ under scenario $s \in \mathcal{S}$
$W_{z,s}$	Wind speed (m/s) for zip code $z \in \mathcal{Z}$ under scenario $s \in \mathcal{S}$
$PSH_{z,s}$	Peak sun hours for zip code $z \in \mathcal{Z}$ under scenario $s \in \mathcal{S}$
First-stage Variables	
W_h	Binary variable indicating whether household $h \in \mathcal{H}$ adopts weatherization intervention
RTS_h	Binary variable indicating whether household $h \in \mathcal{H}$ adopts rooftop solar intervention
$Count_i$	Integer variable for the number of community interventions $i \in \{cs, cw\}$ adopted
Second-stage Variables	
$EB_{h,s}$	Revised energy burden for household $h \in \mathcal{H}$ under scenario $s \in \mathcal{S}$

Each intervention incurs specific costs: $\text{Cost}_{w,b}$ for weatherization based on housing type $b \in \mathcal{B}$, Cost_{rts} for rooftop solar, and Cost_i for community interventions. Cost amortization factors (CAF_w , CAF_{rts} , and CAF_i) are applied to account for the multi-year implementation of these interventions. The budget constraint for the stochastic model is presented in Equation 3.2.

$$\sum_{i \in \{cs, cw\}} \text{Count}_i \cdot \text{Cost}_i \cdot \text{CAF}_i + \sum_{h \in \mathcal{H}} W_h \cdot \text{Cost}_{w,b} \cdot \text{CAF}_w + \sum_{h \in \mathcal{H}} \text{RTS}_h \cdot \text{Cost}_{rts} \cdot \text{CAF}_{rts} \leq T_b \quad (3.2)$$

This constraint ensures that the total expenditure on interventions does not exceed the budget allocated for the model. By maintaining this financial limitation, the optimization model supports economically viable intervention strategies.

Household Intervention Caps

The number of households receiving weatherization or rooftop solar interventions must not exceed the total number of households $|\mathcal{H}|$ included in the set of all selected households $\mathcal{H}$. This constraint ensures that interventions are implemented within realistic resource limits. The following equations enforce these limits:

For weatherization, the total number of households that can receive the intervention is capped by the total count of households in $\mathcal{H}$, as defined by Equation 3.3.

$$\sum_{h \in \mathcal{H}} W_h \leq |\mathcal{H}| \quad (3.3)$$

Similarly, for rooftop solar, the total number of installations is also limited to the number of households in $\mathcal{H}$, as stipulated in Equation 3.4.

$$\sum_{h \in \mathcal{H}} \text{RTS}_h \leq |\mathcal{H}| \quad (3.4)$$

These constraints ensure that the scale of interventions remains practical and achievable within the available household population.

Non-Negativity and Binary Constraints

The decision variables in the stochastic model must satisfy non-negativity and appropriate type

restrictions to reflect their operational definitions. Specifically, the binary nature of household-specific interventions for weatherization (W_h) and rooftop solar (RTS_h) implies that these variables can only take values of 0 or 1, indicating whether the intervention is not adopted or adopted, respectively, by household h . Additionally, the number of community interventions (Count_i) is an integer variable, representing the count of interventions implemented, which must be a non-negative whole number. These constraints are formally represented in Equation 3.5.

$$W_h, RTS_h \in \{0, 1\}, \quad \text{Count}_i \in \mathbb{Z}^+ \quad (3.5)$$

This formulation ensures that the variables are consistent with the operational realities of intervention deployment and the accounting constraints of the optimization model.

Revised Energy Burden

The revised energy burden for each household $h \in \mathcal{H}$ under a specific scenario $s \in \mathcal{S}$ is quantified by Equation 3.6. This formula adjusts the initial energy expenditures Exp_h of household h by accounting for energy savings from weatherization, energy generated from rooftop solar, and contributions from community solar and wind interventions. Specifically, savings from weatherization are calculated based on the applicable percentage savings S_b , multiplied by the energy expenditure Exp_h and the binary variable W_h indicating adoption. Energy generation from rooftop solar is computed by multiplying the generation $\text{Gen}_{rts,s}$, the price of electricity $P_{z,s}$, and the binary variable RTS_h . For community interventions (solar and wind), the generation from each intervention type $i \in \{cs, cw\}$ is considered along with the total number of interventions (Count_i) and their specific contribution to each household ($\text{Contrib}_{h,i}$). All these components are normalized by the household's income HINCP_h , yielding the revised energy burden. This relationship is presented in Equation 3.6.

$$\text{EB}_{h,s} \geq \frac{\text{Exp}_h - S_b \cdot \text{Exp}_{h,s} \cdot W_h - \text{Gen}_{rts,s} \cdot P_{z,s} \cdot RTS_h}{\text{HINCP}_h} - \frac{\sum_{i \in \{cs, cw\}} \text{Gen}_{i,s} \cdot P_{z,s} \cdot \text{Count}_i \cdot \text{Contrib}_{h,i}}{\text{HINCP}_h} \quad (3.6)$$

This formulation ensures an accurate depiction of the financial impact of energy interventions on households, accounting for variability across scenarios and enabling more informed decision-making regarding energy management and policy implementation.

3.3.2 Data

Data collection and preprocessing were conducted as described in Section 1.2.2. In addition to these steps, granular data on electricity prices, zip code-wise wind speed (at an 80-meter hub height), and peak sun hours were collected for both Tennessee and Florida. We also used population projection data from Boyd Center for Business and Economic Research and Weldon Cooper Center for Public Service for both Tennessee and Florida respectively. Furthermore, we also collected some driving-related data such as average annual mileage driven in the USA, and kWh per mile. The respective final price (December 2029) obtained from the Seasonal Autoregressive Integrated Moving Average (SARIMA) model was used for per kWh electricity price.

Electricity price data for both states was sourced from the U.S. Energy Information Administration (EIA), provided as monthly time series data spanning from 2001 to 2024. Data specific to Tennessee was accessed through this link, while Florida’s data was obtained via this link.

To accurately assess peak sun hours across different locations, census tracts were matched to zip codes using the HUD-USPS ZIP Crosswalk Files. Using these zip codes, peak sun hour data was then obtained from NREL’s solar data-based calculator. The resulting data is included in Appendix **Table 18** and **Table 19**.

Wind speed data, considered at an 80-meter hub height to align with specifications for a 1 MW wind turbine (with an 80-meter rotor diameter and 40-meter blade radius), was gathered from the National Renewable Energy Laboratory’s (NREL) Wind Resource Database. Detailed values are presented in Appendix **Table 20** and **Table 21**.

3.3.3 Parameter Calibration

This section details the calculation of various parameter values, including the energy expenditure ($\text{Exp}_{h,s}$), energy generation ($\text{Gen}_{i,s}$), contributions from community interventions ($\text{Contrib}_{h,i}$), the cost amortization factor (CAF_i), and the total budget (T_b). Additional parameter values, such as the discount rate, intervention capacity, cost, and photovoltaic (PV) cost, are provided in section 1.2.3.

Energy Expenditure

The energy expenditure for a household $h \in \mathcal{H}$, denoted as Exp_h , is the sum of expenditures on electricity (ELEM), gas (GASP), and other fuels (FULP). Equation 3.7 provides the formula for calculating Exp_h :

$$\text{Exp}_h = \text{ELEM} + \text{GASP} + \text{FULP} \quad (3.7)$$

Energy Generation

Energy generation from interventions such as rooftop solar, community solar, and wind turbines plays a crucial role in reducing the energy burden for individual households. The energy produced by these interventions derives from wind and solar resources. This section presents the equations and values used for calculating these energy sources.

Wind Energy

The energy generated from community wind under scenario s , represented as $\text{Gen}_{cw,s}$, is calculated based on factors including air density (ρ), the swept area of the rotor (A), the power coefficient (C_p), wind speed ($W_{z,s}$), and the duration of a year (365 days, 24 hours per day). The air density ρ is assumed to be 1.225 kg/m^3 , and the power coefficient C_p , which is dimensionless, is set to 0.40. The rotor diameter is 80 meters, giving a rotor radius of 40 meters, which is used to compute the swept area A using Equation 3.9. The generated energy for the wind turbine is then determined by Equation 3.8 considering 10% more energy loss for miscellaneous reasons.

$$\text{Gen}_{cw,s} = 0.9 \times 0.5 \times \rho \times A \times C_p \times W_{z,s}^3 \times 365 \times 24/1000 \quad (3.8)$$

where the swept area A of the rotor is calculated by:

$$A = \pi R^2 \quad (3.9)$$

Solar Energy

The energy output from solar panels, whether in rooftop or community installations, is determined by several parameters. These include peak sun hours ($\text{PSH}_{z,s}$), the number of solar panels (N_{PV}), the rated power output per panel (P_{rated}), and various efficiency factors. The efficiency considerations include panel efficiency (η_{panel}), inverter efficiency (η_{inverter}), wiring efficiency (η_{wiring}), shading loss factor (η_{shading}), temperature-related efficiency ($\eta_{\text{temperature}}$), and tilt angle loss factor (L_{tilt}).

For rooftop solar, the number of panels (N_{PV}) is 17, while for community solar, it is 2,857. Each panel has a rated power output (P_{rated}) of 0.35 kW. The efficiency values are:

- $\eta_{\text{panel}} = 0.75$ (panel efficiency),
- $\eta_{\text{inverter}} = 0.95$ (inverter efficiency),
- $\eta_{\text{wiring}} = 0.97$ (wiring efficiency),
- $\eta_{\text{shading}} = 0.90$ (shading loss factor),
- $\eta_{\text{temperature}} = 0.98$ (temperature-related efficiency),
- $L_{\text{tilt}} = 0.95$ (tilt angle loss factor).

The generated solar energy for each scenario s and location z is calculated using the following Equation 3.10.

$$\text{Gen}_{\text{rts/cs},s} = \text{PSH}_{z,s} \times N_{\text{PV}} \times P_{\text{rated}} \times \eta_{\text{panel}} \times \eta_{\text{inverter}} \times \eta_{\text{wiring}} \times \eta_{\text{shading}} \times \eta_{\text{temperature}} \times L_{\text{tilt}} \quad (3.10)$$

Contribution from Community Interventions

To address energy burden disparities, we applied a need-based contribution model, where households with higher energy burdens receive a greater share of benefits from community

interventions. The contribution from a community intervention i (where $i \in \{\text{cs}, \text{cw}\}$) for each household h is calculated based on the household's initial energy burden (EB_h) and the total energy burden across all households in $\mathcal{H}$. This proportional approach ensures that households with greater energy burdens receive a larger share of contributions. The contribution calculation is given by Equation 3.11.

$$\text{Contrib}_{h,i} = \frac{\text{EB}_h}{\sum_{h \in \mathcal{H}} \text{EB}_h} \quad (3.11)$$

Cost Amortization Factor

Since different interventions have varied lifetimes, as presented in **Table 2**, we introduced a cost amortization factor (CAF_i) to standardize costs over a one-year period, aligning with the study's stochastic timeframe. The cost amortization factor is calculated based on the discount rate (r) and the lifetime (L_i) of each intervention. The discount rate r is set at 3%. This approach allows for the distribution of intervention costs over a consistent period, regardless of their original lifespans. The formula for the cost amortization factor is given by Equation 3.12.

$$\text{CAF}_i = \frac{r}{1 - (1 + r)^{-L_i}} \quad (3.12)$$

This formulation ensures realistic representation of intervention costs within the budget and scenario constraints of the study.

Creation of Artificial Data for Extra Households in Disadvantaged Community

The timeframe for this study is set to 2030. We assumed that the change in the population of disadvantaged communities would correspond proportionally to the projected state population growth. According to the Boyd Center for Business and Economic Research at the University of Tennessee, the population of Tennessee is projected to grow by 8.7% [76]. Similarly, the population of Florida is expected to increase by 10.5% [77], based on projections from the Weldon Cooper Center for Public Service at the University of Virginia. These growth percentages were used to estimate the number of additional disadvantaged households, resulting in 2,823 new households in Tennessee and 2,635 in Florida.

Household characteristics, such as housing types, were assigned in accordance with the existing data ratios to maintain consistency. Additional household data, including annual income and expenses, were generated using the best-fit distribution from the current dataset, which followed a lognormal distribution. To ensure realism and validity, lower bounds were set for certain variables: energy expenses were restricted to non-negative values, and the minimum household income was set at \$1,000. This approach integrates projected population changes with statistically grounded methods to create a robust dataset for analysis.

Effect on the Energy Demand due to Adoption of Electric Vehicles

The adoption of electric vehicles (EVs) within disadvantaged communities has not been extensively studied. However, one notable study [89] examined EV adoption rates across different income brackets within these communities. Leveraging the adoption percentages from this study, along with vehicle registration data from 2017 to 2022 [90] and projected growth rates [91], we developed **Table 12** to estimate EV adoption percentages for 2030. This analysis provides valuable insights into future EV adoption trends within disadvantaged populations.

Table 12: Adoption percentages by income bracket for 2022 and projected growth to 2030.

Income Bracket	2022 Adoption %	2030 Growth Factor	2030 Adoption %
Below \$25k	0.5% (0.005)	5x	2.5% (0.025)
\$25k – \$50k	0.6% (0.006)	4x	2.4% (0.024)
\$50k – \$75k	1.7% (0.017)	3x	5.1% (0.051)
\$75k – \$100k	2.6% (0.026)	2.5x	6.5% (0.065)
\$100k – \$125k	3.4% (0.034)	2x	6.8% (0.068)
\$125k – \$150k	2.75% (0.0275)	2x	5.5% (0.055)
\$150k – \$200k	6.5% (0.065)	1.5x	9.75% (0.0975)
\$200k+	10.8% (0.108)	1.5x	16.2% (0.162)

3.3.4 Scenario Generation

To construct the scenarios required for the two-stage stochastic problem, month-wise electricity price data was generated using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. The details of the predicted values for both states (Tennessee and Florida) from July 2024 - December 2029 are provided in **Table 22** in **Appendix A**. Historical electricity price data from January 2001 to June 2024 served as the foundation for the SARIMA model, which was subsequently used to predict electricity prices from July 2024 to December 2029. To generate a representative annual spectrum of electricity prices, predicted values for the same month across multiple years were averaged. For example, data for July 2024, July 2025, July 2026, July 2027, July 2028, and July 2029 were averaged to estimate the electricity price for July, and this process was repeated for all other months. This approach resulted in 12 discrete scenarios, each representing a monthly electricity price with equal probability.

In addition to electricity prices, monthly peak sun hour and wind speed data were collected on a zip-code basis to account for geographical variations in renewable energy potential. For Tennessee, data was gathered across 36 zip codes, resulting in 432 distinct scenarios ($12 \text{ months} \times 36 \text{ zip codes}$). Similarly, for Florida, data was collected across 45 zip codes, generating 540 scenarios ($12 \text{ months} \times 45 \text{ zip codes}$). These scenarios form the basis for modeling the stochastic components of renewable energy generation and electricity price variability in the optimization framework. To address computational capacity constraints and improve model efficiency, we employed random sampling for the scenarios in Florida. From an initial set of 540 scenarios, we selected a representative subset of 450 scenarios for final analysis.

3.4. Results and Discussion

This section presents the results of the stochastic optimization model, detailing the adopted interventions for each state—Tennessee and Florida. We considered 432 scenarios for Tennessee and 450 scenarios (out of 540) for Florida, accounting for uncertainties in key parameters such as wind speed, peak sun hours, and electricity prices. Additionally, we incorporated projected population changes and electric vehicle (EV) adoption trends within disadvantaged communities (DACs) over the study period.

The initial average energy burden was found to be 8.23% for Tennessee and 6.44% for Florida, reflecting the current baseline conditions. After applying the stochastic optimization approach, we obtained intervention portfolios designed to minimize energy burden while accounting for real-world variability and future trends.

3.4.1 Tennessee

The stochastic optimization results for Tennessee, including the number of interventions and their corresponding energy burden outcomes, are shown in **Fig. 11(a) and (b)**. The adopted portfolio exhibits a diversification of interventions, consistent with the findings from the monthly granular approach discussed in Chapter 2. This diversification is critical for mitigating the risks associated with uncertain energy production and costs.

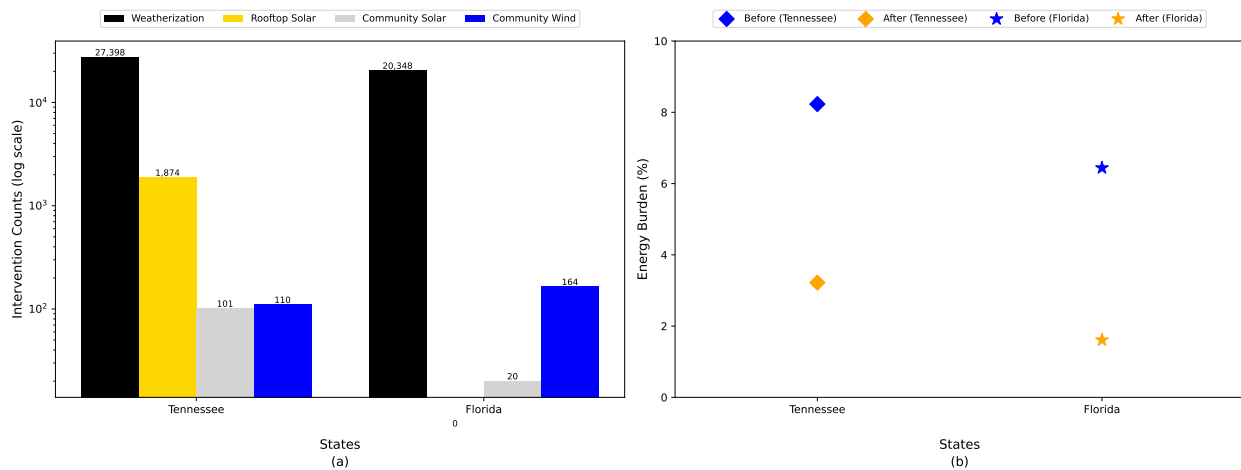


Figure 11: Adopted number of interventions along with revised energy burden for both Tennessee and Florida.

