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

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A R T I C L E I N F O

Keywords:
Energy justice
Equity
Energy burden
DER deployment
Weatherization

A B S T R A C T

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 to 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...
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 participants, PV leasing, and property-assessed financing options have accelerated 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 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 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 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 participants, PV leasing, and property-assessed financing options have driven more equitable rooftop solar adoption.

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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

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<td>( d^w_k )</td>
<td>Annualized costs of rooftop PV installations assigned to the archetype household ( k ).</td>
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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 (T), in which target population groups and their energy-related characteristics are organized in a set of household archetypes (S). 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 (r). 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 (Eb) 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.
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 \( S_k \) associated with the corresponding home type \( h \). Also, we assume that savings are impacted by two coefficients: one associated with the heating fuel \( a_{f_k,h_k} \) and the other associated with the climate conditions \( \beta_{f_k,h_k} \). Both coefficients describe the building environment and determine the weatherization savings. 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 \( c \).

\[
W \cdot S_k = S_h \cdot a_{f_k,h_k} \cdot \beta_{f_k,h_k} \quad \forall k \in \mathbb{K}_w
\]

Similarly, the weatherization investment costs associated with the house type \( h \), \( C_h \), also depend on the heating fuel and the climate zone. Therefore, we assume analogous cost coefficients, representing the impact of fuel, \( \lambda_{f_k,h_k} \), and climate, \( \mu_{f_k,h_k} \), 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 \( c \).

\[
IC_k = C_h \cdot \lambda_{f_k,h_k} \cdot \mu_{f_k,h_k} \quad \forall k \in \mathbb{K}_w
\]

Later in this section, we show how the savings and cost coefficients associated with fuel and climate conditions \( (a_{f_k,h_k}, \beta_{f_k,h_k} \lambda_{f_k,h_k} \text{ and } \mu_{f_k,h_k}) \) 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, \( W \cdot S_k \) and \( IC_k \), 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.

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

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 (\( r_{ts} \)), community solar PV (\( r_s \)) and community wind (\( r_w \)) 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 (\( \tau \)), given by the parameters \( \zeta \) and \( \eta \), 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 (\( \tau \)) has to be divided by the number of households in the tract (\( N_b \)) eligible for community-owned technology interventions, as shown in Eqs. (5) and (6).

\[
g_{\tau_{ts}}^r = d_{\tau_{ts}}^r \cdot \zeta \quad \forall k \in \mathbb{K}_{\tau_{rs}}
\]

\[
g_{\tau}^s = \frac{d_{\tau}^s \cdot \eta_{\tau}}{N_b} \quad \forall k \in \mathbb{K}_{\tau_s}, \quad \forall \tau \in T
\]

\[
g_{\tau}^w = \frac{d_{\tau}^w \cdot \eta_{\tau}}{\sum_{k \in \mathbb{K}_w} N_b} \quad \forall k \in \mathbb{K}_{\tau_w}, \quad \forall \tau \in T
\]

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 (\( e_l \)), gas (\( e_g \)) and other fuels (\( e_f \)). Thus, three
baseline energy parameters per household archetype are represented in the model: $E_{el}^{t}$, $E_{el}^{s}$ and $E_{el}^{f}$.

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, $d_{wk}$, 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 $el_{dk}$ and the electricity price $P_{el}$.

$$ec_{k} = el_{dk} \cdot P_{el} + E_{el}^{s} - (E_{el}^{s} \cdot d_{wk} \cdot W_{S_k}) + E_{el}^{f} \quad \forall k \in K_w$$
(10)

$$ec_{k} = el_{dk} \cdot P_{el} + E_{el}^{s} - (E_{el}^{s} \cdot d_{wk} \cdot W_{S_k}) \quad \forall k \in K_w$$
(11)

The approach to model electricity expenditure is slightly different, because there is a need to capture the actual electricity demand ($el_{dk}$). 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).

$$el_{dk} = \frac{E_{el}^{d_k}}{P_{el}} \quad \forall k \in K_w \setminus K_{w}^{el}$$
(12)

$$el_{dk} = \frac{E_{el}^{d_k}}{P_{el}} - d_{wk} \cdot W_{S_k} + \frac{E_{el}^{d_k}}{P_{el}} \quad \forall k \in K_{w}^{el}$$
(13)

$$ec_{a} = el_{dk} \cdot P_{el} + E_{el}^{s} + E_{el}^{f} \quad \forall k \in K_{w}^{el}$$
(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].

$$eg_{k} = ec_{k}^{\theta} + ec_{k}^{\theta} + ec_{k}^{\theta} \quad \forall k \in K$$
(15)

$$eb_{k} = \frac{eg_{k} - eg_{k} \cdot P_{el}}{I_{k}} \quad \forall k \in K$$
(16)

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

$$eb_{k} - Eb = \Delta eb_{k}^{\theta} - \Delta eb_{k}^{\theta} \quad \forall k \in K$$
(17)

$$\Delta eb_{k}^{\theta}, \Delta eb_{k}^{\theta} \geq 0 \quad \forall k \in K$$
(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).

