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Optimizing equity in energy policy interventions: A quantitative decision-support framework for energy justice

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ABSTRACT

This paper presents a quantitative framework to support policy decision-making around equitable energy interventions. By combining sociodemographic and techno-economic models in the energy space, we propose a linear programming model to calculate the optimal portfolio of energy investments that explicitly minimizes the energy burden of a given population of energy insecure households. The model is formulated as a multi-objective optimization suitable to support the decisions on weatherization and deployment of distributed energy resources. We illustrate our methodology with a case study involving a population of 14,043 energy insecure households in Wayne County, Detroit, United States.

1. Introduction

1.1. Motivation

A growing body of literature recognizes the close tie between socioeconomic status and disparities in energy insecurity. For example, studies focusing on the U.S. have highlighted that low-income families and communities of color are more likely to live in energy inefficient homes – with poor building envelope insulation and inefficient appliances – that require more energy consumption to achieve minimum levels of comfort [1,2]. The result of lower quality housing stock is that one in three American households experience challenges in paying energy bills [3] and millions are at risk of being disconnected from the utility for nonpayment reasons [4]. Energy insecurity can also be observed through energy limiting behaviors, in which energy insecure households and communities refrain to use energy services even to satisfy basic needs [5].

One measure of energy insecurity is energy burden, or the percentage of gross household income spent on energy costs. According the US Department of Energy's Low-Income Energy Affordability Data (LEAD) Tool [6], the national average energy burden is 3%. An affordable energy burden is defined as 6% or less. However, energy burdens vary across sociodemographic characteristics such as income, housing type and age, tenure, race and ethnicity, and occupant age. Low-income households experience an average energy burden three-times the national average, 8.6% (LEAD). Black, Hispanic, and Native American, and older adult households also experience higher energy burdens than the average households [7].

Energy resource plans and policies should be designed to not only mitigate these disproportionate burdens, but enable a just transition that benefits marginalized communities through cleaner sources of energy, reduced emissions from the removal of fossil fuels, employment and economic opportunities [8].

Due to their decentralized nature, renewable Distributed Energy Resources (DERs), together with weatherization and energy efficiency investments, are important decarbonization instruments suitable for place-based implementation of a just energy transition. Behind the meter or community-owned photovoltaics (PV) and storage technologies can reduce consumers' energy bills, by increasing self-sufficiency [9], decreasing peak demand charges [10], and improving the ability to respond to different time-varying electricity prices [11] and solar compensation mechanisms [12]. Similarly, from the perspective of building-level interventions, weatherization and energy efficiency measures can provide significant improvements to thermal comfort, enhanced health and safety, while reducing energy costs [13].

Thus, the economic and social benefits of DER deployment as well as weatherization and energy efficiency investments are evident. From an energy equity perspective, the main challenge is to integrate these technology investments into place-based just transition pathways at the policy level. To achieve that, first we need to recognize the limitations

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Nomenclature

Sets

$\mathcal{T}$	Set of tracts, indexed by τ
$\mathcal{P}$	Set of policy interventions. indexed generically by p and referring to the following interventions {w: weatherization, rts: rooftop solar, cs: community solar, cw: community wind}.
$\mathcal{F}$	Set of fuel types, indexed by f and referring in the model to the following fuel types {el: electricity, gs: gas, of: other fuels}.
$\mathbb{K}_p^\tau$	Set of household archetypes eligible for policy intervention p in tract τ, indexed by k.
$\mathbb{K}_{w-f}$	Set of household archetypes eligible for weatherization policies with f as heating fuel type.
$\mathcal{H}$	Set of home construction types in this study we use small multi-family, large multi-family, single family homes, mobile homes.
$\mathbb{C}$	Set of climate zones.

Parameters

Nb_k	Number of households of archetype k.
ζ_τ	Solar productivity factor for tract τ.
η_τ	Wind productivity factor for tract τ.
IC_p	Investment costs associated with policy intervention p.
L_p	Lifetime of the investments associated with policy intervention p.
Pel	Price of electricity.
WS_k	Percentage of weatherization savings in building k.
E_k^f	Baseline expenditure of building k associated with the consumption of fuel f.
$\overline{RTS}_k$	Maximum rooftop solar allowed in archetype building k.
$\overline{CS}_\tau$	Maximum community solar in tract τ.
$\overline{CW}_\tau$	Maximum of community wind in tract τ.
$\bar{\Psi}$	Social cost of energy insecurity.
$\bar{B}$	Maximum budget available.
θ	Decision marker predisposition to allocate budget to the mitigation of energy insecurity.

Decision Variables

d_k^w	Fraction of households of archetype k to receive weatherization interventions.
d_k^{rts}	Amount of rooftop PV installed in archetype building k.
d_t^{cs}	Amount of community PV installed in tract t.
d_t^{cw}	Amount of community wind installed in tract t.
g_k^{rts}	Amount of electricity generated from rooftop PV by an household archetype k.
g_k^{cs}	Portion of electricity generated from community PV attributed to building k.
g_k^{cw}	Portion of electricity generated from community wind attributed to building k.
c_k^{rts}	Annualized costs of rooftop PV installations assigned to the archetype household k.
c_t^{cs}	Annualized cost of community PV installation in tract t.
c_t^{cw}	Annualized cost of community wind installation in tract t.
eld_k	Electricity demand of an household archetype k.
ec_k	Total energy consumption of an household archetype k.
eg_k	Total energy generation associated with the household archetype k.
eb_k	Energy burden of an household archetype k.

of existing DER policies, such as solar financing and credit score requirements, in addressing equity problems [14,15]. Second, we need concrete decisions and plans to deploy these DER technologies in the field in the form of just energy interventions. These decisions have to be supported by quantitative research that explicitly addresses the disproportionate burden of underserved communities. In other words, we need a new generation of quantitative models capable to support equitable energy policy interventions decisions from national and local governments, energy providers, and communities.

1.2. Literature review

Such quantitative decision-support policy models are still to be developed. So far, quantitative analysis in the energy equity space relies on statistically-based models to identify disproportionate burdens and disparities in access to energy resources. These quantitative frameworks are not conceived to design specific forward-looking energy interventions, but to quantify and reveal causes of injustice and to help us understand the potential of technologies or policies to mitigate them. Examples of these quantitative analyses in solar energy include the work of O'Shaughnessy et al. [16] that examined the adoption impacts of solar rooftop policies and business models on energy injustices. The study finds that, historically, incentives targeted at LMI participants, PV leasing, and property-assessed financing options have driven more equitable rooftop solar adoption. Similarly, in [15], the authors simulated future rooftop and multifamily PV adoption in LMI households and found that covering the cost of a solar system for these consumers would result in deployment parity between LMI and non-LMI in 2025. These simulations used the Distributed Generation Market Demand (dGen) tool, based a national customer adoption model that quantifies future market demand for distributed solar, wind, storage, geothermal, and other DERs at multiple geographic levels through a bottoms-up agent-based approach [17]. Still in the solar equity space, some quantitative studies have focused on understanding disparities between LMI and non-LMI solar adoption [18–20], using energy and sociodemographic data and statistical analysis. These disparity analyses are extended in [21] to evaluate access to energy services, such as having a washing machine or experiencing cold homes, in the context of energy racial injustice. Regarding weatherization, similar empirical and linear regression models have been applied to assess the potential or to evaluate the impact of weatherization [1,22] and energy efficiency [23] policies on LMI consumers. Alternative quantitative models provide equivalent weatherization impact analysis via energy simulations of prototypical buildings, generated by a combination of build stock, weather and sociodemographic data [24,25].

By reviewing these models and quantitative analyses in the energy equity space, we can conclude that they are helpful to capture asymmetries of DER and weatherization interventions in LMI communities, to measure the social and techno-economic potential of technologies, to understand behaviors and evaluate policy impacts. They have the benefit of analyzing energy resources from a sociodemographic perspective, which allows identifying energy burden and injustices. However, due to their statistical nature, and their focus on the present, they are inadequate to produce forward-looking energy resource plans nor suggest an optimal mix of energy interventions to support equitable deployment policies.

