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Framework to select robust energy retrofit measures for residential communities

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ABSTRACT

Residential building energy retrofits are essential for enhancing environmental sustainability and reducing energy costs. The selection of retrofit measures is influenced by factors such as building systems, occupant behavior, government policy, weather variability, and climate change, all of which can significantly impact energy performance. Compared to retrofitting individual homes, evaluating and selecting optimal retrofit solutions for an entire community is challenging due to diverse residential compositions and variability present. Therefore, engineering robustness is crucial for ensuring consistent energy performance and resilience across different conditions. In this context, robustness refers to the ability of a retrofit measure to maintain its functionality and remain an optimal choice despite external disturbances or changes in inputs and conditions. This study presents a framework for evaluating the robustness of multiple retrofit measures across various building systems, occupant behaviors, and environmental scenarios at the community level. The framework comprises five key steps: scenario model development, integration of the National Residential Efficiency Measures database, energy performance simulation, cost-benefit aggregation, and retrofit solution selection. Each step enhances the framework's robustness by incorporating the diversity of building characteristics, occupant behaviors, environmental conditions, retrofit options, and evaluation criteria. The framework's effectiveness is demonstrated through a case study in southern Michigan in the United States, which includes 63 one-story single-family houses, 121 two-story single-family houses, and 8 townhouses. The study identifies furnace retrofits as the most robust solution for the entire community, consistently achieving source energy reductions of 4.7 %–8.0 % and payback period of 10–20 years across various scenarios. These findings are consistent with previous research, indicating the framework's potential for broader applications in optimizing community-scale residential energy retrofits.

1. Introduction

Buildings account for approximately 36 % of global final energy use and 39 % of energy-related greenhouse gas emissions [1]. Building energy retrofits emerge as a critical strategy for reducing source energy and protecting ecological environment [2]. In the United States, building energy retrofits have the potential to mitigate over 600 million metric tons of CO_2 annually and achieve over $1 trillion of energy savings in ten years [3]. The global green building movement, advocating for energy efficiency and low-carbon practices [4], further drives the expansion of energy retrofits and contributes to sustainable and resilient urban development.

Compared to commercial buildings, residential buildings have a greater potential of energy savings from building retrofit. Initially, commercial buildings were the primary focus of energy-efficient retrofit research due to their significant potential for energy savings, regulatory pressures, and economic incentives. Researchers have developed toolkits [5,6] and database [7] to support commercial building retrofits. Simultaneously, the burden of energy costs on 138 million U.S. households, which allocate 8–14 % of their income to energy expenses [8], underscores the importance of making housing more affordable through energy retrofits, particularly for low-income families [9]. This has led to the development of databases for energy retrofits in U.S. residential buildings [10,11]. Residential building retrofit studies have prioritized

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historical [12] and disadvantaged [13] communities, emphasizing energy efficiency improvements in these areas. It is essential to explore the energy-saving potential for retrofitting relatively new residential buildings constructed in recent decades, as future climate changes could affect their energy efficiency [14,15].

However, residential buildings exhibit a wide variety of architectural styles, designs, and systems, introducing more uncertainties than commercial buildings. This diversity, combined with varying occupancy patterns and energy usage behaviors, increases the likelihood of unexpected energy performance variations. As a result, engineering robustness is crucial for ensuring consistent energy performance and resilience in residential buildings across different conditions. The focuses of current retrofit measures are primarily on three areas: heating, ventilation, and air conditioning (HVAC) upgrades, building envelope retrofits, and appliance upgrades. Research in HVAC upgrades focuses on evaluating system performance, including operational efficiency [16] and configuration [17], alongside advancing smart technologies for central plant [18] and indoor environmental controls [19]. Research in building envelope retrofits emphasizes advanced materials—such as phase change materials for exterior facades [20,21]—as well as engineering design optimization [22,23]. Research in appliance upgrades highlights focuses on smart control systems, including energy management based on supply–demand coordination [24] and occupant behavior [24,25], alongside assessments of electrification potential [26,27]. Additionally, integrated strategies combining these three retrofit areas have been explored [28,29]. Despite significant research in energy retrofit measures for specific projects [30], the challenge remains in enhancing the robustness of these strategies so they can be more effectively applied to other projects [31]. Robustness, therefore in this context, refers to the ability of a retrofit measure to sustain its functionality and selection despite external disturbances or variability in inputs and conditions. Factors such as building features [32–34], occupant behavior [32–34], government policy [34], weather variability [33,35], and climate change [35] all impact energy performance. Therefore, robust retrofit solutions are necessary to address the unique challenges of residential buildings, ensuring long-term functionality, efficiency, and occupant comfort.