The most adopted intervention was weatherization, with 27,398 households receiving weatherization upgrades (**Fig. 11(a)**). This high adoption rate is primarily due to the cost-effectiveness of weatherization measures, which offer immediate reductions in energy burden without large capital investments.

Rooftop solar was the second most adopted intervention, with 1,874 households implementing solar installations. The adoption of rooftop solar in Tennessee is driven by favorable solar potential and the ability to offset electricity costs over time.

Community interventions also played a significant role, with 101 community solar and 110 community wind projects adopted. These interventions provide shared renewable energy benefits to communities where individual rooftop installations may not be feasible due to structural, financial, or spatial constraints.

The combined portfolio of interventions reduced the initial average energy burden from 8.23% to 3.22% **Fig. 11(b)**, bringing it well below the 6% threshold commonly used to define energy affordability. This outcome demonstrates that the stochastic approach remains effective even when accounting for uncertainties, population growth, and increased EV adoption. The robustness of this result ensures that Tennessee’s disadvantaged communities can achieve significant energy burden reductions by 2030.

3.4.2 Florida

The results for Florida, presented in **Fig. 11(a) and (b)**, show a distinct pattern of intervention adoption, reflecting the state’s unique characteristics and the influence of stochastic variability. Weatherization emerged as the predominant intervention, with 20,348 households adopting these upgrades (**Fig. 11(a)**). The high adoption rate is due to the low cost and immediate benefits of weatherization, similar to Tennessee.

Community wind projects were notably adopted, with 164 interventions implemented. Despite Florida’s reputation for solar potential, the stochastic model favored wind projects in many scenarios due to uncertainties in solar irradiance and the comparative stability of wind energy generation in the considered regions.

Community solar was adopted in a more limited fashion, with only 20 interventions selected. This reflects the higher variability in solar irradiance and potential economic constraints related to implementing large-scale community solar projects in Florida.

Interestingly, the model found no adoption of rooftop solar in Florida. This result can be attributed to several factors:

- High variability in solar potential, which may reduce the reliability of rooftop solar in stochastic scenarios.
- Economic considerations, where the cost of rooftop solar installations combined with uncertain electricity prices makes this intervention less favorable.
- Policy and infrastructure constraints, which may limit the feasibility of rooftop solar in certain disadvantaged communities.

The adopted intervention portfolio successfully reduced Florida’s initial average energy burden from 6.44% to 1.61% (**Fig. 11(b)**), achieving a substantial reduction well below the 6% threshold. This outcome underscores the effectiveness of the stochastic approach in identifying optimal interventions despite significant uncertainties and regional differences.

3.4.3 Discussion

The results for both Tennessee and Florida highlight the robustness of the stochastic optimization methodology. By considering a diverse set of scenarios, the model identifies intervention portfolios that are resilient to uncertainties in energy generation, costs, and future population dynamics. This ensures that the proposed strategies are not only effective under current conditions but also adaptable to future challenges.

The diversification of interventions—weatherization, rooftop solar, community solar, and community wind—demonstrates a balanced approach to energy burden reduction. While weatherization remains the most cost-effective intervention, community-based projects play a crucial role in regions where individual solutions are less viable.

The state-specific insights further emphasize the importance of flexibility in energy policies. For Tennessee, the adoption of rooftop solar reflects favorable conditions for residential solar

installations. For Florida, the lack of rooftop solar adoption highlights the need to consider uncertainties and regional factors when designing intervention strategies.

These findings provide valuable guidance for policymakers, suggesting that investment in weatherization and community renewable projects can effectively reduce energy burdens in disadvantaged communities. The results also support the need for adaptive policies that can accommodate variability in energy generation and socioeconomic conditions.

3.5. Conclusion

This chapter presented a comprehensive stochastic optimization framework for reducing energy burdens in disadvantaged communities (DACs) in Tennessee and Florida. By integrating uncertainties in key parameters—such as wind speed, peak sun hours, and electricity prices—along with projections for population growth and electric vehicle (EV) adoption, this research offers a robust, realistic, and adaptive approach to energy equity. Unlike traditional deterministic models, this stochastic approach captures the variability inherent in real-world energy systems, ensuring that intervention strategies are resilient to future uncertainties.

The results demonstrate the power of a diversified intervention portfolio. In Tennessee, the optimized combination of weatherization, rooftop solar, community solar, and community wind interventions reduced the initial average energy burden from 8.23% to 3.22%. This outcome highlights the effectiveness of household-level interventions like rooftop solar, which leverage the state’s favorable solar potential to alleviate energy burdens. Additionally, the inclusion of community-based renewable projects ensures that households unable to adopt individual interventions still benefit from shared resources.

In contrast, Florida’s results reveal a distinct pattern shaped by regional characteristics and stochastic variability. The optimized portfolio primarily consists of weatherization, community solar, and community wind interventions, reducing the initial average energy burden from 6.44% to 1.61%. Notably, no rooftop solar interventions were adopted in Florida, reflecting the higher variability in solar irradiance and economic constraints. This finding underscores the importance of tailoring intervention strategies to regional conditions, rather than applying a one-size-fits-all approach.

This study directly addresses several critical gaps in the literature:

- **Incorporating Uncertainty:** While previous studies rely on deterministic frameworks, this research introduces a two-stage stochastic optimization model that captures uncertainties in energy prices, renewable resource availability, and other key parameters. By considering 432 scenarios for Tennessee and 450 scenarios for Florida, the model provides solutions that are resilient to a wide range of real-world conditions.
- **Prioritizing Severely Burdened Households:** The framework ensures that the most vulnerable populations receive the greatest benefit. By adopting a weighted contribution approach, community interventions are distributed based on the severity of energy burden, ensuring equitable outcomes that prioritize those in greatest need.
- **Dynamic Population Changes:** Unlike existing models that ignore demographic shifts, this study incorporates projections for population growth and migration. This ensures that the proposed interventions remain effective not only today but also in the evolving social and economic landscape of 2030 and beyond.
- **Impact of EV Adoption:** As the push toward net-zero emissions accelerates, the adoption of EVs introduces additional loads on energy infrastructure. This study uniquely accounts for the future impact of EV adoption in DACs, ensuring that energy burden mitigation strategies are robust enough to accommodate increased electricity demand.

The insights from this study offer valuable guidance for policymakers, energy providers, and community stakeholders:

- **Diversified Strategies:** Investing in a mix of interventions—weatherization, rooftop solar, community solar, and community wind—enhances resilience and ensures that different households can benefit according to their specific circumstances.
- **Regionally Tailored Solutions:** The differences between Tennessee and Florida highlight the necessity of region-specific policies. In Tennessee, supporting rooftop solar

adoption can significantly reduce energy burdens, while in Florida, community wind projects may offer more reliable benefits.

- **Future-Proof Policies:** By integrating population dynamics and trends in EV adoption, this study underscores the need for forward-thinking policies. Sustainable energy burden reductions require adaptive strategies that can evolve with technological advancements and demographic changes.
- **Equitable Resource Allocation:** Prioritizing the most severely burdened households ensures that resources are allocated where they are needed most. Policymakers should consider need-based distribution models to maximize the impact of interventions.

This study represents the first of its kind to apply a two-stage stochastic optimization framework to energy burden mitigation in Tennessee and Florida, overcoming the limitations of deterministic models used in prior research. By bridging the gap between theoretical models and practical implementation, it provides a pathway toward equitable, resilient, and sustainable energy solutions for DACs. The incorporation of uncertainty, population dynamics, and EV adoption makes this framework a powerful tool for achieving long-term energy justice.

While this research offers significant contributions, it also opens avenues for future work. Expanding the model to include additional sources of uncertainty, such as climate change impacts, could further enhance its robustness. Incorporating more granular demographic data and exploring the long-term socioeconomic impacts of interventions could provide deeper insights into energy equity. Furthermore, extending this framework to other regions and communities would help validate its applicability on a broader scale.

As the world transitions toward clean energy, ensuring that no community is left behind is both a moral imperative and a practical necessity. This research provides a meaningful step toward that goal, offering a comprehensive and adaptive framework for reducing energy burdens in DACs. By addressing real-world uncertainties and future challenges, this study lays the groundwork for policies and interventions that promote true energy justice and sustainability.

Bibliography

- [1] U.S. Census Bureau, “S1701 — Poverty Status in the Past 12 Months, American Community Survey (ACS) 2021, 5-Year Estimates.” <https://data.census.gov/table/ACSST5Y2021.S1701?q=belowpovertyline&tid=ACSST1Y2022.S1701>, 2021. Accessed: 02-01-2024. xii, 11
- [2] U.S. Census Bureau, “S1901 — Income in the Past 12 Months (in 2022 Inflation-Adjusted Dollars), American Community Survey (ACS) 2021, 5-Year Estimates.” <https://data.census.gov/table/ACSST5Y2021.S1901?q=medianhouseholdincomes1901>, 2021. Accessed: 02-01-2024. xii, 11
- [3] U.S. Census Bureau, “S1501 — Educational Attainment, American Community Survey (ACS) 2021, 5-Year Estimates.” <https://data.census.gov/table/ACSST5Y2021.S1501?q=S1501:EducationalAttainment&tid=ACSST1Y2022.S1501>, 2021. Accessed: 02-01-2024. xii, 11
- [4] U.S. Census Bureau, “DP05 — Demographic and Housing Estimates, American Community Survey (ACS) 2021, 5-Year Estimates.” <https://data.census.gov/table/ACSDP5Y2021.DP05?q=DP05>, 2021. Accessed: 02-01-2024. xii, 11
- [5] O. Ma, “Low-income energy affordability data - lead tool - 2018 update.” Available online at: <https://data.openei.org/submissions/573>, last accessed on 06-16-2023. 1, 12, 51
- [6] State and Local Solution Center, “Low-income community energy solutions..” Available online at: <https://www.energy.gov/scep/slsc/low-income-community-energy-solutions>, last accessed on 11-07-2023. 1
- [7] E. Johnson, “Tennessee residents have sky-high electric bills. energy efficiency can help,” 2023. Available online at: <https://www.eesi.org/articles/view/tennessee-residents-have-sky-high-electric-bills-energy-efficiency-can-help>, last accessed on 11-07-2023. 1

- [8] D. Radmacher, “Community members, conservation groups condemn tva’s fossil fuel-driven rate hike,” 2023. Available online at: <https://appvoices.org/2023/08/28/tva-rate-hike/>, last accessed on 11-07-2023. 1
- [9] D. Hernández, “Understanding ‘energy insecurity’ and why it matters to health,” *Social Science & Medicine*, vol. 167, pp. 1–10, 2016. 1
- [10] The White House, “Fact sheet: President Biden to catalyze global climate action through the major economies forum on energy and climate.” <https://www.whitehouse.gov/briefing-room/statements-releases/2023/04/20/fact-sheet-president-biden-to-catalyze-global-climate-action-through-the-major-economies-forum-on-energy-and-climate>, 2023. Available online at: <https://www.whitehouse.gov/briefing-room/statements-releases/2023/04/20/fact-sheet-president-biden-to-catalyze-global-climate-action-through-the-major-economies-forum-on-energy-and-climate>, last accessed on 06-16-2023. 2
- [11] The White House, “Executive order on tackling the climate crisis at home and abroad.” Available online at: <https://www.whitehouse.gov/briefing-room/presidential-actions/2021/01/27/executive-order-on-tackling-the-climate-crisis-at-home-and-abroad/>, 2
- [12] U.S. Energy Information Administration, “Us energy flow, 2022.” Available online at: <https://www.eia.gov/totalenergy/data/flow-graphs/total-energy.php>, last accessed on 06-16-2023. 2
- [13] U.S. Department of Energy, “Weatherization assistance program.” Available online at: https://www.energy.gov/sites/default/files/2022-06/wap-fact-sheet_0622.pdf, last accessed on 06-16-2023. 2
- [14] U.S. Department of Energy, “Weatherization innovation.” Available online at: <https://www.energy.gov/scep/wap/weatherization-assistance-program>, last accessed on 06-16-2023. 2

- [15] P. Gagnon, R. Margolis, and C. Phillips, “Rooftop photovoltaic technical potential in the united states,” *OSTI (Office of Scientific and Technical Information)*, 11 2019. 2
- [16] Solar Energy Technologies Office, “Homeowner’s guide to the federal tax credit for solar photovoltaics.” Available online at: <https://www.energy.gov/eere/solar/homeowners-guide-federal-tax-credit-solar-photovoltaics>, last accessed on 06-16-2023. 2
- [17] Y. huei Wan, “Net metering programs.” Available online at: <https://www.nrel.gov/docs/legosti/old/21651.pdf>, last accessed on 06-16-2023. 2
- [18] E. O’Shaughnessy, G. Barbose, R. Wiser, S. Forrester, and N. Darghouth, “The impact of policies and business models on income equity in rooftop solar adoption,” *Nature Energy*, vol. 6, no. 1, pp. 84–91, 2021. 2
- [19] M. Solomon and M. O’Boyle, “Renewables would provide cheaper energy than 99% of us coal plants and catalyze a just energy transition,” 2023. Available online at: <https://www.utilitydive.com/news/renewables-cheaper-energy-than-99-percent-of-us-coal-plants-just-energy-transition/642393/>, last accessed on 06-16-2023. 2
- [20] X. He, J. Lin, J. Xu, J. Huang, N. Wu, Y. Zhang, S. Liu, R. Jing, S. Xie, and Y. Zhao, “Long-term planning of wind and solar power considering the technology readiness level under china’s decarbonization strategy,” *Applied Energy*, vol. 348, p. 121517, 2023. 2
- [21] A. Aghahosseini, A. Solomon, C. Breyer, T. Pregger, S. Simon, P. Strachan, and A. Jäger-Waldau, “Energy system transition pathways to meet the global electricity demand for ambitious climate targets and cost competitiveness,” *Applied Energy*, vol. 331, p. 120401, 2023. 2
- [22] X. Feng, S. Li, E. L. Kalies, C. Markus, P. Harrell, and D. Patiño-Echeverri, “Low impact siting for wind power facilities in the southeast united states,” *Wind Energy*, vol. 26, no. 12, pp. 1254–1275, 2023. 2

- [23] The Wind Power, “Buffalo mountain wind energy center (usa).” Available online at: https://www.thewindpower.net/windfarm_en_3154_buffalo-mountain-wind-energy-center.php, last accessed on 01-29-2024. 2
- [24] M. Ashraf Fauzi, N. Hanis Zainal Abidin, N. Mohd Suki, and A. Mokhtar Albshir Budiea, “Residential rooftop solar panel adoption behavior: Bibliometric analysis of the past and future trends,” *Renewable Energy Focus*, vol. 45, pp. 1–9, 2023. 3
- [25] H. Du, Q. Han, B. de Vries, and J. Sun, “Community solar pv adoption in residential apartment buildings: A case study on influencing factors and incentive measures in wuhan,” *Applied Energy*, vol. 354, p. 122163, 2024. 3
- [26] N. R. Darghouth, E. O’Shaughnessy, S. Forrester, and G. Barbose, “Characterizing local rooftop solar adoption inequity in the us,” *Environmental Research Letters*, vol. 17, no. 3, 2022. 3, 41
- [27] R. Best, “Energy inequity variation across contexts,” *Applied Energy*, vol. 309, p. 118451, 2022. 3
- [28] A. M. Brockway, J. Conde, and D. Callaway, “Inequitable access to distributed energy resources due to grid infrastructure limits in california,” *Nature Energy*, vol. 6, no. 9, pp. 892–903, 2021. 3
- [29] J. Barlow, R. Tapio, and B. Tarekegne, “Advancing the state of energy equity metrics,” *The Electricity Journal*, vol. 35, no. 10, p. 107208, 2022. 3
- [30] D. Moore and A. L. Webb, “Evaluating energy burden at the urban scale: A spatial regression approach in cincinnati, ohio,” *Energy Policy*, vol. 160, p. 112651, 2022. 4
- [31] S. Cong, D. Nock, Y. L. Qiu, and B. Xing, “Unveiling hidden energy poverty using the energy equity gap,” *Nature Communications*, vol. 13, p. 2456, 2022. 4
- [32] L. Huang, D. Nock, S. Cong, and Y. L. Qiu, “Inequalities across cooling and heating in households: Energy equity gaps,” *Energy Policy*, vol. 182, p. 113748, 2023. 4