To find models built for on-the-ground energy intervention deployment, it is necessary to look into the optimal policy design and energy planning literature. Here we find an extensive list of techno-economic models that optimize the portfolio of investments in energy resources for a given city or neighborhood, considering a variety of geographic, economic and energy factors. However, these models are strictly focused on intervention cost and environmental objectives, discarding how energy technology deployment affects different segments of the population. For example, Zhang et al. [26] present and optimization model for the city-level design of hydro and photovoltaic systems, minimizing the net-present value of the investments. With similar economic objectives, van Beuzekom et al. [27] propose an optimization framework for long-term investment planning in urban integrated energy systems, including explicit carbon dioxide (CO2) emission constraints. At a smaller scale, Orehounig et al. [28] introduce a model to size decentralized energy technologies at the neighborhood level, considering energy autonomy as well as economic and ecological performance. The model explicitly includes life-cycle CO2 emissions in the objective function, but no sociodemographic dimension is introduced. In the field of weatherization interventions, Rogeau et al. [29] present a model to determine the optimal building envelope and heating system retrofits at the utility territory scale. Again, the model exclusively considers cost objectives.

Only a few models in the energy analysis literature attempt to include equity as part of the optimization objective. Still, these models fail to include a sociodemographic layer in their definition of equity. For example, in [30] a community energy resource model, using the Hybrid Optimization of Multiple Energy Resources (HOMER) tool [31], is proposed to simultaneously optimize over three objectives: energy security, environmental sustainability and energy equity. However, equity is defined exclusively by energy affordability and evaluated through two general cost metrics, life cycle costs (LCC) and levelized cost of energy (LCOE). This generic definition does not allow the model to capture the impacts on specific sociodemographic groups. Alternatively, in the energy resource space, it is also important to mention models that optimize equity in the allocation of renewable distributed generation across utility territories [32,33]. These models examine equity exclusively from the geographical distribution of resources, without considering particular sociodemographic benefits, such as burden reduction.

1.3. Contribution

This lack of equity concerns in quantitative policy design models is an important gap in the literature. In 2014, a review of the key challenges of energy systems modeling for the 20th century concluded that energy system models lack integration of human behavior and social risks and opportunities [34]. Still in 2021, an extensive literature review of co-optimization approaches in energy planning [35] could not identify a single model that explicitly includes equity or energy burden among the objectives.

This paper addresses this gap by proposing a new quantitative policy design model to support decisions around energy interventions with equity and justice objectives. We intend to provide a scientific contribution at the intersection of energy justice and quantitative policy modeling: to the energy justice space, we provide a concrete techno-economic framework that puts equity in the center of the deployment of energy resources and interventions; to the modeling literature in the area of energy policy and energy system analysis, we introduce a sociodemographic lens to the optimal energy resource planning and decision-support methodologies.

From a technical point of view, this paper presents an optimization model that explicitly minimizes energy insecurity in the process of defining energy investments in a particular sociodemographic context. Among these investments, we consider a combination of household-level interventions, specifically rooftop solar and weatherization, with the deployment of community-owned renewable generation. The model is formulated as a multi-objective optimization suitable to support energy equity investment decisions. We illustrate our methodology with a case study involving a population of 14,043 energy insecure households in Wayne County, Detroit, U.S.

1.4. Organization of the paper

The rest of paper is divided as follows: Section 2 presents the methodology, including the optimization model and the main datasets required as an input; Section 3 illustrates the main contributions of our model through a case study that plans energy interventions in a sociodemographic context of energy insecurity; Section 4 summarizes the key findings of this work and points out future directions.

2. Equitable energy policy model

2.1. Methodology overview

This section provides a quantitative framework to support policy decision-making around equitable energy interventions. The goal is to offer to decision-makers an optimal portfolio of energy investments that explicitly mitigate energy insecurity for a target population under different scenarios and policy considerations. To produce a place-based design of interventions, the model assumes a spatial census tract-level resolution and distinguishes different sociodemographic groups within the tracts.

Policy implementation is assumed to cover a set of tracts ($\mathcal{T}$), in which target population groups and their energy-related characteristics are organized in a set of household archetypes ($\mathbb{K}$). Each archetype aims at representing a specific reality of the household groups, combining socioeconomic data (*e.g.* income level), building characteristics (*e.g.* type of home) and energy information (*e.g.* energy expenditure).

The optimization model takes these household archetypes as an input together with other location specific data, such as DER generation potential and energy prices. Then, the model calculates the optimal portfolio of energy interventions that explicitly minimizes the energy insecurity of the target population of household archetypes. In particular, the portfolio includes two types of building-level interventions – weatherization and rooftop solar – for each household archetype (k) and two types of community-level interventions – deployment of community solar and community wind generation – for each tract (τ). Besides the optimal portfolio of interventions, the model also provides the resulting energy burden after the interventions.

Fig. 1 provides an illustration of the methodology overview.

2.2. Model formulation

In this section, we present the optimization model formulation. We start by modeling the constraints associated with the interventions: weatherization and DER deployment of rooftop solar, community solar and community wind. Then, we model the household energy costs, the energy burden associated to it, and we present a definition for energy insecurity based on a threshold for energy burden ($\bar{E}b$) above which an household is considered insecure. Finally, we formulate an objective function to explicitly minimize that insecurity and frame it into a policy decision model to explore the trade-offs with policy intervention costs. Formally, this problem can be model as a linear programming (LP) optimization, which can be solved efficiently by different mathematical LP solvers.

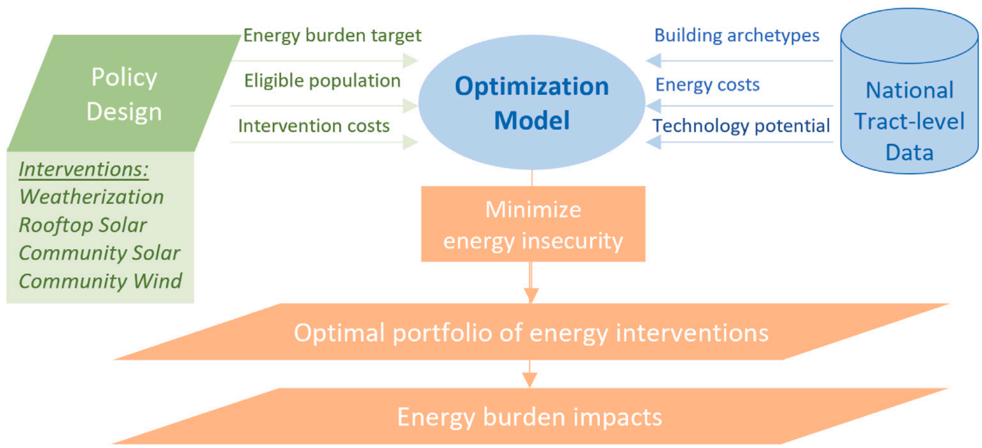

Fig. 1. Methodology overview.

2.2.1. Weatherization interventions

In the proposed model, the impact of weatherization interventions on residential buildings is primarily described in terms of household energy savings and total intervention costs. These impacts vary with the climate conditions of the region in which the weatherization program is implemented as well as with the building-specific characteristics, such as the home type (e.g. single family, small multi-family, etc.) and the main heating fuel.

Thus, for each household archetype k, we consider the reference savings $\bar{S}_h$ associated with the corresponding home type h. Also, we assume that savings are impacted by two coefficients: one associated with the heating fuel α_{f_k,h_k} and the other associated with the climate conditions β_{c_τ,h_k}. Both coefficients describe the building environment and determine the weatherization savings. The Eq. (1) shows the average weatherization savings for an household of the archetype k with a combination of the following characteristics: a home type h; a heating fuel type f; and located in a climate zone c.

$$WS_k = \bar{S}_h \cdot \alpha_{f_k,h_k} \cdot \beta_{c_\tau,h_k} \quad \forall k \in \mathbb{K}_w \tag{1}$$

Similarly, the weatherization investment costs associated with the house type h, $\bar{C}_h$, also depend on the heating fuel and the climate zone. Therefore, we assume analogous cost coefficients, representing the impact of fuel, λ_{f_k,h_k}, and climate, μ_{c_τ,h_k}, on weatherization investments. Eq. (2) presents the weatherization intervention costs dedicated to a household archetype k, that combines the following characteristics: a house type h, a heating fuel type f and it is located in a climate zone c.

$$IC_k^w = \bar{C}_h \cdot \lambda_{f_k,h_k} \cdot \mu_{c_\tau,h_k} \quad \forall k \in \mathbb{K}_w \tag{2}$$

Later in this section, we show how the savings and cost coefficients associated with fuel and climate conditions (α_{f_k,h_k}, β_{c_τ,h_k} λ_{f_k,h_k} and μ_{c_τ,h_k}) can be derived from past weatherization interventions, using data from the evaluation of the U.S Weatherization Assistance Program (WAP). For now, let us take these two parameters, WS_k and IC_k^w, as a reference for weatherization savings and costs per household of the archetype k.

