Energy Equity, Infrastructure and Demographic Analysis with XAI Methods

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Abstract

Understanding the factors influencing energy consumption is crucial to address disparities in energy equity and to promote sustainable solutions. Socio-demographic characteristics can impact energy usage patterns. This study uses XAI methods, e.g. decision trees and PCC, to analyze electricity usage in multiple locales. By correlating the infrastructure and socio-demographic data with energy features, we identify housing tenure & racial demographics as vital predictors, with renters and racially diverse groups facing higher energy burdens. We demonstrate a novel energy equity web portal & energy burden calculator, offering tailored actionable advice to energy stakeholders, with good explainability. This work addresses challenges in energy policy adaptation, and aims for a next-generation framework heading more towards energy equity.

Introduction and Related Work

Energy equity tends to ensure that all locales, especially marginalized ones, have fair access to affordable energy (Fu et al. 2021). Socio-economic and demographic factors e.g. income, race, housing tenure, housing age, and disparities in infrastructure contribute to inequitable access (Simcock et al. 2021; Singh et al. 2023). Underserved communities face challenges: outdated energy infrastructure, inadequate housing, and other structural barriers, limiting access to energy efficiency programs. It exacerbates energy burdens and hinders efforts to transition to more sustainable energy systems (Drehobl et al. 2016). It calls for data-driven approaches with XAI to better inform energy policymakers. We thrive on the literature (Machlev et al. 2022), (Sim et al. 2022), (Shrestha et al. 2023), (Varde et al. 2023), where XAI methods play vital roles in energy and sustainability analysis.

Data, Models and Methods

The region of study in this paper is NJ. Datasets are sourced from NJ energy programs and US census (2008-2022) as:

- Aggregated Community-Scale Utility Energy Data
- Energy Efficiency Program Participation
- Race (Census Table B02001), Hispanic or Latino Origin (Census Table B03003), Year Structure Built (Census Table B25034), Mean Household Income of Quintiles (Census Table B19081), Household Income (Census Table B19001)

XAI models are deployed here. Decision tree classifiers are used to predict energy consumption, quantifying feature importance. Pearson's Correlation Coefficient (PCC) matrix further assesses relationships. The method used to calculate energy burden is the total amount spent on energy divided by median household income of the locale (See Eq1). E_e is annual household electricity consumption *(kWh)*, R_e is electricity rate *($/kWh)*, E_h is annual heating *(therm/BTU)*, R_h is heating rate *($/therm)*, and M_i is median household income.

$$Energy\ Burden\ (\%) = \frac{[(E_e \times R_e) + (E_h \times R_h)]}{M_i} \times 100\% \qquad (1)$$

We design & demonstrate a novel energy web portal with an energy burden calculator. It gets *user zip-code* as input, and finds energy burden (Eq1). If burden is higher than the state average, it offers clear advice with explainable action items, tailored for energy equity. It is synopsized in Algorithm 1.

Algorithm 1: Energy Burden Calculator Prototype

Input: User Zip-code *(Z_c)*, State Data *(D)*
Parameter: Z_c E_e R_e E_h R_h M_i // explained above
Output: *EB* (Energy Burden), Message, Display
Let *SA = n%* // state avg. for EB (constant)
Map (E_e,E_h) → Z_c
Get (R_e,R_h) from *D*
Compute *E-price* = E_e * R_e; *H-price* = E_h * R_h
Compute *T-price = E-price + H-price*
Compute *EB = (T-price / M_i)*100*
    if *(EB > n)* **then**
        Message = "Overburdened";
        Display = Link → {Tips to lower energy burden}
    else Message = "Below State Average";
return Print (*EB%*), Print (Message), [Display: Optional]

Results with Discussion

The results obtained with our classifier model are: *R^2=0.7, RMSE=2.5*, implying a good fit of the model to the data for prediction. It identifies housing tenure and demographics as most significant predictors of electricity consumption (See Fig.1). Renter occupied housing dominates, confirming disparities in energy infrastructure of renters vs. homeowners (Baker et al. 2019). Feature importance of Asian-Americans