- [33] M. Kwon, S. Cong, D. Nock, L. Huang, Y. L. Qiu, and B. Xing, “Forgone summertime comfort as a function of avoided electricity use,” *Energy Policy*, vol. 183, p. 113813, 2023. 4
- [34] E. Ross, M. Day, C. Ivanova, A. McLeod, and J. Lockshin, “Intersections of disadvantaged communities and renewable energy potential: Data set and analysis to inform equitable investment prioritization in the united states,” *Renewable Energy Focus*, vol. 41, pp. 1–14, 2022. 4
- [35] M. Heleno *et al.*, “Optimizing equity in energy policy interventions: A quantitative decision-support framework for energy justice,” *Applied Energy*, vol. 325, p. 119771, 2022. 5, 6, 68
- [36] J.-P. Sasse and E. Trutnevyte, “Distributional trade-offs between regionally equitable and cost-efficient allocation of renewable electricity generation,” *Applied Energy*, vol. 254, p. 113724, 2019. 5, 68
- [37] M. R. Quitoras, P. E. Campana, P. Rowley, and C. Crawford, “Remote community integrated energy system optimization including building enclosure improvements and quantitative energy trilemma metrics,” *Applied Energy*, vol. 267, p. 115017, 2020. 5, 68
- [38] J. Kerby, T. Hardy, J. Twitchell, R. O’Neil, and B. Tarekegne, “A targeted approach to energy burden reduction measures: Comparing the effects of energy storage, rooftop solar, weatherization, and energy efficiency upgrades,” *Energy Policy*, vol. 184, p. 113867, 2024. 5, 68
- [39] E. J. Wilson, C. B. Harris, J. J. Robertson, and J. Agan, “Evaluating energy efficiency potential in low-income households: A flexible and granular approach,” *Energy Policy*, vol. 129, pp. 710–737, 2019. 5
- [40] D. J. Bednar and T. G. Reames, “Recognition of and response to energy poverty in the united states.,” *Nature Energy*, vol. 5, pp. 432–439, 2020. 5
- [41] Department of Energy, “Doe announces \$16 million to support community-driven pathways to clean energy,” 2021. Available online at: <https://www.energy.gov/2021/04/22/doe-announces-16-million-to-support-community-driven-pathways-to-clean-energy>

- [//www.energy.gov/articles/doe-announces-16-million-support-community-driven-pathways-clean-energy](https://www.energy.gov/articles/doe-announces-16-million-support-community-driven-pathways-clean-energy), last accessed on 09-10-2023. 10, 44, 70
- [42] U.S. Department of Energy, “Clean energy for low-income communities - completed,” 2020. Available online at: <https://betterbuildingssolutioncenter.energy.gov/accelerators/clean-energy-low-income-communities/>, last accessed on 06-20-2023. 12
- [43] J. Bauer, K. Rose, L. Romeo, D. Justman, N. Popovich, M. Shah, A. T. Anyikire, C. Russomanno, H. Ho, B. Sigrin, B. White, and J. Heeter, “Datasets for doe 2021 communities leap pilot.” <https://www.energycommunities.gov/>, 9 2021. 12
- [44] Mayor’s Office, City of Knoxville, “Knoxville extreme energy makeover,” 2015. Available online at: https://www.knoxvilletn.gov/government/city_departments_offices/sustainability/buildings/keem, last accessed on 06-22-2023. 14
- [45] G. Jacobs, “Proposed fy2024 budget,” 2023. Available online at: https://www.knoxcounty.org/finance/pdfs/2023_2024_budget/FY24_Proposed_Budget.pdf, last accessed on 06-22-2023. 14, 17
- [46] Solar Direct, “Solar electric system sizing step 4 - determine the sun hours available per day.” Available online at: <https://www.solardirect.com/archives/pv/systems/gts/gts-sizing-sun-hours.html>, last accessed on 06-23-2023. 14, 17
- [47] M. Blasnik, G. Dalhoff, D. Carroll, and F. Ucar, “National weatherization assistance program impact evaluation: Energy impacts for small multifamily buildings,” 2014. Available online at: https://weatherization.ornl.gov/wp-content/uploads/pdf/WAPRetroEvalFinalReports/ORNL_TM-2014_325.pdf, last accessed on 06-22-2023. 15, 17
- [48] M. Blasnik, G. Dalhoff, D. Carroll, and F. Ucar, “National weatherization assistance program impact evaluation: Energy impacts for large multifamily buildings,” 2014. Available online at: https://weatherization.ornl.gov/wp-content/uploads/pdf/WAPRetroEvalFinalReports/ORNL_TM-2014_332.pdf, last accessed on 06-22-2023. 15

- [49] S. Pigg, D. Cautley, P. Francisco, B. Hawkins, and T. Brennan, “Weatherization and indoor air quality: Measured impacts in single-family homes under the weatherization assistance program,” 2014. Available online at: https://weatherization.ornl.gov/wp-content/uploads/pdf/WAPRetroEvalFinalReports/ORNL_TM-2014_170.pdf, last accessed on 06-22-2023. 15
- [50] M. Blasnik, G. Dalhoff, D. Carroll, and F. Ucar, “National weatherization assistance program impact evaluation – energy impacts for mobile homes,” 2014. Available online at: https://weatherization.ornl.gov/wp-content/uploads/pdf/WAPRetroEvalFinalReports/ORNL_TM-2014_84.pdf, last accessed on 06-22-2023. 15
- [51] A. Brooks and L. Saddler, “What is the best angle and orientation for solar panels?,” 2022. Available online at: <https://www.forbes.com/home-improvement/solar/best-angle-for-solar-panels>, last accessed on 06-23-2023. 15
- [52] G. Barbose, N. Darghouth, E. O’Shaughnessy, and S. Forrester, “Tracking the sun: Pricing and design trends for distributed photovoltaic systems in the united states 2022 edition,” 2022. Available online at: https://emp.lbl.gov/sites/default/files/2_tracking_the_sun_2022_report.pdf, last accessed on 06-23-2023. 15, 17
- [53] R. Wiser, M. Bolinger, B. Hoen, D. Millstein, J. Rand, G. Barbose, N. Darghouth, W. Gorman, S. Jeong, and B. Paulos, “Land-based wind market report: 2022 edition,” 2022. Available online at: https://www.energy.gov/sites/default/files/2022-08/land_based_wind_market_report_2202.pdf, last accessed on 02-23-2024. 16, 17
- [54] Knoxville Utility Board, “Residential rates,” 2023. Available online at: <https://www.kub.org/bills-payments/understand-your-bill/residential-rates/>, last accessed on 07-08-2023. 17
- [55] Energy Education, “Discounting.” Available online at: <https://energyeducation.ca/encyclopedia/Discounting>, last accessed on 06-23-2023. 17

- [56] K. Mertens, *Photovoltaic System Technology*, pp. 161–199. WILEY, 2014. Available online at: <https://www.wiley.com/en-us/Photovoltaics:+Fundamentals,+Technology+and+Practice-p-9781118843390>, last accessed on 02-23-2024. 17
- [57] Wind Exchange, “Tennessee potential wind capacity chart.” Available online at: <https://windexchange.energy.gov/maps-data/121>, last accessed on 06-22-2023. 17
- [58] S. Drolet, “Is rooftop solar in tennessee worth it?,” 2023. Available online at: <https://www.cnet.com/home/energy-and-utilities/tennessee-solar-panels/>, last accessed on 06-23-2023. 17
- [59] A. Brooks and L. Saddler, “What is the best angle and orientation for solar panels?,” 2022. Available online at: <https://www.forbes.com/home-improvement/solar/best-angle-for-solar-panels>, last accessed on 01-29-2024. 17
- [60] National Renewable Energy Laboratory, “Best research-cell efficiencies.” Available online at: <https://www.nrel.gov/pv/assets/pdfs/best-research-cell-efficiencies.pdf>, last accessed on 01-29-2024. 17
- [61] G. Cardoso, M. Stadler, M. Bozchalui, R. Sharma, C. Marnay, A. Barbosa-Póvoa, and P. Ferrão, “Optimal investment and scheduling of distributed energy resources with uncertainty in electric vehicle driving schedules,” *Energy*, vol. 64, pp. 17–30, 2014. 20
- [62] NOAA National Centers for Environmental Information, “Climate at a glance: Statewide time series,” December 2024. Retrieved on December 15, 2024. 39
- [63] U.S. Energy Information Administration, “Tennessee state energy profile and energy estimates,” 2024. Accessed: 2024-12-15. 39
- [64] American Council for an Energy-Efficient Economy (ACEEE), “How energy efficiency can help low-income households in tennessee,” October 2017. Accessed: Dec. 15, 2024. 39
- [65] U.S. Energy Information Administration, “Florida state energy profile and energy estimates,” 2024. Accessed: 2024-12-15. 39

- [66] NOAA National Centers for Environmental Information, “Climate at a glance: Statewide time series,” December 2024. Retrieved on December 15, 2024. 39
- [67] American Council for an Energy-Efficient Economy (ACEEE), “How energy efficiency can help low-income households in tennessee,” October 2017. Accessed: Dec. 15, 2024. 39
- [68] S. P. Forrester, C. C. Montañés, E. O’Shaughnessy, and G. Barbose, “Modeling the potential effects of rooftop solar on household energy burden in the united states,” *Nature Communications*, vol. 15, no. 1, p. 4676, 2024. 40, 41, 42
- [69] J. Kerby, T. Hardy, J. Twitchell, R. O’Neil, and B. Tarekegne, “A targeted approach to energy burden reduction measures: Comparing the effects of energy storage, rooftop solar, weatherization, and energy efficiency upgrades,” *Energy Policy*, vol. 184, p. 113867, 2024. 41
- [70] Rocky Mountain Institute (RMI), “1 in 7 Families Live in Energy Poverty. States Can Ease That Burden,” 2024. Accessed: October 19, 2024. 41
- [71] Z. Shen, C. fei Chen, H. Zhou, N. Fefferman, and S. Shrestha, “Community vulnerability is the key determinant of diverse energy burdens in the united states,” *Energy Research & Social Science*, vol. 97, p. 102949, 2023. 42
- [72] American Council for an Energy-Efficient Economy (ACEEE), “Lifting the high energy burden in america’s largest cities: How energy efficiency can improve low-income and underserved communities,” tech. rep., American Council for an Energy-Efficient Economy, 2016. 42
- [73] A. Dreihobl, L. Ross, and R. Ayala, “How high are household energy burdens? an assessment of national and metropolitan energy burden across the u.s.,” Tech. Rep. U2006, American Council for an Energy-Efficient Economy (ACEEE), 2020. 42
- [74] R. Wiser, M. Bolinger, and J. Seel, “Benchmarking utility-scale pv operational expenses and project lifetimes: Results from a survey of u.s. solar industry professionals,” tech. rep., Lawrence Berkeley National Laboratory, June 2020. 65

- [75] R. H. Wiser and M. Bolinger, “Benchmarking anticipated wind project lifetimes: Results from a survey of u.s. wind industry professionals,” 2019. 65
- [76] Tennessee State Data Center, “Tennessee population projections: 2022 to 2070,” tech. rep., Boyd Center for Business and Economic Research, University of Tennessee, Knoxville, August 2024. 65, 79
- [77] Weldon Cooper Center for Public Service, “National 50-state population projections: 2030, 2040, 2050,” tech. rep., Weldon Cooper Center for Public Service, University of Virginia, August 2023. 65, 79
- [78] U.S. Energy Information Administration, “U.s. share of electric and hybrid vehicle sales increased in the second quarter of 2024,” April 2024. Accessed: 2024-12-15. 65
- [79] Rocky Mountain Institute (RMI), “Evs to surpass two-thirds of global car sales by 2030, putting at risk nearly half of oil demand, new research finds,” September 2023. Accessed: 2024-12-25. 65
- [80] Z. Abdmouleh, A. Gastli, L. Ben-Brahim, M. Haouari, and N. A. Al-Emadi, “Review of optimization techniques applied for the integration of distributed generation from renewable energy sources,” *Renewable Energy*, vol. 113, pp. 266–280, 2017. 65
- [81] M. Labriet, R. Loulou, and A. Kanudia, “Is a 2 degrees celsius warming achievable under high uncertainty? analysis with the times integrated assessment model,” Tech. Rep. G-2008-30, Les Cahiers du GERAD, 2008. 65
- [82] G. Mavromatidis, K. Orehounig, and J. Carmeliet, “Design of distributed energy systems under uncertainty: A two-stage stochastic programming approach,” *Applied Energy*, vol. 222, pp. 932–950, 2018. 66
- [83] T. T. D. Tran and A. D. Smith, “Stochastic optimization for integration of renewable energy technologies in district energy systems for cost-effective use,” *Energies*, vol. 12, no. 3, 2019. 66

- [84] M. Sharafi and T. Y. ElMekkawy, “Stochastic optimization of hybrid renewable energy systems using sampling average method,” *Renewable and Sustainable Energy Reviews*, vol. 52, pp. 1668–1679, 2015. 67
- [85] A. Azizi, H. Karimi, and S. Jadid, “Daily operation of multi-energy systems based on stochastic optimization considering prediction of renewable energy generation,” *IET Renewable Power Generation*, vol. 16, no. 2, pp. 245–260, 2022. 67
- [86] M. Ramshani, A. Khojandi, X. Li, and O. Omitaomu, “Optimal planning of the joint placement of photovoltaic panels and green roofs under climate change uncertainty,” *Omega*, vol. 90, p. 101986, 2020. 67
- [87] M. Barah, A. Khojandi, X. Li, J. Hathaway, and O. Omitaomu, “Optimizing green infrastructure placement under precipitation uncertainty,” *Omega*, vol. 100, p. 102196, 2021. 67
- [88] C.-Y. Lee and J. Ahn, “Stochastic modeling of the levelized cost of electricity for solar pv,” *Energies*, vol. 13, no. 11, 2020. 67
- [89] S. L. Locke, “Household characteristics and electric vehicle adoption: changes from 2017 to 2022,” *Applied Economics Letters*, vol. 0, no. 0, pp. 1–4, 2024. 80
- [90] EV HUB, “State ev registration data,” 2024. Accessed: 2024-11-27. 80
- [91] Drive Electric Tennessee, “A roadmap for electric vehicles in tennessee,” 2019. Accessed: 2024-11-27. 80

Appendices

A. Tables

Table 13: Description of different features of LEAD dataset.

S/N	Column name	Description
1	ABV	abbreviation for state, county or city
2	FIP	11 digit code (first two digits are for state, next three for county and the last six digits are for census tract)
3	TEN	owner or renter occupied
4	YBL6	year of building first construction
5	BLD	number of units in the building/ type of dwelling
6	HFL	primary heating fuel type
7	AMI68	area median income
8	UNITS	number of occupied housing units
9	HINCP	Average annual household income (\$/year)
10	HINCP*UNITS	HINCP multiplied by UNITS
11	ELEP*UNITS	ELEP multiplied by UNITS
12	GASP*UNITS	GASP multiplied by UNITS
13	FULP*UNITS	FULP multiplied by UNITS
14	HINCP UNITS	Sum of UNITS with a null value for HINCP
15	ELEP UNITS	Sum of UNITS with a null value for ELEP
16	GASP UNITS	Sum of UNITS with a null value for GASP
17	FULP UNITS	Sum of UNITS with a null value for FULP
18	HCOUNT	Average number of American Community Survey responses per PUMA contributing to the estimate of average household income
19	ECOUNT	Average number of American Community Survey responses per PUMA contributing to the estimate of average electricity expenditures
20	GCOUNT	Average number of American Community Survey responses per PUMA contributing to the estimate of average gas expenditures
21	FCOUNT	Average number of American Community Survey responses per PUMA contributing to the estimate of other fuel expenditures
22	ELEP	Calibrated American Community Survey average household annual electricity expenditure (\$/year)
23	GASP	Calibrated American Community Survey average household annual gas expenditure (\$/year)
24	FULP	Calibrated American Community Survey average household annual other fuel expenditures (\$/year)

Table 14: Description of different features of LEAP dataset.

S/N	Column name	Description
1	Average energy burden	Percentage of gross household income spent on energy costs (average for the Census Tract)
2	Percent low income	Percent of Census Tract Total Population at or Below Low-Income (200% the Federal Poverty Level)
3	Historic Fossil Energy Community	Fossil Energy (FE) census tract overlaps with an area with historical economic dependence on fossil fuel industrial facilities
4	EPA Environmental Justice Screening Index Score	Number of EPA EJSCREEN Environmental Justice Indices within the 60th percentile (e.g., within the top 40% of tracts within the 50 states & D.C. or top 40% of tracts within Puerto Rico)

Table 15: Comparison of socio-demographic data among Census Tracts, Knox County, Tennessee, and USA as per American Community Survey 2021 5-year estimate. M, F, W, B/AA, MHI, PL, 9th, HSG, BS, and GP stand for male, female, white, black or African American, median household income, poverty line, 9th grad, high school graduate, bachelor degree, and graduate or professional degree. * Due to lack of data availability, data collected from 2019 ACS 5-year estimates. Median household income collected from 2018 ACS 5-year estimates.