From the optimization perspective, the actual costs of weatherization interventions depend on the decisions regarding the number of buildings to weatherize. As described in Eq. (3), this decision is expressed by d_k^w, which represents the fraction of household k homes to be weatherized. The equation also annualizes these investment costs, considering a discount rate, r, and an average lifetime L_w for the weatherization measures.

$$c_k^w = IC_k^w \cdot d_k^w \cdot \frac{r}{1-(1+r)^{-L_w}} \quad \forall k \in \mathbb{K}_w \tag{3}$$

2.2.2. DER deployment interventions

The installation of renewable-based distributed generation in LMI neighborhoods aims to reduce the energy costs through the impact on the net electricity demand. In this work, we consider three types of distributed generation to be deployed: rooftop solar PV (rts), community solar PV (cs) and community wind (cw) generation. Eqs. (4) and (5) present the generation associated with the solar energy technology deployment (rooftop and community-owned, respectively), while Eq. (6) represents the generation from the community wind. These annual renewable generations depend on the quantity of technology deployed, d, and on the annual productivity of solar and wind resources in each tract (τ), given by the parameters ζ_τ and η_τ respectively.

It is important to note that electricity generation is expressed per household of archetype k. This means that generation from the renewable capacity deployed at the tract level (τ) has to be divided by the number of households in the tract (Nb_k) eligible for community-owned technology interventions, as shown in Eqs. (5) and (6).

$$g_k^{rts} = d_k^{rts} \cdot \zeta_\tau \quad \forall k \in \mathbb{K}_{rts} \tag{4}$$

$$g_k^{cs} = \frac{d_\tau^{cs} \cdot \zeta_\tau}{\sum_{k \in \mathbb{K}_{cs}^\tau} Nb_k} \quad \forall k \in \mathbb{K}_{cs}^\tau \quad \forall \tau \in \mathcal{T} \tag{5}$$

$$g_k^{cw} = \frac{d_\tau^{cw} \cdot \eta_\tau}{\sum_{k \in \mathbb{K}_{cw}^\tau} Nb_k} \quad \forall k \in \mathbb{K}_{cw}^\tau \quad \forall \tau \in \mathcal{T} \tag{6}$$

Considering the deployment of each technology d and the corresponding reference costs IC, it is possible to write the annualized investment costs for each DER intervention policy, as shown in (7)–(9). Similarly to the weatherization interventions, the annualized costs take into account a discount rate, r, and an average lifetime L of each technology. The annualization of costs based on lifetime follows equivalent annual cost model, used in other energy planning models, such as [36,37].

$$c_k^{rts} = IC_{rts} \cdot d_k^{rts} \cdot \frac{r}{1-(1+r)^{-L_{rts}}} \quad \forall k \in \mathbb{K}_{rts} \tag{7}$$

$$c_\tau^{cs} = IC_{cs} \cdot d_\tau^{cs} \cdot \frac{r}{1-(1+r)^{-L_{cs}}} \quad \forall \tau \in \mathcal{T} \tag{8}$$

$$c_\tau^{cw} = IC_{cw} \cdot d_\tau^{cw} \cdot \frac{r}{1-(1+r)^{-L_{cw}}} \quad \forall \tau \in \mathcal{T} \tag{9}$$

2.2.3. Household energy demand costs

The household energy demand costs are modeled considering the baseline energy bill, which represents annual energy expenditure prior to the weatherization interventions. The baseline expenditure is disaggregated by fuel type, assuming three main energy vectors for space heating: electricity (el), gas (gs) and other fuels (of). Thus, three baseline energy parameters per household archetype are represented in the model: E_k^{el}, E_k^{gs} and E_k^{of}.

Weatherization interventions help reduce annual household energy expenditures. As discussed above, for each household archetype k, this reduction depends on the fraction of buildings weatherized, d_k^w, as well as the heating fuel type associated with k. Eqs. (10) and (11) describe the energy demand costs after the weatherization interventions for buildings where space heating is provided by either gas (10) or other fuels (11). As shown in the equations, only the cost of the primary heating fuel is affected by the weatherization savings. Additionally, it is important to note that the electricity expenditure is expressed by the multiplication of the electricity demand eld_k and the electricity price Pel.

$$ec_k = eld_k \cdot Pel + E_k^{gs} - (E_k^{gs} \cdot d_k^w \cdot WS_k) + E_k^{of} \quad \forall k \in \mathbb{K}_w^{gs} \tag{10}$$

$$ec_k = eld_k \cdot Pel + E_k^{gs} + E_k^{of} - (E_k^{of} \cdot d_k^w \cdot WS_k) \quad \forall k \in \mathbb{K}_w^{of} \tag{11}$$

The approach to model electricity expenditure is slightly different, because there is a need to capture the actual electricity energy demand (eld_k). As discussed next, we need this information to determine the overall electricity bill per building, including the effect of the distributed generation.

When electricity is not the primary heating fuel, the total annual electricity demand is a baseline parameter, given by the ratio between the total electricity expenditure and the average electricity price (12). In contrast, when the electricity is the primary heating fuel, the electric demand is affected by the weatherization interventions, as described in (13), and the total energy expenditure after the intervention can be simply obtain as in (14).

$$eld_k = \frac{E_k^{el}}{Pel} \quad \forall k \in \mathbb{K}_w \setminus \mathbb{K}_w^{el} \tag{12}$$

$$eld_k = \frac{E_k^{el}}{Pel} - d_k^w \cdot WS_k \cdot \frac{E_k^{el}}{Pel} \quad \forall k \in \mathbb{K}_w^{el} \tag{13}$$

$$ec_k = eld_k \cdot Pel + E_k^{gs} + E_k^{of} \quad \forall k \in \mathbb{K}_w^{el} \tag{14}$$

2.2.4. Energy burden and energy insecurity

Besides the energy expenditure presented above, it is necessary to compute the total distributed electricity generation per household (15). Then, considering the total energy costs, revenues from renewable generation, and the annual income (I_k), it is possible to calculate the energy burden per household of archetype k (16). As shown in the equation, we consider a widely used definition of energy burden, i.e. the percentage of annual household income spent on annual energy bills [7].

$$eg_k = g_k^{rts} + g_k^{cs} + g_k^{cw} \quad \forall k \in \mathbb{K} \tag{15}$$

$$eb_k = \frac{ec_k - eg_k \cdot Pel}{I_k} \quad \forall k \in \mathbb{K} \tag{16}$$

Assuming that the policy interventions have an energy burden target $\bar{Eb}$, above which an household is considered energy insecure, Eq. (18) expresses the positive and negative deviations in relation to that target. Thus, Δeb_k^+ captures the energy insecurity (*i.e.* the energy burden gap in relation to a threshold $\bar{Eb}$). Ideally, an equitable deployment of energy interventions should bring this gap to 0 for all k households. In the opposite direction, Δeb_k^- represents a policy overtarget, *i.e.* the amount of burden reduction beyond $\bar{Eb}$.

$$eb_k - \bar{Eb} = \Delta eb_k^+ - \Delta eb_k^- \quad \forall k \in \mathbb{K} \tag{17}$$

$$\Delta eb_k^+, \Delta eb_k^- \geqslant 0 \quad \forall k \in \mathbb{K} \tag{18}$$

It is important to note that this definition of energy insecurity, i.e. as a function household energy burden, is just one form of measuring vulnerability in the planning horizon. Other forms of energy insecurity experienced by consumers at the operational level, such as utility disconnections [4] or limiting energy behaviors [5] are not fully included in this definition.