There is a critical need for evaluation methods that can assess the performance of multiple retrofit measures across a large scale of building types in communities. Studies have proposed methods to evaluate multiple measures on individual buildings—using a modeling or simulation approach [36,37]. These approaches are time-consuming, data-intensive, and difficult to scale across building clusters with varying characteristics. On the other hand, some studies focus on assessing the impact of a single retrofit measure applied to multiple building clusters [38,39], without an ability to compare the effectiveness of multiple measures. To address these limits, there is a need for evaluation methods that can assess the effectiveness of diverse retrofit measures across buildings with diverse characteristics.

This study proposes a framework for evaluating the robustness of multiple retrofit measures across various building systems, occupant behaviors, and environmental scenarios. Unlike existing research, which has primarily focused on the performance of multiple retrofit measures to individual building or single measure across different buildings, this framework examines the application of multiple retrofit measures across diverse contexts. The framework enables the identification of robust retrofit solutions that maintain consistent performance and selection under a range of operating conditions, including variety, unexpected changes and uncertainties. The outcomes of this framework identify high-efficiency retrofits that are broadly applicable across most buildings, enabling large-scale implementation of effective retrofit measures across diverse building types and settings. It also highlights key factors that significantly affect retrofit performance and selection. Buildings exhibiting these influential factors can then be targeted with tailored, optimized retrofit measures.

2. Framework development

Fig. 1 displays the five-steps process of the proposed evaluation framework which leverages the national database of National Residential Efficiency Measures (NREM) by the U.S. Department of Energy (DOE). Unlike conventional evaluation methods, this framework incorporates the consideration of weather variability, climate change, utility economics, and energy policies. The five steps in this framework are: (1) development of scenario models, (2) integration of NREM retrofit database, (3) energy performance simulations, (4) aggregation of cost and benefits, and (5) selections of retrofit solutions.

Each step serves a specific purpose to enhance the framework's robustness. Step 1 builds diverse scenario models to capture variations in building systems, occupant behaviors, and environmental conditions. Step 2 integrates a comprehensive database to provide a wide range of retrofit measures. Step 3 incorporates weather variability and climate trajectory to capture spatiotemporal variations. Step 4 ensures environmental and economic feasibility. Step 5 uses multi-criteria evaluation to assess the performance and choices of various retrofit measures across diverse scenarios, enabling the selection of robust measures. The followings detail each step.

In Step 1, data on building systems, occupant behaviors, and environmental conditions are collected from the target building scenarios. The most common parameter is selected to develop a baseline building energy model scenario that represents the majority. The second most common parameter is then used to create a control scenario, keeping other parameters consistent with the baseline. For example, in the building systems category, the most common number of floors (two floors) is used to develop the prototype building model in the baseline scenario, while the second most common number of floors (one floor) is used to create a control scenario.

The data sets for building energy modeling scenarios are stored in three formats: EnergyPlus input files (IDF), EnergyPlus weather files (EPW), and Microsoft Excel worksheets (XLSX). The IDF files contain data on building systems and occupant behaviors. The EPW files include data on the natural environment, while the XLSX files store information of utility rates and rebate.

In step 2, which is conducted in Python, information of residential retrofit measures is extracted from the NREM database (see Fig. 2 (a) for a sample code of the data extraction process). Technical data are related to retrofit measures for building envelope, HVAC systems, appliances, lighting, and water heating [40]. Table 1 provides detailed descriptions of the extracted technical data. This information is then used to modify IDF files used for energy simulations [22,41] (see Fig. 2 (b) for a sample code of the IDF modification process). Cost data of measures is extracted for financial analysis in the fourth step.