Socio-economic Indicator Geography	Population (%)				Economy		Education (≥ 25 years, %)			
	Gender		Race		MHI (\$)	Below PL (%)	≤ 9 th	$\geq$ HSG	$\geq$ BS	GP
	M	F	W	B/AA						
USA	49.5	50.5	68.2	12.6	69021	12.6	4.8	88.9	33.7	13.1
Tennessee	49	51	75.8	16.5	58516	14.3	4.0	88.8	29	10.8
Knox County	48.9	51.1	83.9	8.5	62911	12.7	2.6	92.1	38.8	15.3
Census Tract 9.02	44.1	55.9	91.2	6.2	2500-	95.2	29.4	70.6	44.1	0
Census Tract 14	45.4	54.6	59.9	33.4	21438	45.7	24.7	64.5	2.2	2.2
Census Tract 19	56.2	43.8	36.1	51.8	31680	31.8	3.7	80.7	11	1.9
Census Tract 20	41.5	58.5	14.3	81.1	29028	32.6	1.5	85.3	7.6	0.7
Census Tract 68	46.4	53.6	46.3	51.4	16915	50	4	76.5	16.9	2.4
Census Tract 70	43	57	44.5	37.7	25333	35.6	4.2	88.6	30.3	9.4
Davidson County	48.3	51.7	61.1	26.7	66047	14.3	3.9	90.1	44.4	16.6
Census Tract 136.02 *	44.1	55.9	91.2	6.2	32845	30.1	0	100	33	10.7
Census Tract 139	30.1	69.9	14.9	82.3	38693	38.1	6.4	74	20	7.4
Census Tract 142	45.2	54.8	18.4	69.4	26193	52.1	4	77.3	26.8	9.9
Census Tract 148	40.7	59.3	0	100	17092	82.6	8	68.2	0	0
Census Tract 193	46.4	53.6	42.8	57.2	20763	57.7	3.8	74.4	18.4	12.6
Gibson County	48.2	51.8	77.5	16.3	49615	14.5	5.3	87.1	18.2	6.5
Census Tract 9669	46.5	53.5	38.2	58.7	35147	24.8	11.2	75.6	7.9	3.4
Hamblen County	49.3	50.7	87.5	3.7	45275	17.2	6.2	84.8	18	6
Census Tract 1003	53.4	46.6	65.1	11.8	22361	49.4	24.6	56.8	2.9	0.8
Hardeman County	55.5	44.5	54.4	40.9	41138	16.6	5.1	82.1	11.4	4.1
Census Tract 9506	44.7	55.3	36.6	59.7	37551	13.1	8.5	75.5	7.5	2.7
Haywood County	47.6	52.4	44.6	50.4	39952	20.7	4.8	82.8	11.8	4.4
Census Tract 9302	49.5	50.5	69.9	28.9	53910	26.8	5.8	84.2	16.2	6.7
Lauderdale County	51.7	48.3	61.2	34.1	43025	18.6	5.7	79.6	9.2	3.8
Census Tract 505.05	50.3	49.7	21.8	71.3	29750	28.7	6.6	73.2	9.5	2.5
Weakley County	49.5	50.5	87.8	7.9	43773	19.3	4.5	87.2	21.3	8.3
Census Tract 9682.02	42	58	71.6	22.9	11563	77.9	13.2	69.8	21.7	10.6
Sevier County	49.2	50.8	92.5	1.1	54363	13.8	4.3	86.6	18.8	6.5
Census Tract 808.01	51	49	75.3	3.8	26429	45.4	14.3	73.5	6.9	1.4
Census Tract 811.01	53.1	46.9	59.2	6.6	42143	22.7	8.7	86.5	34.1	15.3
Hamilton County	48.5	51.5	73.1	18.5	61050	12.7	3.4	90.5	34.1	12.3
Census Tract 4	43.4	56.6	11.6	87.7	26763	41.6	7.8	81	11.9	2.3
Census Tract 16	48.9	51.1	20.8	73.5	16507	43.8	6.7	83.1	17.9	7.4
Census Tract 19	40.7	59.3	9.4	80.2	23578	32.9	3.7	73.8	8.5	1.7
Census Tract 122	52.7	47.3	10.3	76.8	28036	33.8	8.8	73.9	8.2	1.5
Madison County	47.4	52.6	56.1	37.1	51526	18.7	3.2	89.5	27	10.7
Census Tract 4	44.5	55.5	22.4	76.9	29808	39.3	2.7	83.6	19.3	8
Census Tract 5	41.8	58.2	12.9	85.1	19077	53.2	8	78.8	5.6	1.6
Census Tract 7	60.2	39.8	38.3	52.5	28431	37.2	1.9	88.4	21.5	6.7
Census Tract 8	68.1	31.9	34.9	61.9	20000	39.2	4.9	75.1	7.3	1.2
Census Tract 9	41.3	58.7	3.4	88.8	22951	52.3	8.5	70.2	7.7	2
Census Tract 10	42.6	57.4	11.8	86.6	29808	28	4.1	78.6	0.8	0.3
Census Tract 11	44.1	55.9	6.7	92.5	15341	62.2	0.9	78.4	0	0

Table 16: Comparison of socio-economic data among Census Tracts, Shelby County, Tennessee, and the USA as per American Community Survey 2021 5-year estimate. For USA and Tennessee data, refer to Table 15. * Due to lack of data availability, data collected from 2019 ACS 5-year estimates.

Socio-economic Indicator Geography	Population (%)				Economy		Education (≥ 25 years, %)			
	Gender		Race		MHI (\$)	Below PL (%)	≤ 9 th	$\geq$ HSG	$\geq$ BS	GP
	M	F	W	B/AA						
Shelby County	47.7	52.3	37.5	53.8	55015	18.6	3.5	89.3	33.3	13.5
Census Tract 2	48.6	51.4	0	97.7	21354	44.5	4	74	8.8	2
Census Tract 3	66.5	33.5	0.3	98.9	25375	21	7.3	83.5	3	0
Census Tract 4	56.6	43.4	0.9	97.8	30565	42.3	7.7	76.4	1.3	1.3
Census Tract 6	41	59	0	98.6	17328	45.8	2	74.2	10.7	4.3
Census Tract 7	44.7	55.3	7.8	89.2	25796	35.3	2.1	82.2	14.4	5.1
Census Tract 8	39	61	1	98.6	21342	48.5	7.2	69.9	2.7	0.8
Census Tract 9	43.5	56.5	7.8	87.7	22039	40.8	7	76.1	19	11.7
Census Tract 11	47.1	52.9	27.1	29.4	28750	27.7	12.6	70.5	11.2	4.7
Census Tract 13	51.8	48.2	13.3	50.6	25054	47.1	15.4	70.7	10.3	4.1
Census Tract 14	52.1	47.9	2.1	89.3	31210	34.1	6.5	66.4	7.1	0.5
Census Tract 19	52.8	47.2	0.8	98.8	27647	23.2	11.7	68.8	4.2	0.9
Census Tract 20	50.8	49.2	11.1	83.7	34591	33.1	4.7	83.7	22	4.9
Census Tract 45	36.8	63.2	10.8	88.7	15990	71	4.5	77.9	1	0
Census Tract 50	42.4	57.6	3.9	96.1	12738	70.2	10.2	74.6	6.9	6.9
Census Tract 53	44.2	55.8	0.2	93.3	21597	43	4.8	78.3	4.8	0.9
Census Tract 55	48.1	51.9	2.6	97.4	18214	55.7	2	71.9	7.5	2.4
Census Tract 56	46.7	53.3	0.6	99.2	27388	32.8	3.7	75.4	19.1	6.9
Census Tract 57	45.9	54.1	2.7	96	29144	40.2	2.7	89.2	12.4	2.7
Census Tract 58	41.1	58.9	2.8	97.3	22273	51.4	0	83.3	13	8.2
Census Tract 59	53.7	46.3	1.4	98.3	25194	66.7	10.9	84.1	4.4	2
Census Tract 60	42.8	57.2	0	100	23503	30	1.8	85.4	9.3	1.9
Census Tract 62	51.5	48.5	6.3	85.8	22048	33.6	9.8	82.1	17.4	5.7
Census Tract 65	47.6	52.4	1.5	95.7	31106	36.9	4.4	81.9	16.3	7.5
Census Tract 67	46.9	53.1	2.1	97	31343	28	4.5	73.5	12.8	3.8
Census Tract 68	46.1	53.9	0.8	98.1	24462	27.2	3	82	8.5	2.9
Census Tract 69	42.4	57.6	0.4	98.8	27477	34.9	5.9	81.4	8	1
Census Tract 75	54	46	1	98.1	29239	11.8	1.1	84.3	17.7	7
Census Tract 78.10	49.2	50.8	0	99.9	17246	50	2.4	84.4	5.9	1.2
Census Tract 78.21	50.8	49.2	0.9	98.1	38728	41.1	8.6	78.7	11	1.8
Census Tract 78.22	36.8	63.2	12.2	81.4	31780	26.7	2.5	89.6	17.4	2.3
Census Tract 81.10	42.3	57.7	8	81.3	17583	42.3	8.4	73.5	2.9	0
Census Tract 89	59.1	40.9	48.2	34.8	31293	35.4	15	79.3	5.7	1
Census Tract 91	54	46	54.6	7.8	30082	56.2	24.8	63.4	6.6	0.9
Census Tract 99.02	49.4	50.6	17.5	81.6	20677	58.1	4.1	74.9	6.5	3.6
Census Tract 101.10*	45.4	54.6	10.3	86	21286	51.9	4.2	74.9	5.8	0.4
Census Tract 101.20	45.2	54.8	5.5	91	24130	56.9	4.4	78.2	6.8	3.4
Census Tract 103	45.3	54.7	7.1	92.9	20266	41.8	6.2	79.9	22.3	19.4
Census Tract 105	46.3	53.7	14.5	80.1	20147	47.7	14.8	68.2	6.1	4.3
Census Tract 106.10	49.1	50.9	8.8	69.4	31438	37.7	17.7	77.2	7.4	2.7
Census Tract 106.30	46	54	13.1	61.3	32535	44	20.8	70	7.3	0
Census Tract 110.20	40.2	59.8	8.1	90.7	40000	31.8	4.9	83.6	11.4	1.1
Census Tract 111	52.1	47.9	0.3	97.3	16543	53.2	3.9	75.8	4.9	0.7
Census Tract 112	45.8	54.2	0.3	99.7	17083	41.5	7.8	63.5	4.3	0
Census Tract 115	57.8	42.2	11.9	88.1	27971	47.5	7.5	64.8	7	0.7
Census Tract 116	33.8	66.2	1.9	96	14505	63.6	7	76.8	9.9	1.5
Census Tract 117	38.1	61.9	6.5	91.7	31033	47.7	8.6	77.7	10.6	2.9
Census Tract 205.12*	38.5	61.5	12.4	85.6	29338	34.8	5.7	83.6	13.1	3.9
Census Tract 205.21	43.2	56.8	2.3	95.9	30027	33.8	3.8	77.8	7.4	3.3
Census Tract 205.23	47.7	52.3	12.2	81.1	30837	49	2.2	77.1	3.1	1.5
Census Tract 220.22*	45.9	54.1	1.3	94.3	24414	50	3.3	80.7	8	1.7
Census Tract 220.23	58	42	1.3	96	49115	32.1	6.7	86.7	21.5	5.4
Census Tract 222.20	46.1	53.9	4.8	92.7	25491	50.9	9.2	81.3	8.4	1.2
Census Tract 223.10	46.1	53.9	0	99.2	26967	45.1	5.3	81.3	11.7	2.7
Census Tract 227	47.2	52.8	3.5	95	29630	24.3	2.9	85.7	4.7	1

Table 17: Optimized count of interventions for energy-burdened people of Hamilton, Davidson, Sevier, Madison, and Knox County, Tennessee within a limited allocated budget.

S/N	County	Census Tracts	W	RTS	CS	CW
1	Davidson	47037013602	131	128	1	1
		47037013900	317	311		
		47037014200	726	715		
		47037014800	358	355		
		47037019300	1020	995		
2	Sevier	47155080801	1030	243	1	1
		47155081101	666	158		
3	Madison	47113000400	335	183	1	1
		47113000500	392	196		
		47113000700	462	228		
		47113000800	215	120		
		47113000900	337	186		
		47113001000	258	127		
		47113001100	258	165		
4	Knox	47093000902	50	52	1	1
		47093001400	401	374		
		47093001900	481	482		
		47093002000	303	291		
		47093006800	448	400		
		47093007000	469	467		
5	Hamilton	47065000400	490	225	1	1
		47065001600	460	249		
		47065001900	464	231		
		47065012200	281	142		

Table 18: Peak sun hour values for Tennessee (monthly averages) by zip code.

Zip Code	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
37203	3.47	4.08	4.82	5.32	5.49	5.71	5.46	5.75	5.4	4.82	4.04	3.28
37206	3.47	4.08	4.82	5.32	5.49	5.71	5.46	5.75	5.4	4.82	4.04	3.28
37208	3.47	4.08	4.82	5.32	5.49	5.71	5.46	5.75	5.4	4.82	4.04	3.28
37210	3.47	4.08	4.82	5.32	5.49	5.71	5.46	5.75	5.4	4.82	4.04	3.28
37402	3.77	4.37	4.93	5.33	5.57	5.72	5.48	5.72	5.28	4.89	4.15	3.51
37403	3.77	4.4	4.98	5.38	5.58	5.63	5.49	5.74	5.31	4.89	4.18	3.52
37406	3.77	4.4	4.98	5.38	5.58	5.63	5.49	5.74	5.31	4.89	4.18	3.52
37408	3.77	4.37	4.93	5.33	5.57	5.64	5.46	5.72	5.28	4.89	4.15	3.51
37738	3.79	4.25	4.88	5.2	5.39	5.37	5.26	5.44	5.18	4.71	4.08	3.54
37813	3.8	4.38	5.05	5.44	5.69	5.62	5.44	5.82	5.48	4.92	4.19	3.58
37863	3.77	4.21	4.91	5.34	5.61	5.61	5.48	5.72	5.39	4.76	4.12	3.54
37914	3.78	4.29	5.05	5.39	5.68	5.72	5.53	5.89	5.46	4.87	4.1	3.5
37915	3.78	4.29	5.05	5.39	5.68	5.72	5.53	5.89	5.46	4.87	4.1	3.5
37916	3.8	4.33	5.03	5.41	5.69	5.7	5.47	5.82	5.44	4.87	4.11	3.48
37921	3.8	4.33	5.03	5.41	5.69	5.7	5.47	5.82	5.44	4.87	4.11	3.48
38037	3.57	4.24	4.85	5.55	5.64	5.9	5.81	6.13	5.54	4.95	4.08	3.39
38039	3.56	4.24	4.88	5.52	5.63	5.88	5.67	5.94	5.46	4.94	4.14	3.45
38063	3.55	4.22	4.84	5.56	5.61	5.9	5.82	6.13	5.59	4.94	4.04	3.41
38104	3.61	4.23	4.91	5.58	5.72	5.97	5.83	6.07	5.46	4.93	4.14	3.46
38105	3.61	4.23	4.91	5.58	5.72	5.97	5.83	6.07	5.46	4.93	4.14	3.46
38106	3.61	4.23	4.91	5.58	5.72	5.97	5.83	6.07	5.46	4.93	4.14	3.46
38107	3.61	4.23	4.91	5.58	5.72	5.97	5.83	6.07	5.46	4.93	4.14	3.46
38108	3.63	4.21	4.93	5.57	5.67	5.9	5.7	6.03	5.47	4.96	4.18	3.46
38109	3.63	4.21	4.92	5.55	5.73	5.89	5.69	6.19	5.53	4.95	4.16	3.46
38111	3.63	4.21	4.93	5.57	5.67	5.9	5.7	6.03	5.47	4.96	4.18	3.46
38112	3.63	4.21	4.93	5.57	5.67	5.9	5.7	6.03	5.47	4.96	4.18	3.46
38114	3.63	4.21	4.93	5.57	5.67	5.9	5.7	6.03	5.47	4.96	4.18	3.46
38116	3.62	4.23	4.94	5.58	5.72	5.96	5.86	6.12	5.52	4.98	4.17	3.46
38118	3.56	4.17	4.87	5.52	5.67	5.86	5.69	5.98	5.54	4.88	4.09	3.46
38122	3.63	4.21	4.93	5.57	5.67	5.9	5.7	6.03	5.47	4.96	4.18	3.46
38126	3.61	4.23	4.91	5.58	5.72	5.97	5.83	6.07	5.46	4.93	4.14	3.46
38127	3.62	4.22	4.89	5.56	5.68	5.94	5.8	6.04	5.5	4.95	4.18	3.49
38128	3.62	4.22	4.89	5.56	5.68	5.94	5.8	6.04	5.5	4.95	4.18	3.49
38237	3.5	4.06	4.81	5.45	5.58	5.83	5.78	5.98	5.56	4.91	4.01	3.29
38301	3.6	4.15	4.82	5.47	5.63	5.81	5.71	5.93	5.42	4.92	4.02	3.36
38343	3.54	4.16	4.81	5.49	5.61	5.85	5.75	5.99	5.55	4.9	4.0	3.34

Table 19: Peak sun hour values for Florida (monthly averages) by zip code.