2.2.5. Intervention limits

We also consider physical and regulatory constraints on the deployment of different interventions. For example, the number of buildings weatherized cannot exceed the number of buildings represented by the corresponding archetype (19); there are physical and regulatory limits to capacity of solar and wind technologies per building and per tract, as in (20)–(22). Finally, in order to comply with net-metering policy rules, we require the annual electricity balance, *i.e.* electricity household demand minus distributed generation, to be positive (23).

$$d_k^w \leqslant Nb_k \quad \forall k \in \mathbb{K}_w \tag{19}$$

$$d_k^{rts} \leqslant \overline{RTS}_k \quad \forall k \in \mathbb{K}_{rts} \tag{20}$$

$$d_\tau^{cs} \leqslant \overline{CS}_\tau \quad \forall \tau \in \mathcal{T} \tag{21}$$

$$d_\tau^{cw} \leqslant \overline{CW}_\tau \quad \forall \tau \in \mathcal{T} \tag{22}$$

$$eld_k - eg_k \geqslant 0 \quad \forall k \in \mathbb{K} \tag{23}$$

2.2.6. Objective function and policy decision model

The objective function minimizes a combination of (i) the sum of the intervention costs and (ii) energy insecurity, or the burden gap eb_k^+, of each archetype. This combination is weighted by the parameter θ, which expresses the relative importance (between 0 and 1) of the energy burden target in the overall policy deployment. In other words, a θ closer to 1 means that the policy decision-maker gives a high priority to the energy burden reduction, regardless the cost of the interventions. On the other hand, a θ closer to 0 reflects a low interest in allocating budget to the energy insecurity problem. It is important to note that this approach of weighting different objectives is widely used multi-objective optimization models, as explained in [38].

$$\begin{aligned} min\ (1-\theta) \cdot \Big(& \sum_{k \in \mathbb{K}_w} c_k^w \cdot Nb_k + \sum_{k \in \mathbb{K}_{rts}} c_k^{rts} \cdot Nb_k + \sum_{\tau \in \mathcal{T}} c_\tau^{cs} + c_\tau^{cw} \Big) \\ & + \theta \cdot \sum_{k \in \mathbb{K}} \Psi \cdot \Delta eb_k^+ \cdot Nb_k \end{aligned} \tag{24}$$

As shown in (24), to model the relative preference between intervention costs and energy burden reduction, it is necessary to assign a cost penalty to the excess of energy burden, given by Ψ. In reality, this parameter can correspond to a social cost of having segments of the population living in energy insecure conditions.

It is important to note that, in some applications, this social cost, Ψ, might be difficult to determine. Also, instead of selecting a single θ, some decision-makers might prefer to explore the whole space of potential trade-offs between intervention costs and energy insecurity before committing to a decision. To address these cases, the multi-objective function (24) can be written in its equivalent form, using (25) and (26).

$$min \sum_{k \in \mathbb{K}} \Delta eb_k^+ \cdot Nb_k \tag{25}$$

$$\sum_{k \in \mathbb{K}_w} c_k^w \cdot Nb_k + \sum_{k \in \mathbb{K}_{rts}} C_k^{rts} \cdot Nb_k + \sum_{\tau \in \mathcal{T}} c_\tau^{cs} + c_\tau^{cw} - \theta \bar{B} \leqslant 0 \tag{26}$$

Under this alternative form of seeing the same decision problem, instead of a social cost, Ψ, the decision-maker selects a maximum budget admissible for these policy interventions $\bar{B}$. On the other hand, θ plays a similar role in modeling the relative importance between budget and energy insecurity mitigation. However, with a different formal meaning: as presented in (26), θ captures the predisposition of the decision maker to allocate budget to the energy insecurity problem.

Table 1
Average national cost of weatherization interventions per house type (WAP).

Home type	Cost per home ($) [2008 values]
Small Multi-family buildings	2645
Large Multi-family buildings	2159
Single Family Homes	2846
Mobile Homes	2721

Table 2
Fuel cost factors per type of home ($\lambda_{f,h}$).

Home type	Natural gas	Electricity	Fuel oil	Propane	Other
Small Multi-family buildings	1.09	0.92	0.80	0.82	0.93
Large Multi-family buildings	0.88	1.00	1.15	1.00	1.00
Single Family Homes	0.97	0.98	1.21	1.03	0.96
Mobile Homes	0.92	1.18	0.93	0.95	1.06

Table 3
Climate cost factors per type of home ($\mu_{c,h}$).

Home type	Very cold	Cold	Moderate	Hot–Humid	Hot–Dry
Small Multi-family buildings	1.31	0.73	0.91	0.91	0.91
Large Multi-family buildings	1.31	0.73	0.91	0.91	0.91
Single Family Homes	1.42	0.79	0.88	1.15	0.89
Mobile Homes	1.24	0.82	0.86	0.86	0.86

Table 4
Average national energy savings per home type (WAP).

Home type	Savings per home (%)
Small Multi-family buildings	13.9
Large Multi-family buildings	12.3
Single Family Homes	12.4
Mobile Homes	8.2

Table 5
Fuel type savings factors per type of home ($\alpha_{f,h}$).

Home type	Natural gas	Electricity	Fuel oil	Propane	Other
Small Multi-family buildings	1.01	1.01	0.96	0.81	0.92
Large Multi-family buildings	1.02	1.02	1.95	0.81	0.92
Single Family Homes	0.99	0.84	1.06	1.12	0.92
Mobile Homes	0.96	0.82	1.07	1.21	0.87

Table 6
Climate savings factors per home type ($\beta_{c,h}$).

Home type	Very cold	Cold	Moderate	Hot–Humid	Hot–Dry
Small Multi-family buildings	1.07	1.05	0.60	0.60	0.60
Large Multi-family buildings	1.07	0.57	0.60	0.60	0.60
Single Family Homes	1.10	1.12	0.82	0.86	0.42
Mobile Homes	1.14	1.18	0.72	0.72	0.72

2.3. Datasets

2.3.1. Weatherization costs and savings

In this paper, we assume weatherization cost and savings per home that resulted from a retrospective evaluation of the U.S. Weatherization Assistance Program (WAP). This evaluation was gathered in a series of reports from Oak Ridge National Laboratory [39]. The report accounts for a set of four types of homes ($\mathcal{H}$). The average weatherization costs of each type is shown in 1.

These costs were also reported by heating fuel, considering a set of common fuel categories ($\mathcal{F}$): Natural Gas, Electricity, Fuel Oil, Propane and Others. using the average costs per home, $\bar{C_h}$, and the cost per fuel type, $C_{f,h}$, it is possible to calculate the fuel cost coefficients, $\lambda_{f,h}$, that express the relation between the weatherization intervention costs and the fuel type, as shown in Eq. (27). Table 2 presents the results for these coefficients.

$$\lambda_{f,h} = \frac{C_{f,h}}{\bar{C_h}} \quad \forall f \in \mathcal{F} \quad \forall h \in \mathcal{H} \tag{27}$$

Additionally, the report gathers the weatherization measure costs per geographical location, taking into account a set of five climate zones ($\mathbb{C}$) described as: Very Cold, Cold, Moderate, Hot–Humid, Hot–Dry.

Thus, similarly to the fuel cost, it is possible to express the climate impact coefficients, $\mu_{c,h}$, associated with the weatherization costs per building type, as in Eq. (28). The results of these coefficients are presented in Table 3.

$$\mu_{c,h} = \frac{C_{c,h}}{\bar{C_h}} \quad \forall c \in \mathbb{C} \quad \forall h \in \mathcal{H} \tag{28}$$

It is important to stress that $\bar{C_h}$ represents the national average weatherization costs for each house type across all climate zones and for all fuel types. In other words, these costs are not equivalent to the averages of the individual dimensions, as shown in (29). In fact, this is why the costs per fuel type and climate cannot be obtained directly from the results reported and the coefficients $\lambda_{f,h}$, $\mu_{c,h}$ are needed. Such coefficients can translate these impacts separately, assuming that house types (h) across climate zones and heating fuels categories follow a national distribution.

$$\bar{C_h} \neq \frac{\sum_{f\in\mathcal{F}} C_{f,h}}{|\mathcal{F}|} \neq \frac{\sum_{c\in\mathbb{C}} C_{c,h}}{|\mathbb{C}|} \quad \forall h \in \mathcal{H} \tag{29}$$

The method to estimate the savings factors is analogous to the process described above. We take as a reference the reported average national energy savings per home type ($\bar{S_h}$) in percentage, presented in Table 4. It is important to note these are assumed to be the actual savings and not the projected ones. Errors in savings forecasts, very typical in weatherization programs (due to rebound effects), are out of the scope of the methodology presented.

Using this reference savings, and considering the national average of savings per fuel and per climate zone, we calculate the respective saving coefficients, $\alpha_{f,h}$ and $\beta_{c,h}$, as show in Eqs. (30) and (31).

$$\alpha_{f,h} = \frac{S_{f,h}}{\bar{S_h}} \quad \forall f \in \mathcal{F} \quad \forall h \in \mathcal{H} \tag{30}$$

$$\beta_{c,h} = \frac{C_{c,h}}{\bar{C_h}} \quad \forall c \in \mathbb{C} \quad \forall h \in \mathcal{H} \tag{31}$$

The results of these coefficients are presented in Tables 5 and 6, respectively. As shown, for example, in Table 6, the savings tend to be higher in cold and very cold climate areas in comparison with hot–humid and hot–dry zones.