$$d_{wk} \leq N_{bh} \quad \forall k \in K_w$$
(19)

$$d_{wk}^{\text{res}} \leq RT S_{k} \quad \forall k \in K_{\text{res}}$$
(20)

$$d_{wk}^{\text{serv}} \leq CW_{t} \quad \forall t \in T$$
(21)

$$d_{wk}^{\text{serv}} \leq CW_{t} \quad \forall t \in T$$
(22)

$$el_{dk} - eg_{k} \geq 0 \quad \forall k \in K$$
(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 $eb_{k}^{\theta}$ of each archetype. This combination is weighted by the parameter $\theta$, which expresses the relative importance (between 0 and 1) of the energy burden target in the overall policy deployment. In other words, a $\theta$ 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 $\theta$ 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].

$$\min (1 - \theta) \cdot \left( \sum_{k \in K_w} c_{k}^{\text{t}} \cdot N_{bh} + \sum_{k \in K_{\text{res}}} c_{k}^{\text{tr}} \cdot N_{bh} + \sum_{t \in T} c_{t}^{\text{tr}} + c_{t}^{\text{serv}} \right)$$
$$+ \theta \cdot \sum_{k \in K} \Psi \cdot \Delta eb_{k}^{\theta} \cdot N_{bh}$$
(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 $\Psi$. 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, $\Psi$, might be difficult to determine. Also, instead of selecting a single $\theta$, 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).

$$\min \sum_{k \in K_w} \Delta eb_{k}^{\theta} \cdot N_{bh}$$
(25)

$$\sum_{k \in K_w} c_{k}^{\text{t}} \cdot N_{bh} + \sum_{k \in K_{\text{res}}} c_{k}^{\text{tr}} \cdot N_{bh} + \sum_{t \in T} c_{t}^{\text{tr}} + c_{t}^{\text{serv}} - \theta \hat{B} \leq 0$$
(26)

Under this alternative form of seeing the same decision problem, instead of a social cost, $\Psi$, the decision-maker selects a maximum budget admissible for these policy interventions $B$. On the other hand, $\theta$ 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), $\theta$ captures the predisposition of the decision maker to allocate budget to the energy insecurity problem.
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 (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 (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, \( \alpha_{f,h} \), 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.

\[
\alpha_{f,h} = \frac{C_{f,h}}{\bar{C}_h} \quad \forall f \in F \quad \forall h \in H \tag{27}
\]

Additionally, the report gathers the weatherization measure costs per geographical location, taking into account a set of five climate zones (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.

\[
\mu_{c,h} = \frac{C_{c,h}}{\bar{C}_h} \quad \forall c \in C \quad \forall h \in H \tag{28}
\]

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 \( \alpha_{f,h}, \mu_{c,h} \) 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.

\[
\bar{C}_h = \frac{\sum_{f \in F} C_{f,h}}{|F|} = \frac{\sum_{c \in C} C_{c,h}}{|C|} \quad \forall h \in H \tag{29}
\]

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, \( a_{f,h} \) and \( \beta_{c,h} \), as show in Eqs. (30) and (31).

\[
a_{f,h} = \frac{S_{f,h}}{\bar{S}_h} \quad \forall f \in F \quad \forall h \in H \tag{30}
\]

\[
\beta_{c,h} = \frac{C_{c,h}}{\bar{C}_h} \quad \forall c \in C \quad \forall h \in H \tag{31}
\]

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 \( r \) in the climate zone \( c_r \), 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 (r), were the following: house type (h), heating fuel type (f), number of household per archetype (\( N_{h_k} \)), baseline household annual energy expenditure (\( E_{k}^{b} \)), household annual energy expenditure (\( E_{k}^{\text{b}} \)), and household annual income (\( I_{k} \)).
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 [46]. For our model, we extracted the solar productivity parameter \( \eta \) from the available average annual solar 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 \( CW_\text{Tr} \), which includes most of Detroit. The tracts considered in this study are from a data source that examines the onshore wind resource potential for the conterminous US [41]. We obtained the wind productivity coefficient \( \psi \) 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 wind productivity coefficient \( CW_\text{Tr} \) for sites suitable for wind deployment.

The average price of electricity \( (Pei) \) 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 \( \geq 30\% \) and median household energy burden \( \geq 6\% \). 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 in 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 \( (EB) \) 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 \( (T) \) and represented by 2920 household archetypes \( (K) \).

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.

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 \( (14,043 \text{ households}) \) 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 \( \Delta eb_\text{h} = 0.1 \% \) 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 \( (14,043 \text{ households}) \) 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 \( \Delta eb_\text{i} \). 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 \( \Delta eb_\text{i} = 0 \) for all households. This happens for three main reasons: first, the DER deployment can only offset the electricity costs \( (i.e. \text{it cannot decrease gas and other fuel expenditures}) \); second, DER policies are limited by the net-metering constant (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 ($\theta = \text{baseline}$). 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 $\Delta eb_{k} > 0$. Since the optimization objective is strictly focused on minimizing insecurity ($\Delta eb_{k}$), 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 $\theta$, 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 $\theta$. 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 $\theta$. As energy security becomes a priority, the distribution shifts to the left, leading to a large concentration of household energy burden around the 6% threshold for $\theta = 0.5$. The increase of $\theta$ to 1 results in the mitigation of the severe energy insecurity cases (placed
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 $\theta$, 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.
References