Zip Code	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
32052	4.45	5.14	5.78	6.15	6.17	5.45	5.59	5.43	5.15	5.2	4.92	4.17
32055	4.63	5.24	5.84	6.24	6.18	5.4	5.57	5.41	5.1	5.2	4.96	4.28
32091	4.75	5.27	5.87	6.29	6.14	5.34	5.43	5.41	4.99	5.1	4.93	4.32
32204	4.75	5.21	5.89	6.29	6.17	5.41	5.47	5.45	4.96	5.03	4.8	4.3
32206	4.75	5.21	5.89	6.29	6.17	5.41	5.47	5.45	4.96	5.03	4.8	4.3
32209	4.75	5.21	5.89	6.29	6.17	5.41	5.47	5.45	4.96	5.03	4.8	4.3
32219	4.67	5.19	5.77	6.21	6.13	5.42	5.53	5.42	4.93	4.98	4.77	4.21
32254	4.74	5.16	5.83	6.25	6.15	5.37	5.49	5.4	4.93	4.96	4.79	4.25
32304	4.58	5.2	5.79	6.17	6.15	5.45	5.35	5.56	5.32	5.47	4.94	4.23
32324	4.41	5.01	5.72	6.15	6.2	5.59	5.52	5.6	5.28	5.27	4.78	4.07
32344	4.46	5.18	5.76	6.16	6.24	5.52	5.52	5.54	5.19	5.24	4.85	4.16
32351	4.51	5.15	5.78	6.17	6.17	5.5	5.39	5.51	5.29	5.34	4.88	4.18
32401	4.51	5.15	5.9	6.39	6.41	5.75	5.5	5.4	5.37	5.43	5.02	4.2
32431	4.46	5.05	5.72	6.11	6.18	5.55	5.53	5.51	5.3	5.24	4.83	4.1
32501	4.39	5.05	5.79	6.05	6.19	5.75	5.42	5.49	5.39	5.4	4.99	4.14
32503	4.39	5.05	5.79	6.05	6.19	5.75	5.42	5.49	5.39	5.4	4.99	4.14
32505	4.39	5.05	5.79	6.05	6.19	5.75	5.42	5.49	5.39	5.4	4.99	4.14
32507	4.39	5.05	5.79	6.05	6.19	5.75	5.42	5.49	5.39	5.4	4.99	4.14
32535	4.2	4.9	5.58	5.96	6.02	5.6	5.45	5.52	5.36	5.24	4.76	3.99
32608	4.77	5.27	5.9	6.29	6.17	5.34	5.37	5.28	5.04	5.17	5.02	4.38
32609	4.76	5.25	5.89	6.27	6.14	5.34	5.36	5.31	4.99	5.16	5.02	4.35
32615	4.73	5.2	5.87	6.26	6.1	5.3	5.41	5.34	5	5.2	4.99	4.35
32641	4.77	5.21	5.94	6.36	6.2	5.38	5.44	5.39	5.08	5.17	5.02	4.36
32686	4.83	5.3	5.93	6.38	6.15	5.31	5.34	5.37	5.13	5.18	5.03	4.43
32696	4.83	5.29	5.99	6.36	6.23	5.34	5.27	5.26	5.12	5.28	5.03	4.45
32703	5.04	5.26	5.99	6.49	6.21	5.4	5.52	5.56	5.22	5.28	5.02	4.6
32726	5.02	5.28	5.99	6.5	6.23	5.38	5.45	5.57	5.19	5.34	5.06	4.57
32809	5.07	5.37	5.98	6.46	6.15	5.37	5.37	5.49	5.14	5.28	5.07	4.58
32967	5.02	5.49	5.97	6.43	6.05	5.39	5.5	5.55	5.18	5.2	4.96	4.47
33030	5.15	5.47	6.01	6.44	5.86	5.11	5.37	5.38	5.1	5.21	5.01	4.66
33033	5.22	5.48	6.04	6.45	5.89	5.08	5.41	5.4	5.06	5.28	5.08	4.71
33142	5.08	5.5	5.91	6.37	5.85	5.02	5.34	5.3	4.98	5.14	4.95	4.49
33147	5.08	5.5	5.91	6.37	5.85	5.02	5.34	5.3	4.98	5.14	4.95	4.49
33404	5.07	5.48	5.96	6.45	6.14	5.23	5.62	5.6	5.23	5.3	4.92	4.46
33440	5.26	5.73	6.19	6.58	6.26	5.37	5.47	5.5	5.35	5.66	5.38	4.8
33470	5.19	5.47	6.03	6.37	5.97	5.14	5.37	5.35	5.07	5.26	5	4.59
33538	4.92	5.24	5.96	6.52	6.21	5.34	5.27	5.42	5.18	5.38	5.12	4.57
33613	5.08	5.42	6.08	6.51	6.23	5.33	5.12	5.25	5.1	5.51	5.28	4.6
33712	5.23	5.57	6.31	6.82	6.52	5.78	5.53	5.59	5.39	5.81	5.41	4.79
33714	5.23	5.57	6.3	6.72	6.47	5.64	5.4	5.46	5.34	5.75	5.47	4.83
33837	5.02	5.28	5.96	6.42	6.15	5.38	5.39	5.52	5.16	5.33	5.09	4.59

Table 19: Continued

Zip Code	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
33853	5.12	5.41	6.08	6.47	6.13	5.38	5.39	5.52	5.25	5.38	5.16	4.66
33873	5.2	5.46	6.09	6.47	6.21	5.38	5.42	5.49	5.26	5.55	5.19	4.69
34950	5.06	5.61	6.1	6.48	6.18	5.42	5.59	5.62	5.3	5.32	5.13	4.6
34972	5.24	5.63	6.12	6.51	6.22	5.35	5.52	5.55	5.28	5.44	5.17	4.73

Table 20: Monthly wind speed (average) data for Tennessee by zip code.

Zip Code	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
37203	6.24	6.35	6.88	6.39	6.19	5.85	3.47	3.92	5.03	5.45	5.77	6.71
37206	6.06	6.24	6.7	6.29	6.08	5.74	3.37	3.9	4.97	5.31	5.67	6.5
37208	6.01	6.18	6.7	6.23	6.05	5.72	3.35	3.86	4.94	5.25	5.58	6.39
37210	6.24	6.35	6.88	6.39	6.19	5.85	3.47	3.92	5.03	5.45	5.77	6.71
37402	5.75	6.18	5.59	5.7	5.08	4.71	2.98	3.63	4.22	5.29	5.61	6.19
37403	5.75	6.18	5.59	5.7	5.08	4.71	2.98	3.63	4.22	5.29	5.61	6.19
37406	5.62	6.23	5.36	5.7	5.12	4.83	3.03	3.68	4.19	5.15	5.55	5.95
37408	5.8	6.14	5.63	5.67	5.11	4.7	2.97	3.59	4.19	5.3	5.47	6.18
37738	6.52	5.87	5.63	6.64	5.88	4.49	2.93	3.12	3.4	3.79	5.16	5.97
37813	6.21	6.39	6.54	6.78	5.9	5.49	3.68	3.94	5.12	4.55	5.65	6.02
37863	6.04	5.34	5.13	6.11	5.1	4.43	2.78	2.83	3.26	3.27	3.95	5.49
37914	5.4	6.05	6.14	6.18	5.29	4.79	2.98	3.56	4.06	3.99	4.35	5.19
37915	5.31	6.07	6.04	6.21	5.25	4.81	3.07	3.55	4.02	3.97	4.33	5.12
37916	5.28	6.11	6.11	6.24	5.21	4.85	3.14	3.57	4.03	3.96	4.29	5.13
37921	5.28	6.11	6.11	6.24	5.21	4.85	3.14	3.57	4.03	3.96	4.29	5.13
38037	7.63	7.76	8.1	7.38	7.67	7.19	4.58	5.21	6.8	6.73	7.56	8.16
38039	7.83	8.4	7.89	7.54	7.6	7.01	4.32	5.21	7.1	7.01	7.79	8.25
38063	7.73	8.01	8.18	7.43	7.82	7.13	4.63	5.38	7.04	6.88	7.75	8.18
38104	6.79	7.18	7.27	6.5	6.95	6.12	3.76	4.29	6.2	6.07	6.6	7.38
38105	6.85	7.28	7.35	6.6	7.02	6.24	3.82	4.34	6.29	6.14	6.66	7.47
38106	6.85	7.26	7.33	6.61	7.02	6.15	3.78	4.33	6.32	6.12	6.68	7.47
38107	6.77	7.2	7.29	6.52	6.96	6.22	3.76	4.3	6.22	6.05	6.59	7.35
38108	6.63	7.04	7.16	6.37	6.83	6.08	3.64	4.24	6.08	5.89	6.42	7.2
38109	6.93	7.33	7.37	6.76	7.15	6.29	3.9	4.37	6.44	6.26	6.79	7.67
38111	6.79	7.16	7.24	6.53	6.91	6.07	3.68	4.28	6.2	6.06	6.61	7.32
38112	6.79	7.18	7.27	6.5	6.95	6.12	3.76	4.29	6.2	6.07	6.6	7.38
38114	6.75	7.16	7.22	6.49	6.9	6.05	3.68	4.27	6.18	6.04	6.57	7.32
38116	6.88	7.3	7.34	6.7	7.11	6.3	3.84	4.33	6.39	6.27	6.78	7.51
38118	6.93	7.3	7.37	6.72	7.11	6.45	3.88	4.4	6.39	6.31	6.75	7.47
38122	6.72	7.08	7.21	6.43	6.91	6.07	3.66	4.28	6.12	6	6.52	7.31
38126	6.89	7.3	7.37	6.63	7.05	6.21	3.82	4.36	6.33	6.17	6.71	7.5
38127	6.84	7.24	7.38	6.54	7.05	6.25	3.8	4.36	6.2	6.05	6.7	7.37
38128	6.77	7.13	7.23	6.44	6.9	6.04	3.73	4.29	6.12	5.91	6.56	7.22
38237	7.77	7.78	8.34	7.59	7.86	7.31	4.7	5.29	6.98	6.9	7.89	8.08
38301	6.95	7.17	7.28	6.88	7.05	6.75	3.97	4.86	6.58	6.05	6.8	7.19
38343	7.4	7.52	7.86	7.23	7.57	7.04	4.34	5.2	6.94	6.58	7.47	7.81

Table 21: Monthly wind speed (average) data for Florida by zip code.

Zip Code	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
32641	7.39	7.5	5.86	6.8	6.16	5.16	4.65	4.8	5.4	6.7	7.65	7.25
32091	7.68	7.79	6.21	7.03	6.57	5.4	4.78	4.95	5.66	6.8	7.86	7.7
32254	6.84	7.03	5.32	6.24	5.87	4.57	4.19	4.38	5.42	5.73	6.77	6.98
32503	7.48	7.44	6.26	6.88	6.09	5.91	4.4	4.72	6.02	6.95	7.52	6.85
32507	7.61	7.54	6.4	7.01	6.2	6.09	4.64	4.91	6.17	7.08	7.66	7.09
32351	7.43	7.84	5.98	6.82	6.15	5.19	4.4	4.48	5.81	6.68	7.7	7.88
33440	7.9	7.58	7.27	7.38	6.84	5.41	4.65	5.41	4.5	7.21	9	7.24
32726	7.39	7.29	6.02	7.21	5.98	5.07	4.31	4.91	4.81	6.46	7.49	7.35
33142	7.34	7.25	7	6.52	6.46	5.37	4.58	5.54	4.26	7.39	8.91	6.71
34972	7.97	7.45	6.97	7.35	6.91	5.28	4.77	5.49	4.62	6.98	8.41	7.41
33714	7.01	6.85	5.86	6.88	5.95	5.12	4.51	5.15	4.36	6.62	7.71	6.86
33538	7.33	7.36	6.18	7.29	6.08	5.35	4.43	5.09	4.88	6.73	7.7	7.22
32608	7.31	7.47	5.94	6.86	6.35	5.39	4.84	5	5.44	6.75	7.62	7.48
32055	7.59	7.98	6.04	6.85	6.51	5.2	4.78	4.69	5.76	7.07	7.77	7.74
32501	7.78	7.69	6.44	7.06	6.22	6.15	4.65	4.97	6.29	7.22	7.82	7.08
32505	7.43	7.41	6.24	6.85	6.08	5.86	4.39	4.62	5.93	6.91	7.5	6.8
32052	7.45	7.93	6.01	6.7	6.45	5.17	4.52	4.59	5.86	7	7.74	7.75
33613	6.93	6.94	5.74	6.73	5.65	4.77	4.12	4.73	4.19	6.25	7.46	6.84
32304	7.1	7.35	5.59	6.39	5.89	4.96	4.01	4.17	5.5	6.79	7.69	7.41
33030	7.89	7.63	7.5	6.76	6.85	5.63	4.63	5.8	4.39	7.58	8.92	7.11
32809	6.64	6.68	5.6	6.6	5.83	4.57	4.02	4.78	4.35	5.92	7.12	6.62
33712	7.13	6.97	5.97	7.02	6.02	5.32	4.67	5.26	4.53	6.9	8.04	6.95
32615	7.6	7.8	6.09	7	6.42	5.34	4.78	4.79	5.6	6.93	7.89	7.61
32206	6.84	7.19	5.33	6.28	5.83	4.53	4.23	4.33	5.52	5.89	6.9	6.86
32204	6.99	7.3	5.43	6.36	5.94	4.62	4.3	4.44	5.57	5.93	6.94	7.15
32535	7.13	7.36	6.24	6.69	5.91	5.64	4.24	4.37	5.92	6.5	7.09	6.74
32967	7.81	7.28	7.04	7.36	6.98	5.45	5.37	5.85	5.08	7.18	9.03	7.82
32696	7.49	7.54	6.11	6.98	6.34	5.56	4.73	5.13	5.45	6.96	7.71	7.58
32703	7.3	7.31	5.79	7.16	5.91	4.83	4.38	4.88	4.57	6.02	7.33	7.05
33837	7.36	7.47	6.6	7.51	6.55	5.05	4.4	5.25	4.65	6.64	7.75	7.15
32609	7.23	7.28	5.67	6.67	6.04	5.03	4.45	4.65	5.19	6.5	7.4	7.15
32209	6.89	7.12	5.34	6.27	5.91	4.57	4.21	4.34	5.55	5.82	6.93	6.98
32219	7.03	7.15	5.43	6.37	6.13	4.6	4.45	4.39	5.39	5.85	7.04	7.24
32324	7.35	8.07	6.04	6.81	6.23	5.33	4.07	4.41	6	7.03	7.98	8.3
33873	7.75	7.52	7.01	7.51	6.69	5.25	4.44	5.47	4.67	7.1	8.11	7.3
32431	7.47	8.11	6.14	6.9	6.33	5.55	4.45	4.56	6.03	7.04	8	7.79
32686	7.46	7.56	6.12	7.24	6.29	5.4	4.85	5.08	5.3	6.83	7.6	7.56
33404	7.91	7.48	7.24	7.37	6.92	5.59	4.92	5.66	4.78	7.63	9.53	7.29
33853	7.54	7.53	6.91	7.57	6.69	5.23	4.61	5.41	4.83	6.89	8	7.01
32401	7.31	7.7	5.95	6.92	6.01	5.53	4.32	4.53	5.48	6.88	7.7	7.73
32344	7.92	8.39	6.4	7.03	6.69	5.59	4.61	4.77	6.29	7.24	8.07	8.52

Table 21: Continued

Zip Code	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
33147	7.29	7.17	6.89	6.45	6.42	5.3	4.57	5.47	4.2	7.33	8.83	6.58
33033	7.78	7.56	7.41	6.68	6.75	5.54	4.58	5.65	4.28	7.48	8.9	7.06
33470	7.89	7.34	7.12	7.17	6.77	5.27	4.82	5.47	4.31	7.14	8.71	7.36
34950	7.74	7.04	7.04	7.18	6.87	5.38	5.18	5.79	4.9	7.14	9.03	7.46

Table 22: Predicted per kWh electricity price for both Tennessee and Florida using SARIMA model.