Thus, for each archetype household, k, with a house type h_k with fuel type f_k, located in tract τ in the climate zone c_τ, the weatherization savings (in percentage) can be calculated according to Eq. (1) reported above. Similarly, the costs of the weatherization interventions associated with each household archetype k can be obtained by Eq. (2).

2.3.2. Household archetypes and sociodemographic data

The household archetypes were constructed based on information extracted from the Low-Income Energy Affordability Data (LEAD) tool [6], which provides data on housing unity counts, average monthly housing electricity, gas, and other fuel expenditures, and average energy burden by census tract, household income level, and housing unit type.

The set of parameters of our model extracted from the LEAD dataset, at the tract level (τ), were the following: house type (h), heating fuel type (f), number of household per archetype (Nb_k), baseline household annual energy expenditure (E_k^{el}, E_k^{gs} and E_k^{of}), household annual income (I_k).

Table 7
Cost of interventions considered in the analysis.

Intervention	Cost (/MW or /building)	Lifetime
Rooftop solar	\$2.369M	20
Community solar	\$1.554M	20
Community wind	\$2.494M	15
Weatherization	Table 1 costs converted to 2021	35

2.3.3. Energy prices and renewable generation

Solar generation data were obtained from the Rooftop Energy Potential of Low Income Communities in America (REPLICA) Dataset, which is a tract-level dataset (vintage = 2015) that provides estimates of LMI rooftop solar characteristics [40]. For our model, we extracted the solar productivity parameter (ζ_τ) from the available average annual solar capacity factor (kWh/kW) in AC terms for a south-facing system, located in tract (τ) centroid, with a panel tilt equal to the latitude. Similarly, the rooftop technical limits per building ($\overline{RTS}_k$) were obtained from the rooftop solar technical potential (kW) for buildings suitable for solar deployment. The community solar technical limits were left unconstrained (i.e. $\overline{CS}_k = \infty$)

For the community wind technologies, we used data from a study that examines the onshore wind resource potential for the conterminous US [41]. We obtained the wind productivity coefficient (η_τ) from the average annual wind capacity factor (kWh/kW) for a 1.5 MW turbine at 80 m hub height in tract centroid. From the same source, we obtained the community wind technical potential ($\overline{CW}_k$) for sites suitable for wind deployment.

The average price of electricity (Pel) was gathered from the REPLICA Dataset. According to the documentation [42], the average price was obtained per utility territory from the Annual Electric Power Industry Report from the 2018 U.S. Energy Information Administration [43]. These prices were later tagged to tracts using geospatial information of the utility territories.

3. Case study

3.1. Case study description

This section presents a case study to illustrate the equitable energy resource model proposed herein. We use the model to analyze weatherization and DER deployment policy interventions in Wayne County, Michigan, which includes most of Detroit. The tracts considered in the intervention are those that correspond to the US Department of Energy (DOE) Communities Local Energy Action Planning (LEAP) program [44]. To qualify for Communities LEAP, a tract must have a low-income population ⩾30% and median household energy burden ⩾6%. Furthermore, the tract must meet at least one of the following criteria: (1) the community has an historical economic dependence on fossil fuel industrial facilities including extraction, processing, or refining; or (2) the tract is classified as experiencing moderate or high susceptibility on the U.S. Environmental Protection Agency's Environmental Justice Screening (EJSCREEN) tool [45]. The datasets to determine eligibility are available from the DOE [46].

We model a mock policy that provides weatherization and DERs to households living the eligible tracks in Wayne County with an annual income of 80%–100% of the Area Median Income (AMI). We use an energy burden target ($\bar{E}b$) of 6%, used as a reference for energy affordability [47]. By applying this energy burden criterion, we obtain an eligible population of 14,043 buildings, located in 560 census tracts ($\mathcal{T}$) and represented by 2920 household archetypes ($\mathbb{K}$).

The model parameters were derived from the national dataset described in the previous section. The rest of the data specific to the analysis includes the cost of interventions, the lifetime and the discount rate used to annualize the investments. The weatherization costs were taken directly from the WAP evaluation (Table 1) and converted to 2021 values, considering a factor of 1.29. A discount rate (r) of 3% was assumed in the analysis. The costs of interventions and corresponding lifetimes are summarized in Table 7. These values were assumed to represent typical costs and lifetimes of the different technologies for the purpose of this case study. In reality, these costs can vary with the location, the technologies, and the policy mechanisms used to deploy the technologies on the ground.

Table 8
Interventions deployed: base case ($\theta = 1$).

Intervention	Quantity (MW or # buildings)	Annualized investments (\$M/year)
Rooftop solar	8.36	1.36
Community solar	81.13	8.48
Community wind	1.73	0.36
Weatherization	2374	1.01
Total	91.23 MW + 2374 buildings	11.22

Table 9
Intervention performance ($\theta = 1$).

Performance	Value
Average energy burden	5.04%
Average energy burden reduction	2.49%
Average energy insecurity remaining (Δeb_k^+)	0.1 pp
Number of energy insecure households remaining	631

3.2. Results

3.2.1. Base case results

Table 8 presents the resulting optimal set interventions to be deployed in Wayne County, assuming that a high priority is given to the mitigation of energy insecurity ($\theta = 1$). As shown in the table, the interventions result in 91.23 MW of renewable distributed generation deployed (a significant portion of which is community solar installations) and 2374 buildings weatherized. The total cost of these interventions is \$11.22M per year.

These investments were able to bring the average energy burden of the eligible population (14,043 households) below the threshold target of 6%, as presented in Table 9. Given the average burden of 5% that resulted from the investments, we can conclude that a significant portion of the energy insecure households saw their burden decrease beyond the threshold level. However, as shown in the table, these interventions were insufficient to fully correct the problem of 631 households and an average energy insecurity of $\Delta eb_k^+ = 0.1\%$ remained to be solved.

Fig. 2 helps illustrate the impact of the investments on energy insecurity, by presenting a histogram of the energy burden of the eligible population (14,043 households) before and after the interventions. As shown in the figure, optimal investments were made to alleviate households energy burden, according to the 6% threshold assumed as a criterion for energy insecurity. It is interesting to note that, for most households, the resulting energy burden was exactly 6%, as the objective function (Eq. (25)) only minimizes the upper deviations of energy burden (Δeb_k^+).On the other hand, panel b shows that some households were left above the energy burden threshold. It is important to note that, although the interventions are optimal and minimize energy insecurity, they cannot guarantee a $\Delta eb_k^+ = 0$ for all households. This happens for three main reasons: first, the DER deployment can only offset the electricity costs (*i.e.* it cannot decrease gas and other fuel expenditures); second, DER policies are limited by the net-metering constraint (23) and by the technical potential of each technology; third, in some cases, the energy burden baseline is so extreme that all interventions combined can only solve part of the problem. This is visible in the baseline panel of Fig. 2, where a significant number of households appear with energy burden levels above

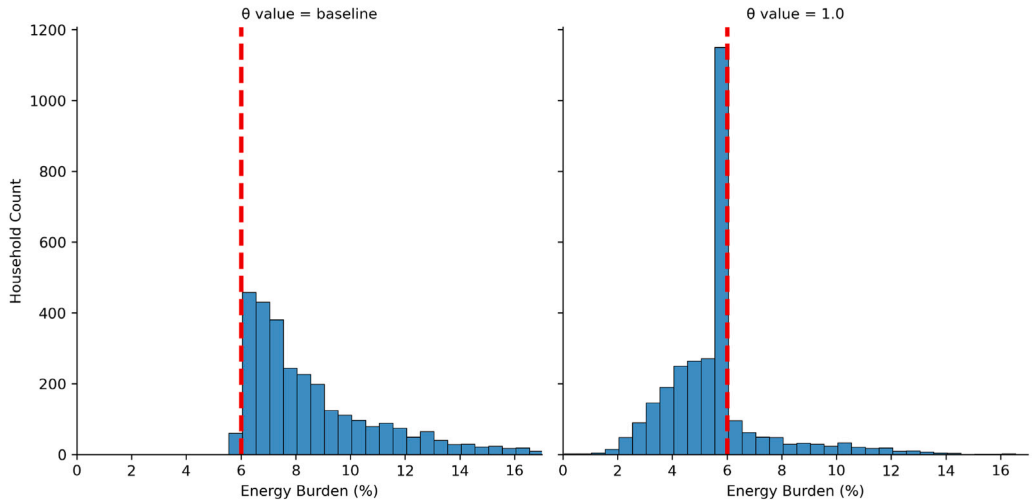

Fig. 2. Impact of the interventions on the energy burden of the eligible population. Panel a shows the distribution of household energy burden before the interventions($\theta = baseline$). Panel b shows the energy burden for the same households with the maximum weight placed on energy insecurity, $\theta = 1$.