(15.75%) and owned housing *(13.12%)* shows homeownership impact. PCC analysis reveals more Whites as homeowners *(r=0.93)*, African-Americans as renters *(r=0.71)*, corroborating systemic disparities in housing infrastructure (Patterson et al. 2019). Asian-Americans exhibit moderate positive correlations with new housing *(r = 0.52)* vs. other POCs, substantiating differences in energy infrastructure (Raymundo 2020). XAI analysis reveals alignment of modern infrastructure & affluence perpetuating energy inequity. Based on such results and other data, Fig. 2 has demo snapshots from the web portal & energy burden calculator.

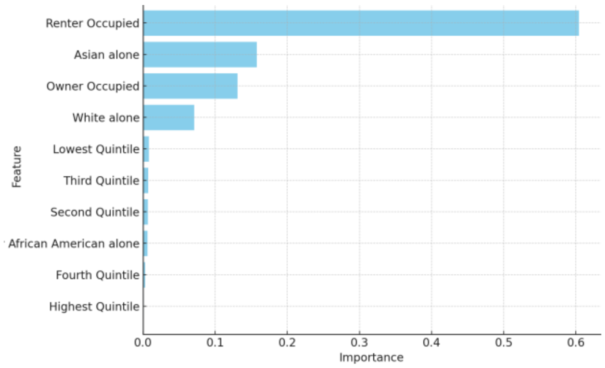

Figure 1: Feature importance learned from XAI model

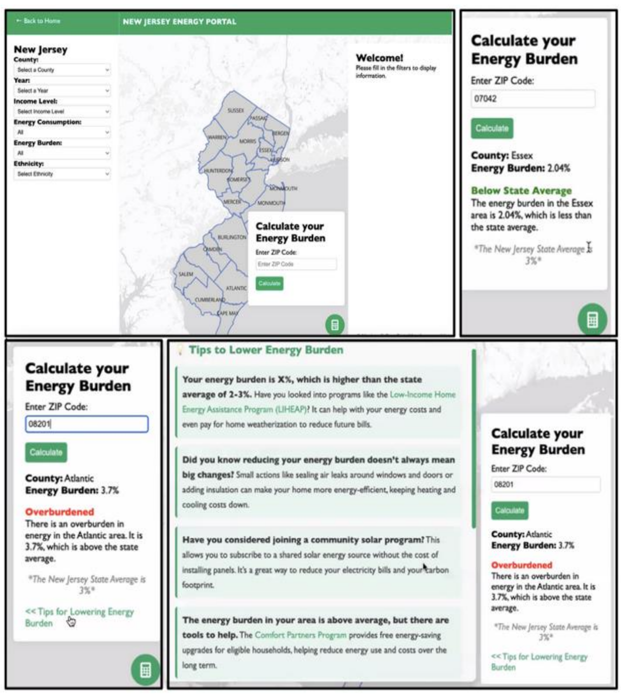

Figure 2: Energy Web Portal & Energy Burden Calculator Prototype

Conclusions

To the best of our knowledge, ours is among the first works on XAI-based energy equity analysis encompassing a novel energy web portal and energy burden calculator. It addresses crucial challenges in energy adaptation, aiming for higher energy equity, heading towards next-generation systems. Future work entails: (1) making the portal more interactive to enhance explainability; (2) macro/micro analysis with countrywide/statewide energy burden, separation of energy sources (gas, solar etc.); summer/winter, monthly/annual, finer granularity in attributes; (3) using XRRF (explainable reasonably randomized forest) to obtain more robustness & accuracy, yet offering explainable solutions; and (4) further enhancing the calculator with expected energy use analysis in targeted schemes. Note that XAI plays a vital role in making methods transparent, and fostering trust among users.

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