Month	Tennessee (¢/kWh)	Florida (¢/kWh)	Month	Tennessee (¢/kWh)	Florida (¢/kWh)
Jul-24	12.65	13.85	Apr-27	13.41	14.31
Aug-24	12.77	14.15	May-27	13.47	14.61
Sep-24	12.52	14.02	Jun-27	13.52	14.56
Oct-24	12.77	14.11	Jul-27	13.55	14.59
Nov-24	12.91	13.94	Aug-27	13.59	14.90
Dec-24	12.56	14.09	Sep-27	13.35	14.76
Jan-25	12.41	14.41	Oct-27	13.67	14.86
Feb-25	12.37	14.06	Nov-27	13.79	14.68
Mar-25	12.66	14.26	Dec-27	13.41	14.84
Apr-25	12.80	13.82	Jan-28	13.27	15.15
May-25	12.92	14.11	Feb-28	13.22	14.81
Jun-25	12.96	14.06	Mar-28	13.64	15.01
Jul-25	12.99	14.09	Apr-28	13.70	14.56
Aug-25	13.01	14.40	May-28	13.75	14.86
Sep-25	12.78	14.27	Jun-28	13.81	14.81
Oct-25	13.10	14.36	Jul-28	13.84	14.84
Nov-25	13.23	14.19	Aug-28	13.88	15.15
Dec-25	12.84	14.34	Sep-28	13.64	15.01
Jan-26	12.70	14.66	Oct-28	13.95	15.11
Feb-26	12.65	14.31	Nov-28	14.08	14.93
Mar-26	13.09	14.51	Dec-28	13.70	15.08
Apr-26	13.13	14.06	Jan-29	13.55	15.40
May-26	13.18	14.36	Feb-29	13.51	15.06
Jun-26	13.23	14.31	Mar-29	13.92	15.26
Jul-26	13.27	14.34	Apr-29	13.98	14.81
Aug-26	13.31	14.65	May-29	14.03	15.11
Sep-26	13.07	14.52	Jun-29	14.09	15.06
Oct-26	13.38	14.61	Jul-29	14.12	15.09
Nov-26	13.50	14.44	Aug-29	14.16	15.40
Dec-26	13.13	14.59	Sep-29	13.92	15.26
Jan-27	12.98	14.91	Oct-29	14.24	15.36
Feb-27	12.94	14.56	Nov-29	14.36	15.18
Mar-27	13.35	14.76	Dec-29	13.98	15.33

B. Figures

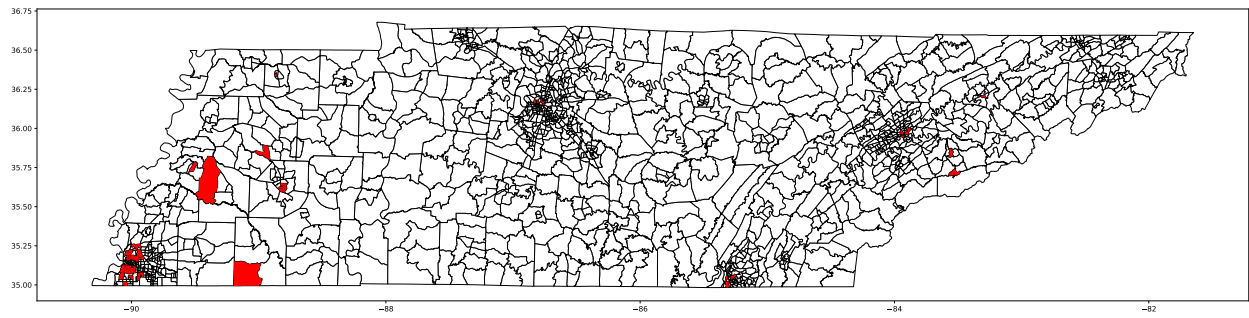


Figure 12: Selected census tracts were marked red within the map of Tennessee state to provide viewers a brief idea about the relative location of DACs.

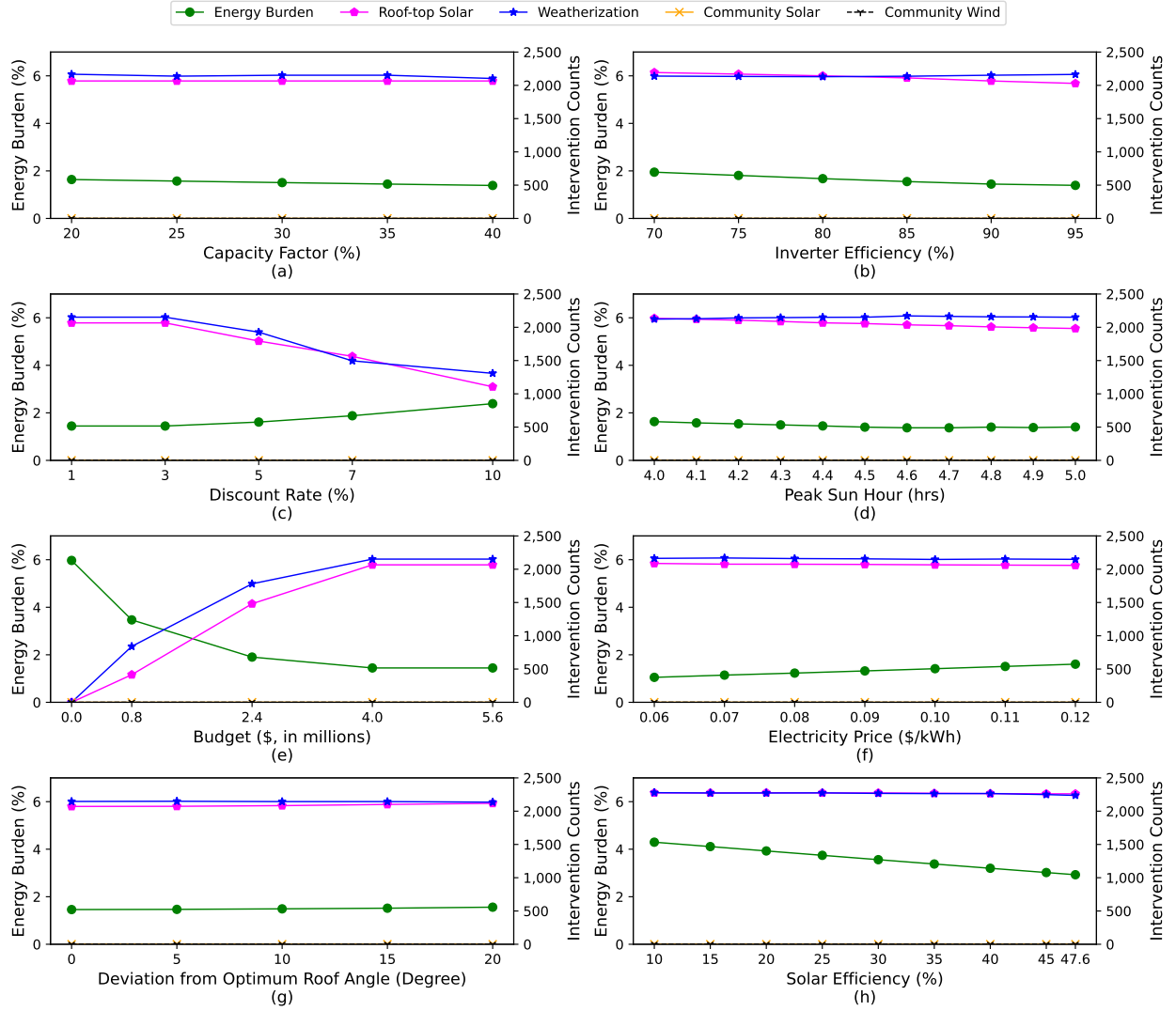


Figure 13: Change of energy burden and intervention counts in selected census tracts from Knox County, Tennessee, USA with the change of different parameters. The community intervention capacity of 1 MW was considered.

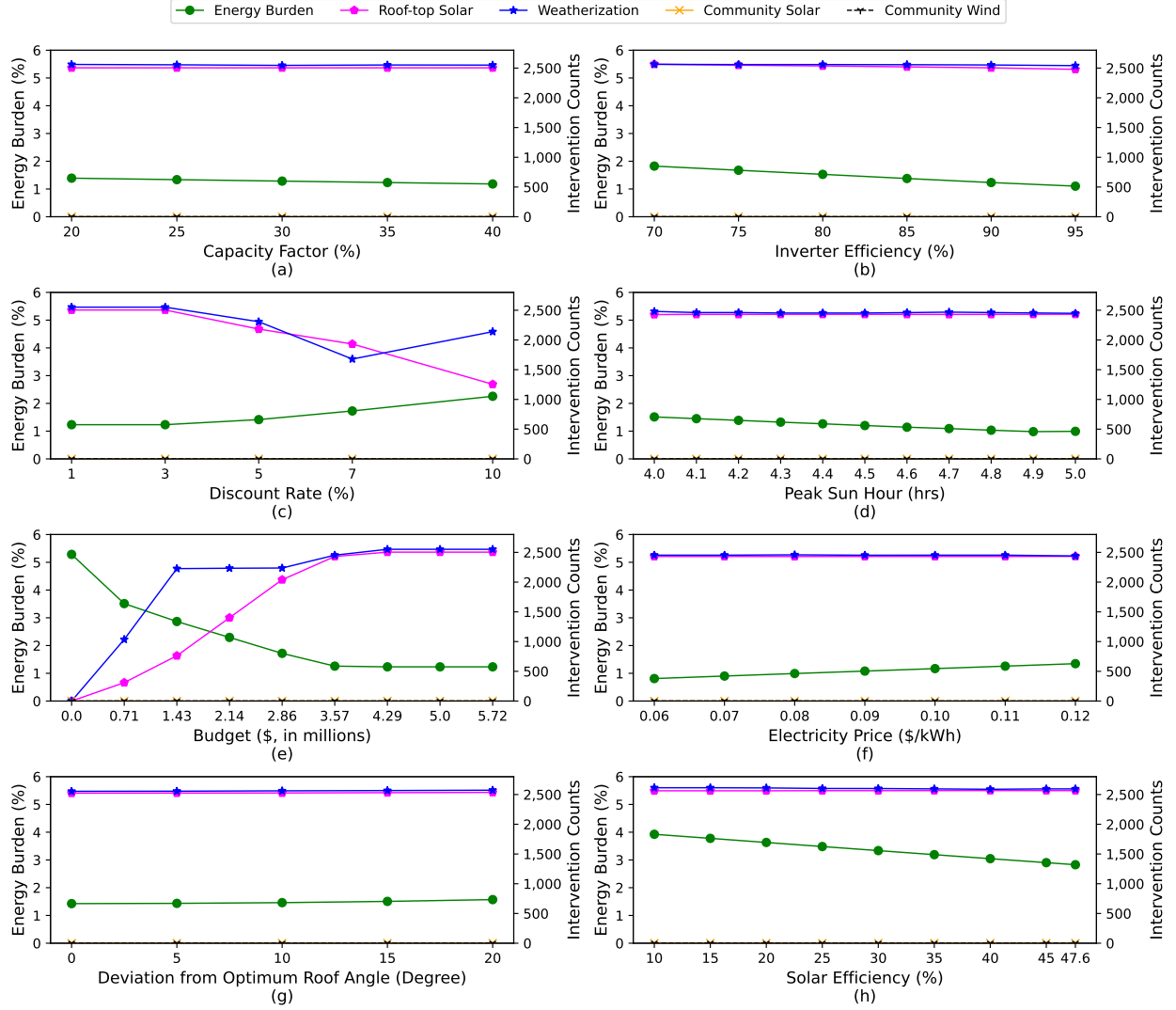


Figure 14: Change of energy burden and intervention counts in selected census tracts from Davidson County, Tennessee, USA with the change of different parameters. The community intervention capacity of 1 MW was considered.

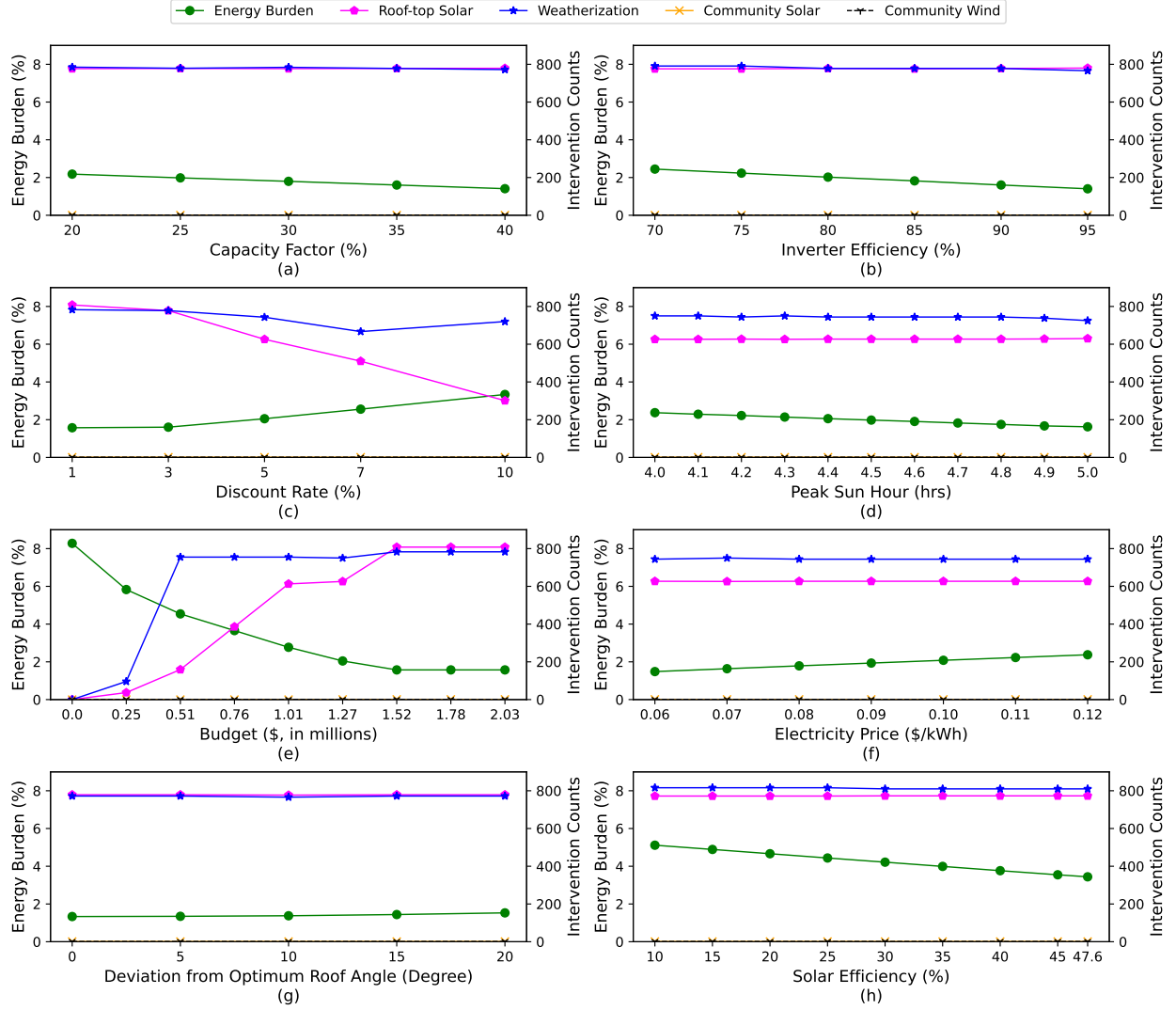


Figure 15: Change of energy burden and intervention counts in selected census tracts from Gibson County, Tennessee, USA with the change of different parameters. The community intervention capacity of 1 MW was considered.

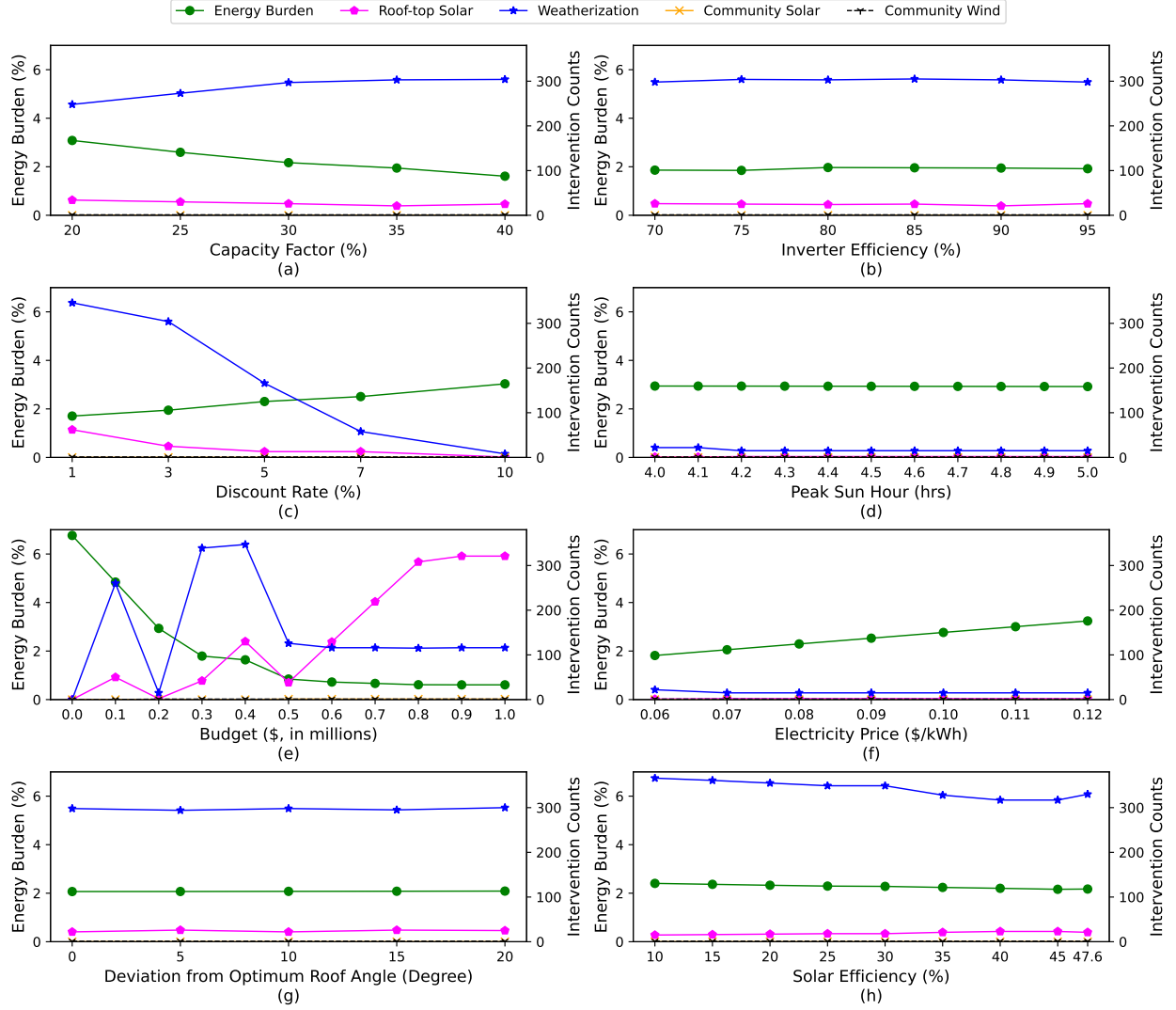


Figure 16: Change of energy burden and intervention counts in selected census tracts from Hamblen County, Tennessee, USA with the change of different parameters. The community intervention capacity of 1 MW was considered.