10% before the interventions. When compared to the intervention panel (right-hand side), we can conclude that, even not solving the problem completely, the investments were able to address these extreme cases and substantially reduce the tail of this distribution.

Another relevant aspect to analyze in Fig. 2 is the amount of households whose energy burden was reduced to levels significantly below the threshold limit. In other words, they show values of Δeb_k^- > 0. Since the optimization objective is strictly focused on minimizing insecurity (Δeb_k^+), an overtarget reduction of this goal may look sub-optimal from an economic perspective. An explanation for this fact relies on the community-based investments (community solar and wind), which benefit the entire eligible population of the tract. In many cases, community investments are a cost-effective way of reducing electricity bills: for example, as seen in Table 7, community solar is the most competitive technology. When using these community resources to solve extreme energy insecurity cases in a given tract, it becomes economically rational to reduce the energy cost of other (less extreme) cases beyond the insecurity threshold.

3.2.2. Exploring equity policy priorities

In this subsection, we run the optimization model for different values of θ, exploring the entire space of the solutions available to the decision-maker, as defined by Eqs. (25) and (26). This solution space is summarized in Fig. 3, which presents the Pareto front of the energy insecurity (dark blue line) for different options of θ. As expected, when energy equity becomes a priority, the annualized investments increase and significantly reduce the energy insecurity and the burden. For values of $\theta \approx 0.25$, corresponding to annualized costs of around \$3M/year, there is a point of intersection. This means that investments higher than this value will reduce more energy burden than the energy insecurity remaining in the population. After values of $\theta \approx 0.5$ (and annualized investments around \$6M/year), energy insecurity reaches a saturation point and the marginal impact of investments is limited.

Despite this saturation effect on energy insecurity, the same does not occur to the energy burden reduction curve in Fig. 3. In fact, for values of $\theta > 0.5$, energy interventions continue to have significant impact on the average burden of the targeted population. The main explanation for this phenomenon is related to the effect of the community-owned renewable investments discussed above. Indeed, when used to address extreme insecure household cases, community wind and solar interventions end up reducing the overall energy burden of the households that benefit from these assets. This effect can be observed in Fig. 4 that presents the density function of the energy burden distribution for different values of θ. As energy security becomes a priority, the distribution shifts to the left, leading to a large concentration of household

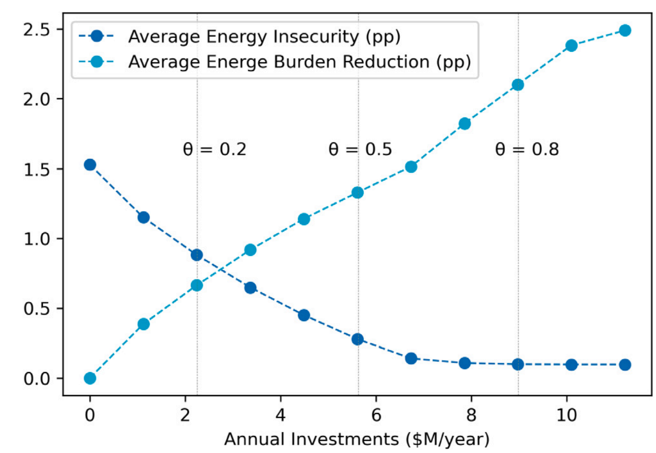

Fig. 3. Pareto front of energy insecurity as a function of the intervention costs. Comparison with the energy burden reduction for the same values of θ.

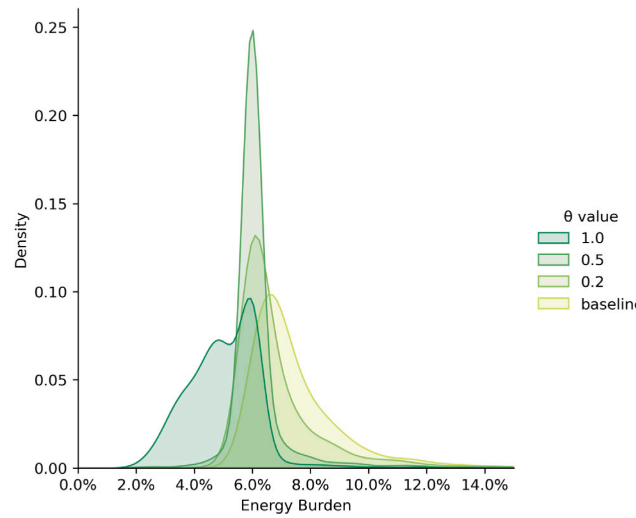

Fig. 4. Intervention total investments, considering different levels of θ.

energy burden around the 6% threshold for $\theta = 0.5$. The increase of θ to 1 results in the mitigation of the severe energy insecurity cases (placed

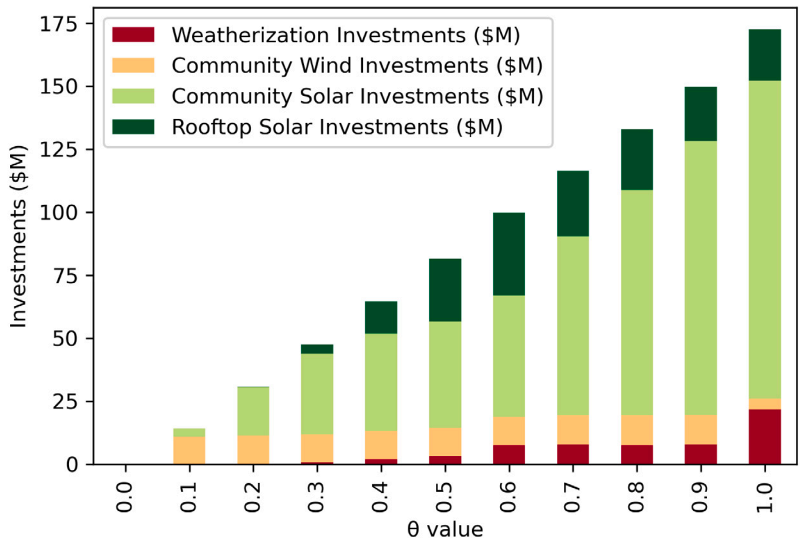

Fig. 5. Intervention total investments, considering different levels of θ.

on the right tail of the distribution), but it creates an overtarget energy burden on the left side of the distribution.

It is important to note that this overtarget also depends on the policy mechanisms used to share the community generation benefits amongst the energy insecure population. For the sake of simplicity, and to keep the focus on the modeling contributions of this paper, we assumed a community solar and wind policy that apportions credits equally amongst insecure households living in the same tract, as seen in Eqs. (5) and (6). Future studies could use our model to study this overtarget from a policy perspective and discuss the impact of different community generation sharing mechanisms.

Comparing the nature of the interventions, Fig. 5 shows the total investments considering different policy prioritization levels regarding energy insecurity. It is clear that community solar is the main driver of energy burden reduction, regardless of the prioritization, due to its lower costs (see Table 7). On the other hand, it interesting to observe that the share of technologies slightly changes with the priority given to the energy insecurity problem. For low levels of θ, only community investments (solar and wind) become competitive. When the predisposition to invest in energy security increases, household level interventions start to appear, with rooftop solar being more significant than weatherization measures. For $\theta = 1$, weatherization interventions increase, becoming an effective solution when the policy priority is reducing energy insecurity, regardless the intervention costs. In other words, the only possibility of addressing higher levels of energy insecurity is via structural interventions at the building level, which reduces the energy needs and, consequently, the energy bill. Additionally, it is interesting to observe that these weatherization interventions also reduce the need for the installation of distributed generation, in cases where the primary heating fuel is electricity. As shown in the figure, when the weatherization interventions increase there is a slight decrease of community wind and rooftop solar investments.

The way these investments are distributed per tract is illustrated in Fig. 6, which compares tract-level interventions for two different policy priority levels: ($\theta = 0.5$) and ($\theta = 1$). To allow a better comparison among tracts with different population, renewable investments are presented per building and weatherization is shown in percentage of buildings weatherized. When $\theta = 0.5$, tract-level solutions to reduce energy burden are based on multiple combinations of community-owned renewable and rooftop solar investments, while the share of weatherized buildings is insignificant. This situation changes when a high priority is given to the energy insecurity problem, with more tracts being weatherized.

Nonetheless, the most relevant aspect of Fig. 6 is the heterogeneity of the energy interventions across tracts. This clearly demonstrates that optimal interventions to address energy insecurity can assume multiple combinations, depending on the specific sociodemographic characteristics of the tract. Unlike other areas of energy resource planning, interventions in equity space cannot be standardized and require place-based approaches to deploy these interventions on the field.

4. Conclusion

This paper introduces a new contribution at the intersection of energy justice and quantitative policy modeling, by presenting a framework to support policy decision-making around equitable energy interventions. The results show that the linear programming model proposed is able to derive an optimal mix of interventions that minimizes energy insecurity, considering budget preferences and constraints. From the policy decision making perspective, this allows to explore the different trade-offs between intervention costs and energy burden reduction and to make quantitative informed decisions on equitable deployment of energy generation and efficiency technologies.

The optimal portfolio of energy interventions depends on the techno-economic characteristics of each technology (efficiencies, capacity potential, costs), but also on a combination of energy, climate and household living conditions particular to each place. The results show that, when capturing these different sociodemographic dimensions, equitable policy interventions become heterogeneous, specific to each community, which indicates a need for holistic (place-based) implementations. Thus, rather than prescriptive, the techno-economic analysis in the energy equity space should be presented to the communities as a set of (efficient and technically feasible) solutions that informs the decision-process. Our model is the first step in that direction.

Some limitations of our model should be addressed in future works to improve the accuracy and to expand the scope of the results presented. Modeling limitations to be addressed include the expansion of the portfolio of interventions (such as energy efficiency measures and storage technologies) as well as a time-resolution model for energy balance and costs. On the other hand, our work should be expanded to include information on community capacity and help identify non-technical needs, at the community level, to support the implementation of equitable energy interventions. Additionally, this model can be used to understand equity impacts of different renewable generation policies, for example technology incentives, apportion mechanisms for community assets, or solar compensation mechanisms.

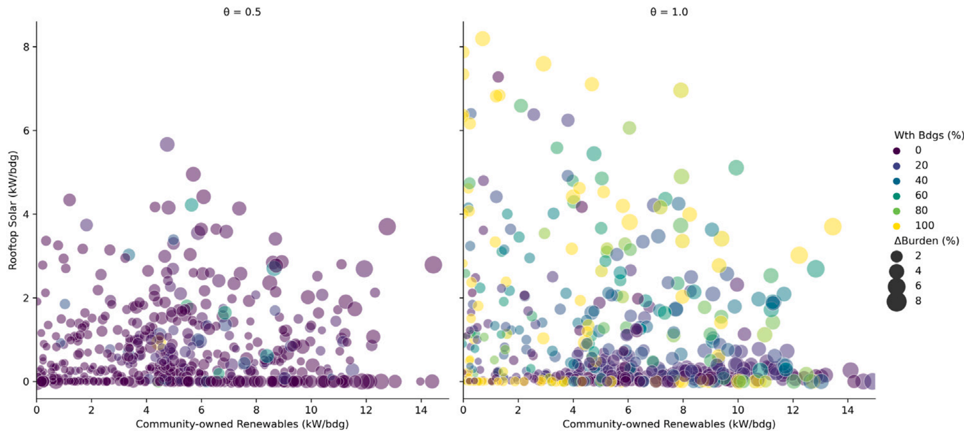

Fig. 6. Number of rooftop solar interventions per tract under different policy weights. Panel a displays the optimal number of interventions when energy insecurity is weighted equally with cost ($\theta = .5$). Panel b displays the optimal number of interventions when energy insecurity is fully prioritized ($\theta = 1$).

CRediT authorship contribution statement

Miguel Heleno: Conceptualization, Investigation, Software, Methodology, Writing – original draft. **Benjamin Sigrin:** Conceptualization, Software, Methodology. **Natalie Popovich:** Investigation, Writing – review & editing. **Jenny Heeter:** Investigation, Writing – review & editing. **Anjuli Jain Figueroa:** Writing, Reviewing. **Michael Reiner:** Writing, Reviewing. **Tony Reames:** Writing, Reviewing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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References

[1] Reames TG. Targeting energy justice: Exploring spatial, racial/ethnic and socioeconomic disparities in urban residential heating energy efficiency. Energy Policy 2016;97:549–58. http://dx.doi.org/10.1016/j.enpol.2016.07.048, URL https://www.sciencedirect.com/science/article/pii/S0301421516304098.

[2] Bird S, Hernández D. Policy options for the split incentive: Increasing energy efficiency for low-income renters. Energy Policy 2012;48:506–14. http://dx.doi.org/10.1016/j.enpol.2012.05.053, Special Section: Frontiers of Sustainability. URL https://www.sciencedirect.com/science/article/pii/S0301421512004661.

[3] U.S. energy information administration (EIA), U.S. residential energy consumption survey (2015). 2022, https://www.eia.gov/todayinenergy/detail.php?id=37072, Accessed: 2022-01-05.

[4] Memmott T, Carley S, Graff M, Konisky DM. Sociodemographic disparities in energy insecurity among low-income households before and during the COVID-19 pandemic. Nature Energy 2021;6(2):186–93. http://dx.doi.org/10.1038/s41560-020-00763-9.

[5] Cong S, Nock D, Qiu YL, Xing B. Unveiling hidden energy poverty using the energy equity gap. Nature Commun 2022;13(1):2456. http://dx.doi.org/10.1038/s41467-022-30146-5.

[6] Ma O, Laymon K, Day M, Oliveira R, Weers J, Vimont A. Low-income energy affordability data (LEAD) tool methodology. Tech. rep. NREL/TP-6A20-74249, National Renewable Energy Laboratory; 2019, URL https://www.nrel.gov/docs/fy19osti/74249.pdf.

[7] Drehobl A, Ross L, Ayala R. How high are household energy burdens? Tech. rep., American Council for an Energy-Efficient Economy; 2020, URL https://www.aceee.org/research-report/u2006.

[8] Carley S, Konisky DM. The justice and equity implications of the clean energy transition. Nature Energy 2020;5(8):569–77. http://dx.doi.org/10.1038/s41560-020-0641-6.

[9] von Appen J, Braun M. Interdependencies between self-sufficiency preferences, techno-economic drivers for investment decisions and grid integration of residential pv storage systems. Appl Energy 2018;229:1140–51. http://dx.doi.org/10.1016/j.apenergy.2018.08.003, URL http://www.sciencedirect.com/science/article/pii/S0306261918311589.

[10] Ren Z, Grozev G, Higgins A. Modelling impact of PV battery systems on energy consumption and bill savings of Australian houses under alternative tariff structures. Renew Energy 2016;89:317–30. http://dx.doi.org/10.1016/j.renene.2015.12.021, URL http://www.sciencedirect.com/science/article/pii/S0960148115305280.

[11] Milis K, Peremans H, Passel SV. Steering the adoption of battery storage through electricity tariff design. Renew Sustain Energy Rev 2018;98:125–39. http://dx.doi.org/10.1016/j.rser.2018.09.005.

[12] Ratnam EL, Weller SR, Kellett CM. Scheduling residential battery storage with solar PV: Assessing the benefits of net metering. Appl Energy 2015;155:881–91. http://dx.doi.org/10.1016/j.apenergy.2015.06.061, URL http://www.sciencedirect.com/science/article/pii/S0306261915008193.

[13] Hernández D, Phillips D. Benefit or burden? Perceptions of energy efficiency efforts among low-income housing residents in New York city. Energy Res Soc Sci 2015;8:52–9. http://dx.doi.org/10.1016/j.erss.2015.04.010, URL https://www.sciencedirect.com/science/article/pii/S2214629615000535.

[14] Cook JJ, Bird LA. Unlocking solar for low- and moderate-income residents: A matrix of financing options by resident, provider, and housing type. 2018, http://dx.doi.org/10.2172/1416133, URL https://www.osti.gov/biblio/1416133.

[15] Heeter J, Sekar A, Fekete E, Shah M, Cook JJ. Affordable and accessible solar for all: barriers, solutions, and on-site adoption potential. Tech. rep. NREL/TP-6A20-80532, National Renewable Energy Laboratory; 2021, URL https://www.nrel.gov/docs/fy21osti/80532.pdf.

[16] O'Shaughnessy E, Barbose G, Wiser R, Forrester S, Darghouth N. The impact of policies and business models on income equity in rooftop solar adoption. Nature Energy 2021;6(1):84–91. http://dx.doi.org/10.1038/s41560-020-00724-2.