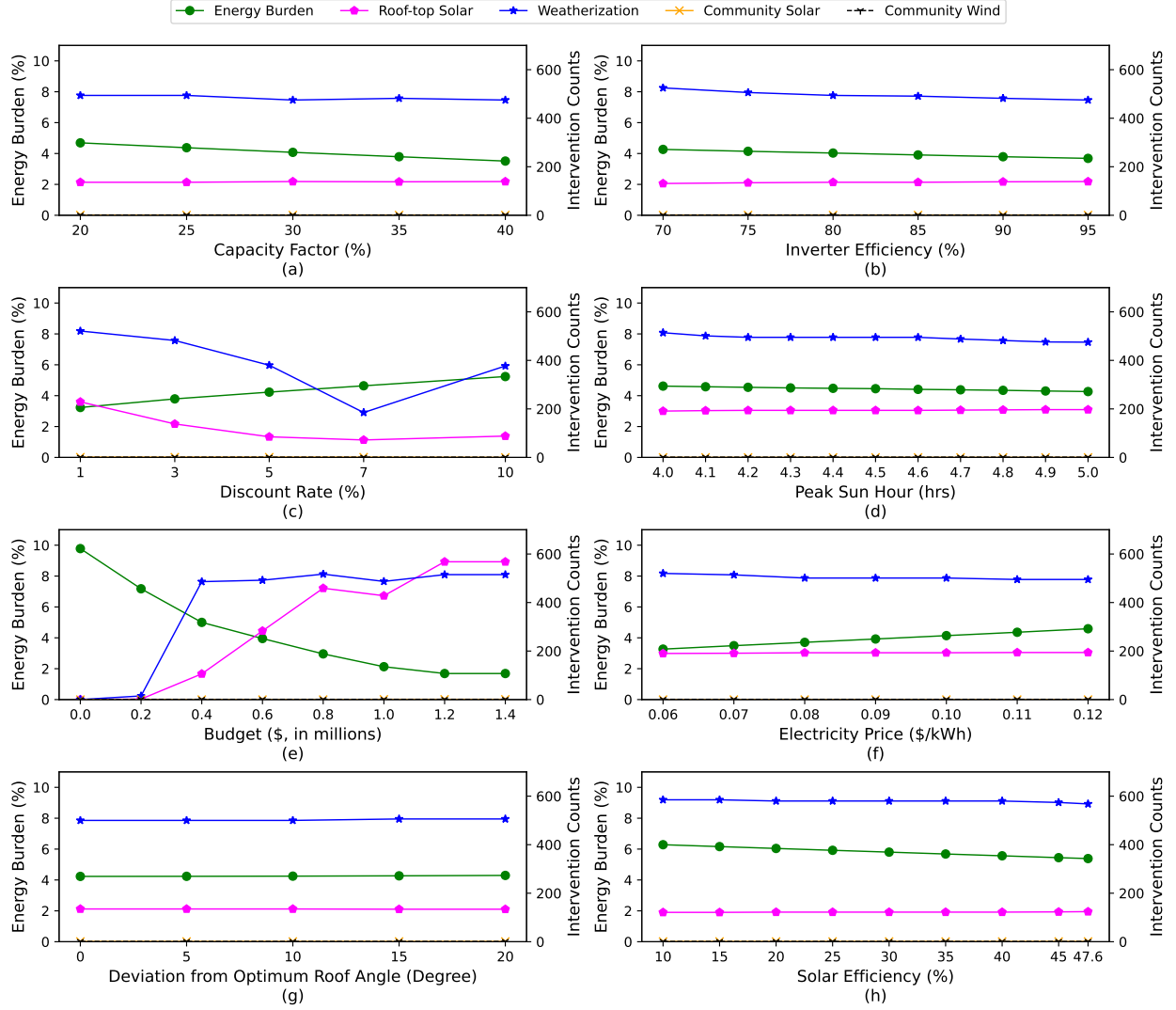


Figure 17: Change of energy burden and intervention counts in selected census tracts from Hardeman County, Tennessee, USA with the change of different parameters. The community intervention capacity of 1 MW was considered.

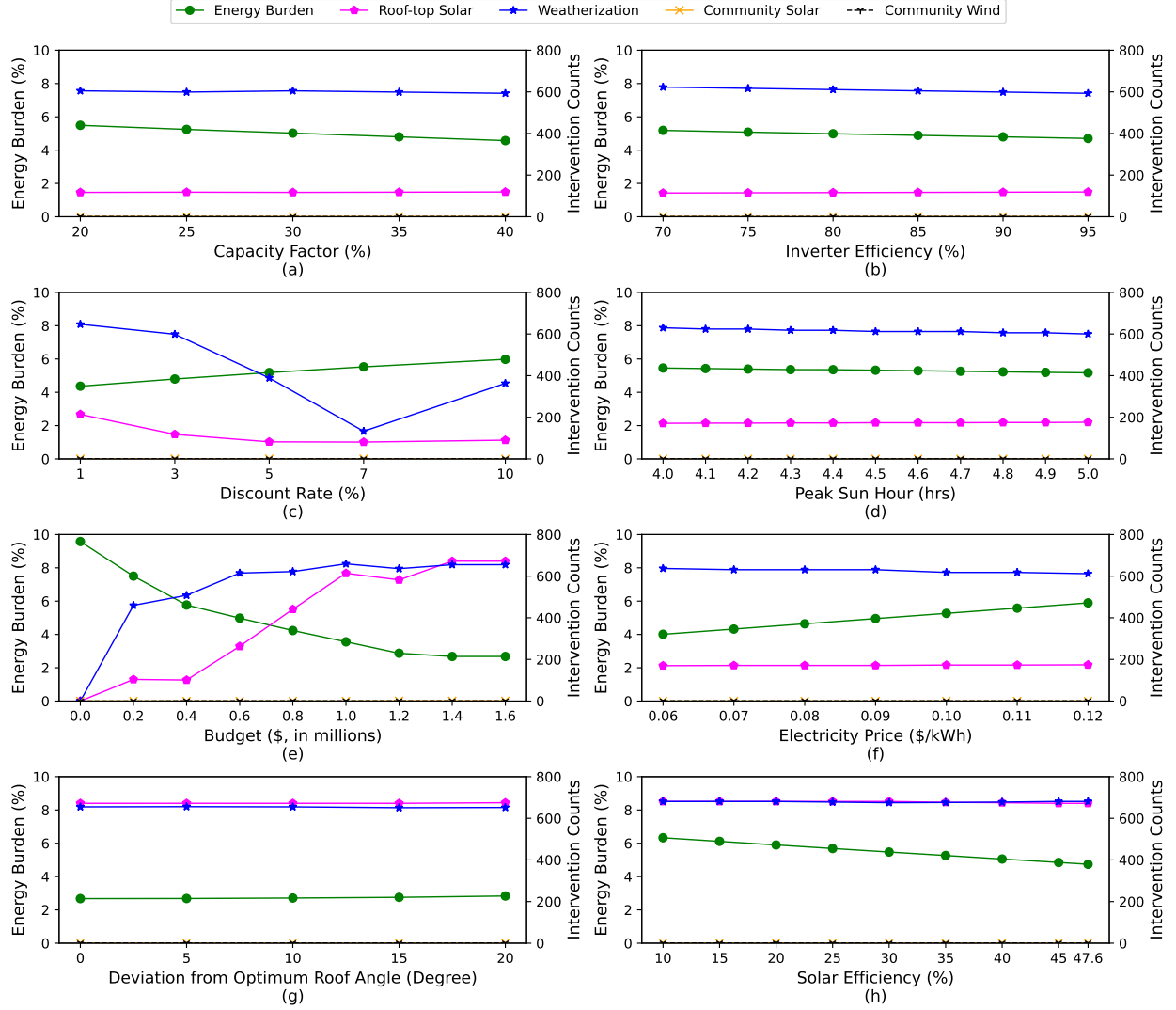


Figure 18: Change of energy burden and intervention counts in selected census tracts from Haywood County, Tennessee, USA with the change of different parameters. The community intervention capacity of 1 MW was considered.

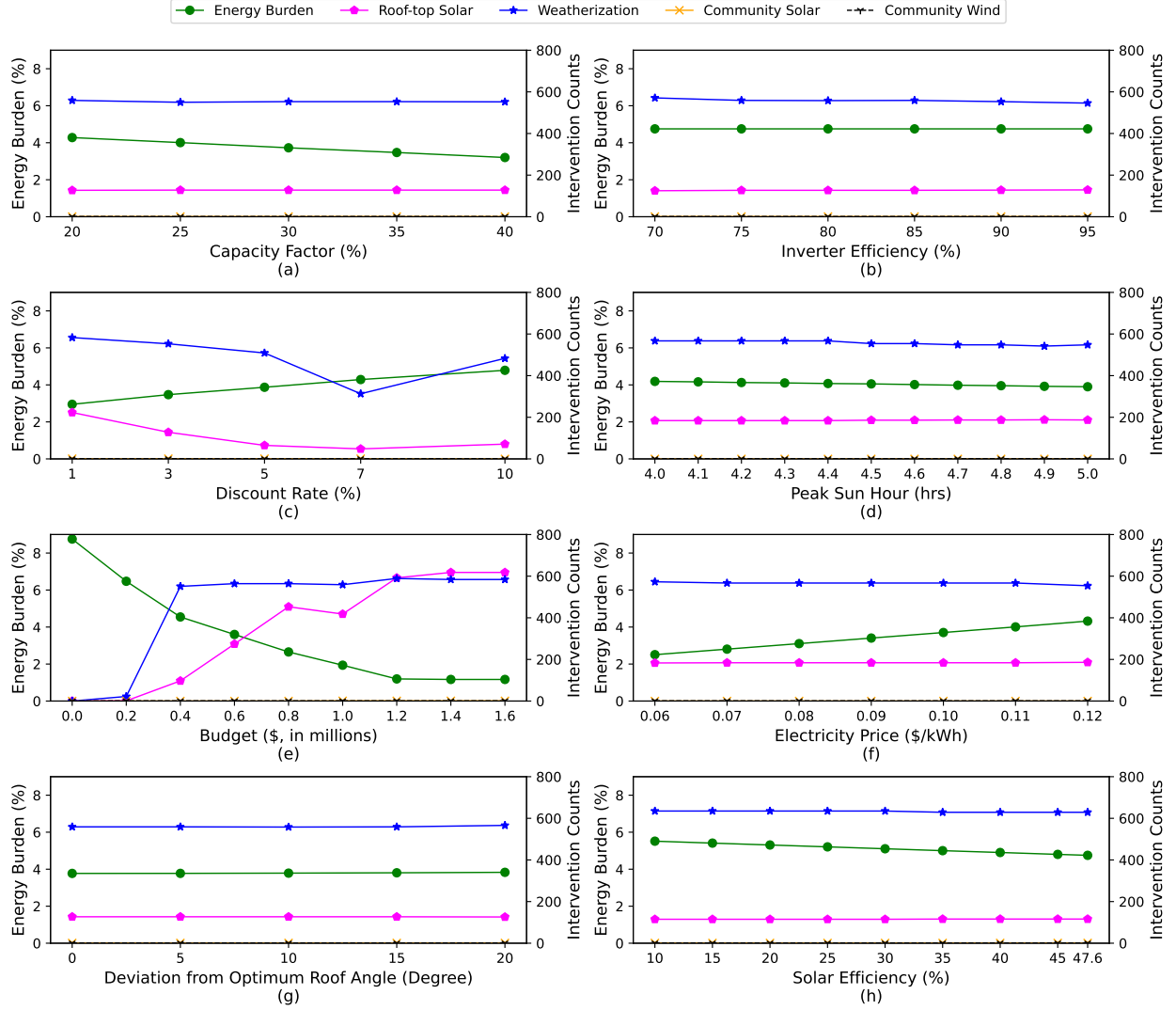


Figure 19: Change of energy burden and intervention counts in selected census tracts from Lauderdale County, Tennessee, USA with the change of different parameters. The community intervention capacity of 1 MW was considered.

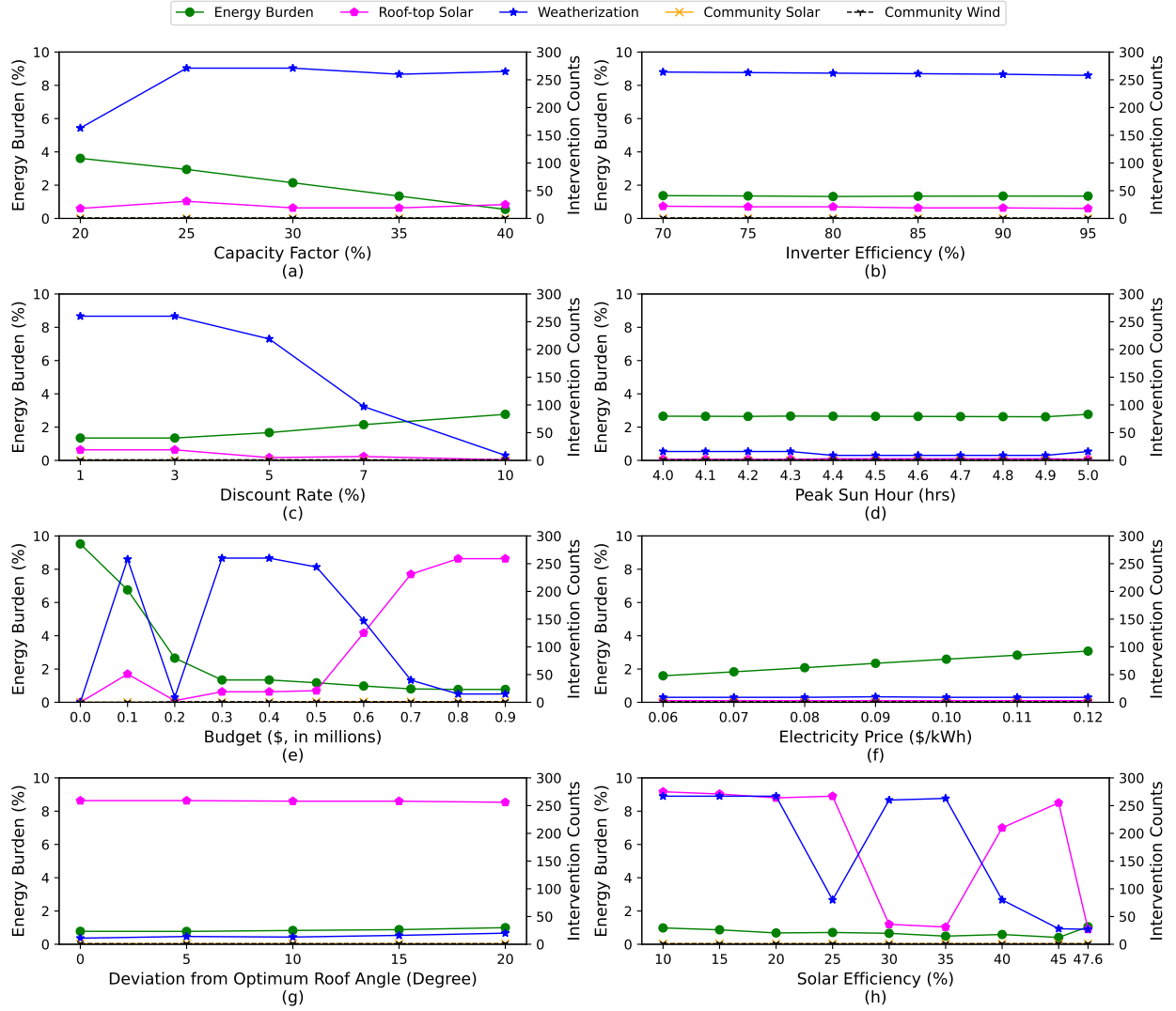


Figure 20: Change of energy burden and intervention counts in selected census tracts from Weakley County, Tennessee, USA with the change of different parameters. The community intervention capacity of 1 MW was considered.