[17] Distributed generation market demand model (dgen), national renewable energy laboratory. 2022, https://www.nrel.gov/analysis/dgen/. Accessed: 2022-02-05.

[18] Barbose GL, Forrester S, Darghouth NR, Hoen B. Income trends among U.S. residential rooftop solar adopters. Tech. rep., 2020.

[19] Reames TG. Distributional disparities in residential rooftop solar potential and penetration in four cities in the United States. Energy Res Soc Sci 2020;69:101612. http://dx.doi.org/10.1016/j.erss.2020.101612, URL https://www.sciencedirect.com/science/article/pii/S2214629620301870.

[20] Lukanov BR, Krieger EM. Distributed solar and environmental justice: Exploring the demographic and socio-economic trends of residential PV adoption in California. Energy Policy 2019;134:110935. http://dx.doi.org/10.1016/j.enpol.2019.110935, URL https://www.sciencedirect.com/science/article/pii/S0301421519305221.

[21] Best R. Energy inequity variation across contexts. Appl Energy 2022;309:118451. http://dx.doi.org/10.1016/j.apenergy.2021.118451, URL https://www.sciencedirect.com/science/article/pii/S0306261921016767.

[22] Xu X, fei Chen C. Energy efficiency and energy justice for U.S. low-income households: An analysis of multifaceted challenges and potential. Energy Policy 2019;128:763–74. http://dx.doi.org/10.1016/j.enpol.2019.01.020, URL https://www.sciencedirect.com/science/article/pii/S0301421519300205.

[23] Forrester SP, Reames TG. Understanding the residential energy efficiency financing coverage gap and market potential. Appl Energy 2020;260:114307. http://dx.doi.org/10.1016/j.apenergy.2019.114307, URL https://www.sciencedirect.com/science/article/pii/S0306261919319944.

[24] Bradshaw JL, Bou-Zeid E, Harris RH. Comparing the effectiveness of weatherization treatments for low-income, American, urban housing stocks in different climates. Energy Build 2014;69:535–43. http://dx.doi.org/10.1016/j.enbuild.2013.11.035, URL https://www.sciencedirect.com/science/article/pii/S0378778813007329.

[25] Harris C, Wilson E, Robertson J. ResStock county/household income assignment CHIA. Tech. rep., National Renewable Energy Laboratory; 2019, URL https://data.nrel.gov/submissions/113.

[26] Zhang B, Qiu R, Liao Q, Liang Y, Ji H, Jing R. Design and operation optimization of city-level off-grid hydro–photovoltaic complementary system. Appl Energy 2022;306:118000. http://dx.doi.org/10.1016/j.apenergy.2021.118000, URL https://www.sciencedirect.com/science/article/pii/S0306261921013027.

[27] van Beuzekom I, Hodge B-M, Slootweg H. Framework for optimization of long-term, multi-period investment planning of integrated urban energy systems. Appl Energy 2021;292:116880. http://dx.doi.org/10.1016/j.apenergy.2021.116880, URL https://www.sciencedirect.com/science/article/pii/S0306261921003664.

[28] Orehounig K, Evins R, Dorer V. Integration of decentralized energy systems in neighbourhoods using the energy hub approach. Appl Energy 2015;154:277–89. http://dx.doi.org/10.1016/j.apenergy.2015.04.114, URL https://www.sciencedirect.com/science/article/pii/S0306261915005772.

[29] Rogeau A, Girard R, Abdelouadoud Y, Thorel M, Kariniotakis G. Joint optimization of building-envelope and heating-system retrofits at territory scale to enhance decision-aiding. Appl Energy 2020;264:114639. http://dx.doi.org/10.1016/j.apenergy.2020.114639, URL https://www.sciencedirect.com/science/article/pii/S0306261920301513.

[30] Quitoras MR, Campana PE, Rowley P, Crawford C. Remote community integrated energy system optimization including building enclosure improvements and quantitative energy trilemma metrics. Appl Energy 2020;267:115017. http://dx.doi.org/10.1016/j.apenergy.2020.115017, URL https://www.sciencedirect.com/science/article/pii/S0306261920305298.

[31] Hybrid optimization of multiple energy resources, HOMER pro. 2021, https://www.homerenergy.com/. Accessed: 2021-01-10.

[32] Sasse J-P, Trutnevyte E. Distributional trade-offs between regionally equitable and cost-efficient allocation of renewable electricity generation. Appl Energy 2019;254:113724. http://dx.doi.org/10.1016/j.apenergy.2019.113724, URL https://www.sciencedirect.com/science/article/pii/S0306261919314114.

[33] Wang G, Zhang Q, Li Y, Mclellan BC. Efficient and equitable allocation of renewable portfolio standards targets among China's provinces. Energy Policy 2019;125:170–80. http://dx.doi.org/10.1016/j.enpol.2018.10.044, URL https://www.sciencedirect.com/science/article/pii/S0301421518306955.

[34] Pfenninger S, Hawkes A, Keirstead J. Energy systems modeling for twenty-first century energy challenges. Renew Sustain Energy Rev 2014;33:74–86. http://dx.doi.org/10.1016/j.rser.2014.02.003, URL https://www.sciencedirect.com/science/article/pii/S1364032114000872.

[35] Dranka GG, Ferreira P, Vaz AIF. A review of co-optimization approaches for operational and planning problems in the energy sector. Appl Energy 2021;304:117703. http://dx.doi.org/10.1016/j.apenergy.2021.117703, URL https://www.sciencedirect.com/science/article/pii/S0306261921010588.

[36] Cardoso G, Stadler M, Bozchalui M, Sharma R, Marnay C, Barbosa-Póvoa A, Ferrão P. Optimal investment and scheduling of distributed energy resources with uncertainty in electric vehicle driving schedules. Energy 2014;64:17–30.

[37] Heleno M, Sehloff D, Coelho A, Valenzuela A. Probabilistic impact of electricity tariffs on distribution grids considering adoption of solar and storage technologies. Appl Energy 2020;279:115826. http://dx.doi.org/10.1016/j.apenergy.2020.115826, URL https://www.sciencedirect.com/science/article/pii/S0306261920313040.

[38] Risk-constrained multi-period investment model for distributed energy resources considering technology costs and regulatory uncertainties. Appl Energy 2022;319:119210. http://dx.doi.org/10.1016/j.apenergy.2022.119210, URL https://www.sciencedirect.com/science/article/pii/S030626192200575X.

[39] WAP retrospective evaluation, oakridge national laboratory. 2014, URL https://weatherization.ornl.gov/wap-retrospective/. Accessed: 2021-09-22.

[40] Mooney M, Sigrin B. Rooftop energy potential of low income communities in America REPLICA. Tech. rep., National Renewable Energy Laboratory; 2018, URL https://data.nrel.gov/submissions/81.

[41] Lopez A, Mai T, Lantz E, Harrison-Atlas D, Williams T, Maclaurin G. Land use and turbine technology influences on wind potential in the United States. Energy 2021;223:120044. http://dx.doi.org/10.1016/j.energy.2021.120044, URL https://www.sciencedirect.com/science/article/pii/S0360544221002930.

[42] Sigrin B, Mooney M. Rooftop solar technical potential for low-to-moderate income households in the United States. Tech. rep. NREL/TP-6A20-70901, National Renewable Energy Laboratory; 2018, URL https://www.nrel.gov/docs/fy18osti/70901.pdf.

[43] U.S. energy information administration (EIA), annual electric power industry report, form EIA-861 detailed data files. 2021, https://www.eia.gov/electricity/data/eia861/. Accessed: 2021-12-12.

[44] USDepartment of Energy. Communities LEAP (local energy action program) pilot competitive technical assistance opportunity. 2021, https://www.energy.gov/sites/default/files/2021-11/U.S.DOECommunitiesLEAPOpportunityAnnouncement11.8.21.pdf.

[45] USEnvironmental Protection Agency. EJSCREEN: Environmental justice screening and mapping tool. 2021, URL https://www.epa.gov/ejscreen.

[46] Bauer J, Rose K, Romeo L, Justman D, Popovich N, Shah M, Anyikire AT, Russomanno C, Ho H, Sigrin B, et al. Datasets for DOE 2021 communities LEAP pilot. Tech. rep., Pittsburgh, PA, Morgantown, WV ...: National Energy Technology Laboratory (NETL); 2021.

[47] Colton RD. Home energy affordability in New York: the affordability gap (2008–2010). Tech. rep., New York State Energy Research Development Authority (NYSERDA); 2011.