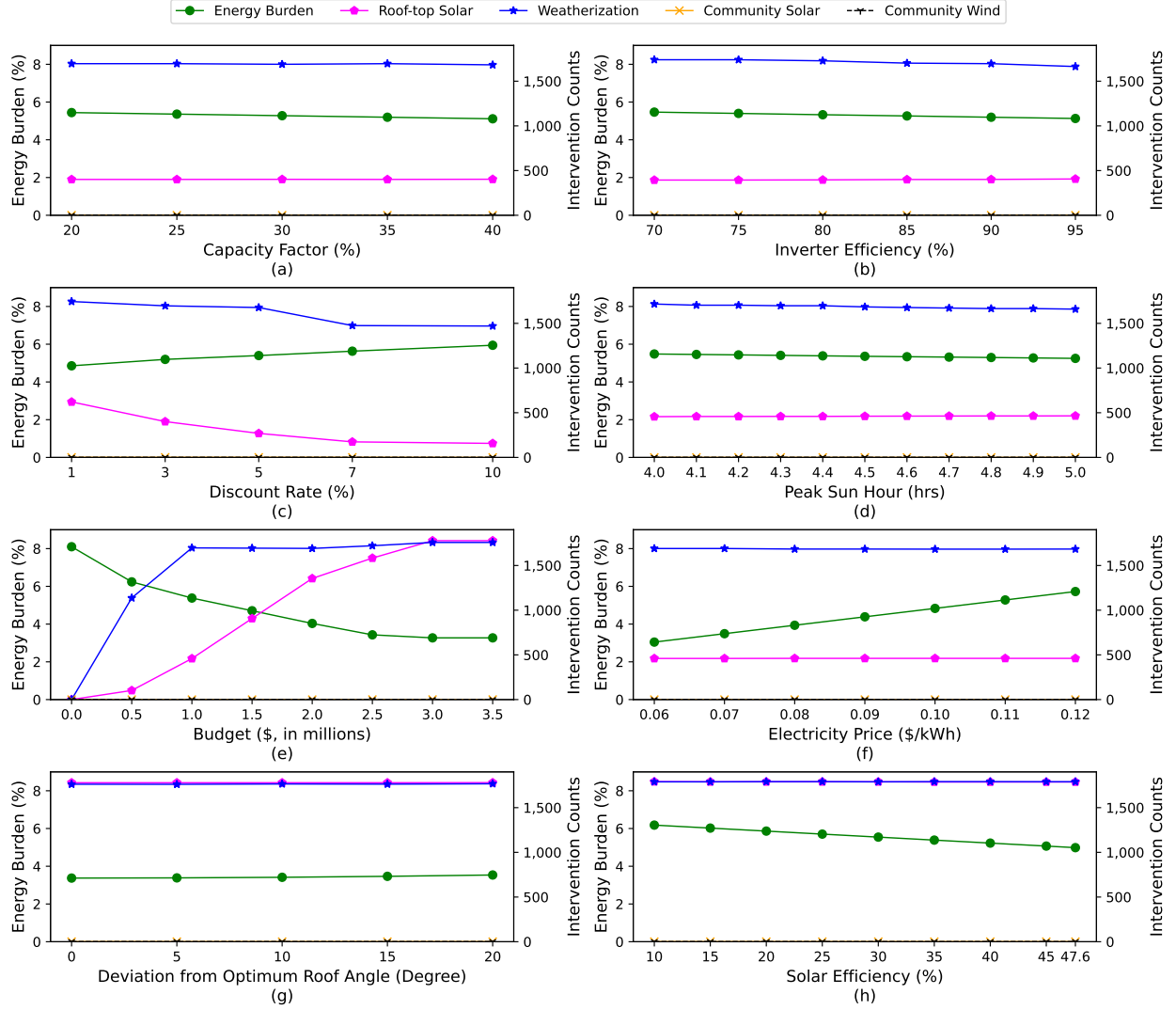


Figure 21: Change of energy burden and intervention counts in selected census tracts from Sevier County, Tennessee, USA with the change of different parameters. The community intervention capacity of 1 MW was considered.

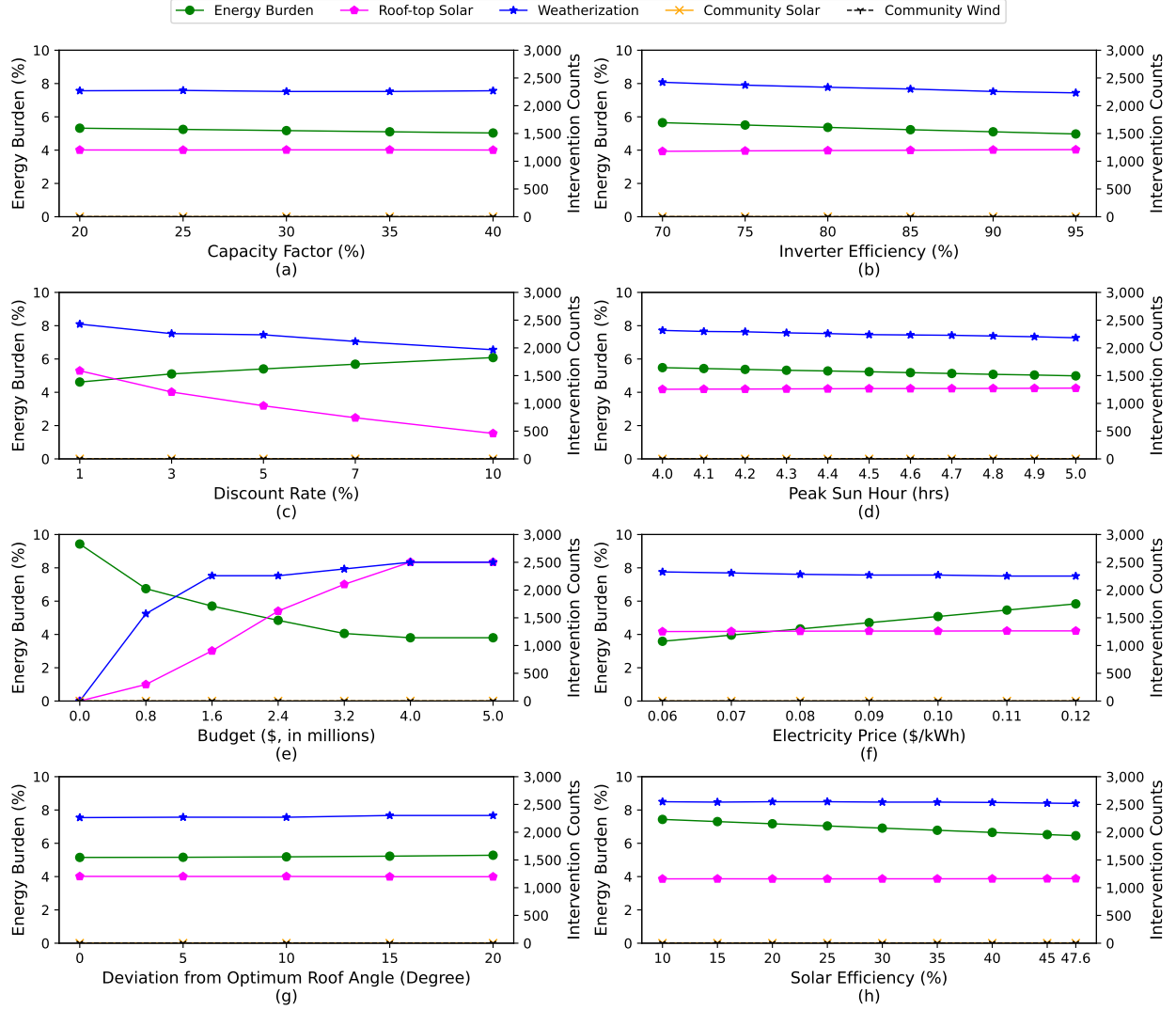


Figure 22: Change of energy burden and intervention counts in selected census tracts from Madison County, Tennessee, USA with the change of different parameters. The community intervention capacity of 1 MW was considered.

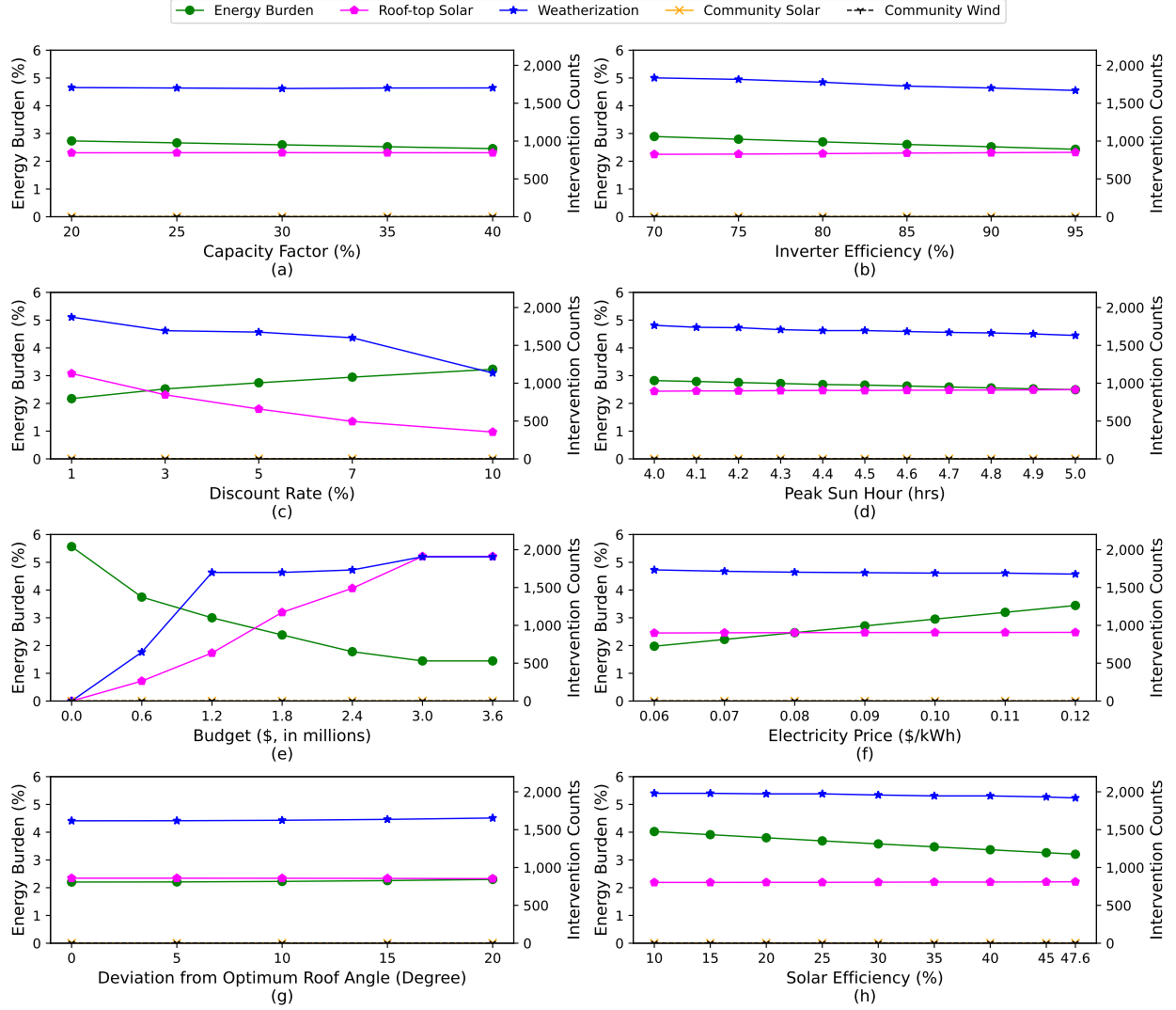


Figure 23: Change of energy burden and intervention counts in selected census tracts from Hamilton County, Tennessee, USA with the change of different parameters. The community intervention capacity of 1 MW was considered.

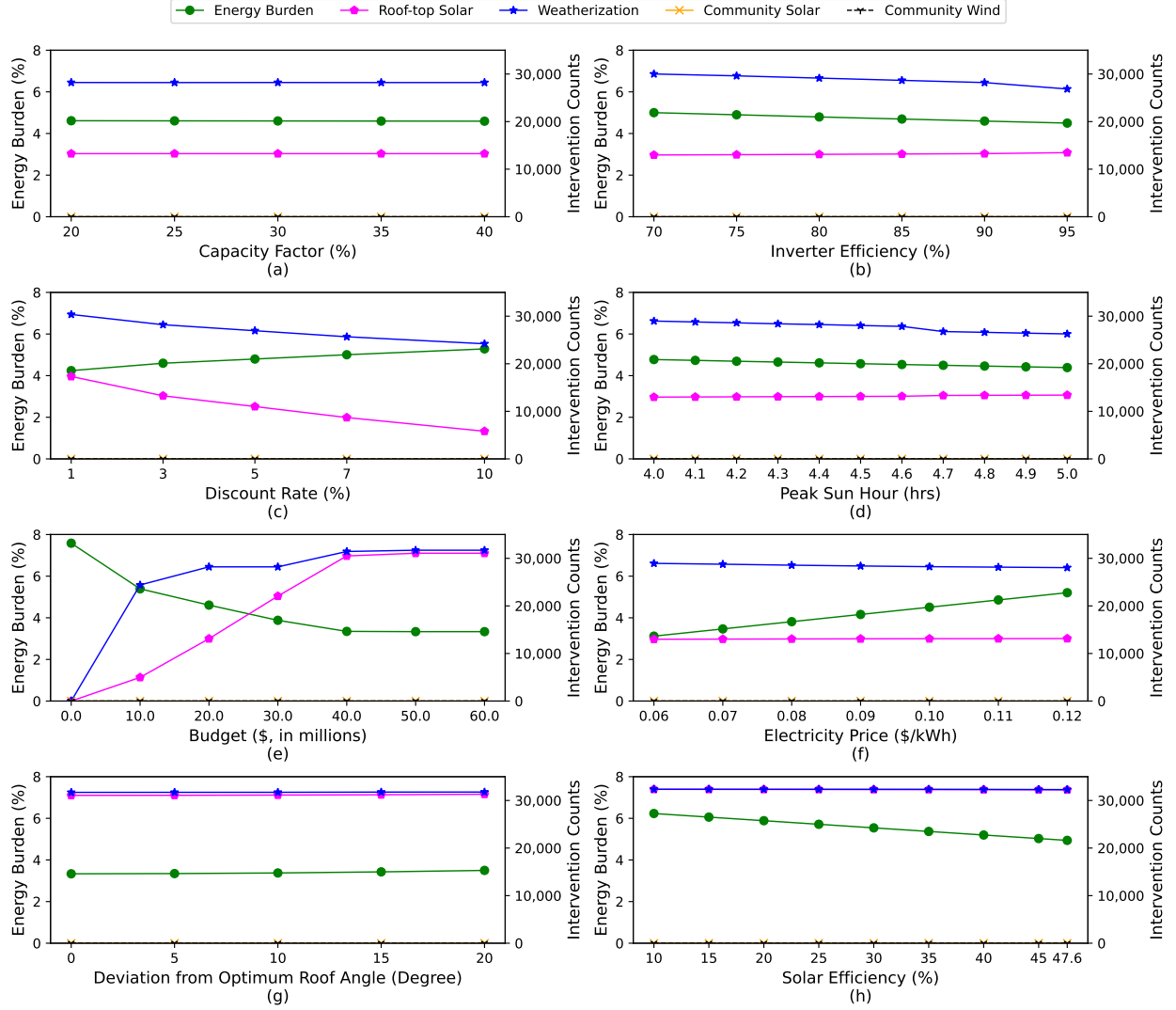


Figure 24: Change of energy burden and intervention counts in selected census tracts from all 12 Counties (combined) with the change of different parameters. The community intervention capacity of 1 MW was considered.

Vita

Rupam Kumar Dey developed a passion for Industrial and Production Engineering in 2011, choosing it as his field of undergraduate study. He graduated in 2016 from the Bangladesh University of Engineering and Technology (BUET) and began his professional journey in the manufacturing sector, joining Abul Khair Steel Melting Limited (AKSML), a leading producer of TMT bars in Bangladesh. Over the following years, he built a career in the industry, gaining experience at both AKSML and its sister concern, Abul Khair Steel Products Limited (AKSPL).

In pursuit of higher education, Rupam joined the PhD program in Industrial Engineering at The University of Tennessee, Knoxville, in Spring 2021. He earned a concurrent Master's degree in Industrial Engineering from the same institution in 2023. His research focuses on the intersection of energy equity, policy, and clean energy, employing methodologies such as data science, machine learning, and operations research.

Rupam's work addresses critical challenges in reducing energy burdens for disadvantaged communities, providing actionable insights for policymakers and stakeholders. His academic journey reflects a commitment to solving complex challenges in energy systems and advancing equitable and sustainable energy solutions.