In Step 3, EnergyPlus simulations are executed using both the initial and modified IDF files in Python [22,41–43] (see Fig. 2 (c) for a sample code of the simulation execution process), exporting energy consumption data such as source energy, along with building geometry data, including living room wall area and roof area. EnergyPlus performs energy analysis by dynamically simulating heat and mass transfer within building components, calculating energy loads based on factors like weather, occupancy, and internal gains. It operates as a console-based program with high flexibility and configurability, making it easily adaptable for automated workflows in Python environments.

In Step 4, energy consumption data, building geometry data, and cost data are used to calculate evaluation indicators. The source energy reduction and payback year are then applied to rank the top three optimal retrofit options for each measure across different scenarios. Source energy reduction reflects the environmental impact of the building retrofits, while payback year assesses the financial return on investment. Using both indicators enables a comprehensive evaluation of the environmental and economic performance of the retrofit measures, directly reflecting the priorities of key stakeholders: community managers focus on overall environmental impact, while homeowners

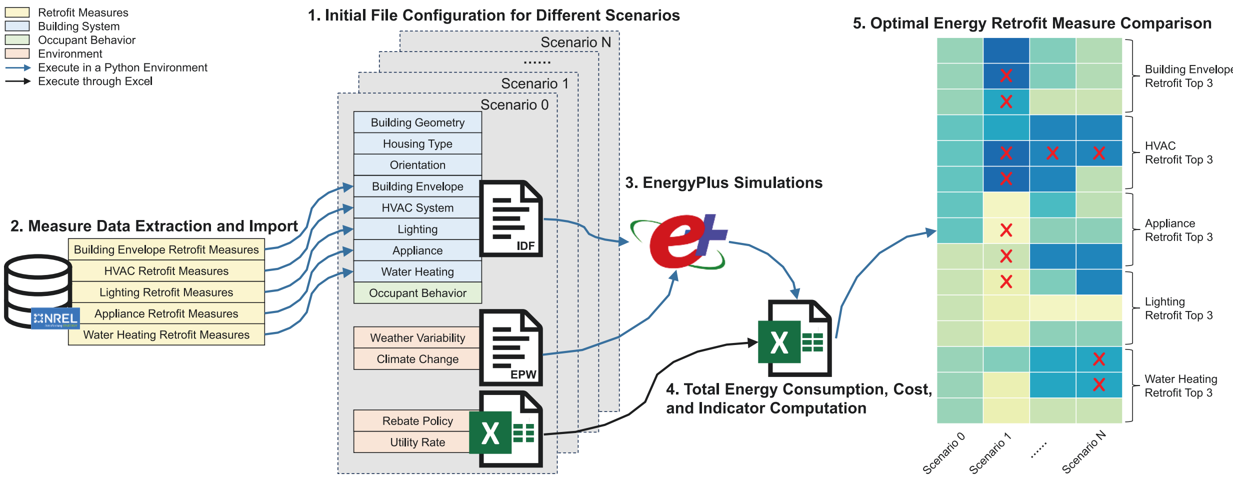

Fig. 1. Framework to analyze performance and robustness of energy retrofit.

```python
# Extract properties and average cost from XML file
def extract_properties_and_average_cost_from_measure_id(xml_string, measure_id):
    root = ET.fromstring(xml_string)
    measure = root.find(f".//measure[@id='{measure_id}']")
    if measure is None:
        return {}, None
    properties = {}
    average_cost = None

    # Extract properties
    component_after = measure.find(".//component[component_startfinish='after']")
    if component_after is not None:
        for property_ in component_after.findall("properties/property"):
            property_type_id = property_.find("property_type").attrib.get("id")
            property_value_element = property_.find("property_value")
            if property_value_element is not None and property_value_element.text:
                property_value = float(property_value_element.text)
                if property_type_id == "74":
                    properties["Solar Absorptivity"] = property_value
                elif property_type_id == "144":
                    properties["Conductivity"] = property_value * 0.1441
                elif property_type_id == "145":
                    properties["Density"] = property_value * 16.018
                elif property_type_id == "146":
                    properties["Specific Heat"] = property_value * 4186.8
                elif property_type_id == "708":
                    properties["Thickness"] = property_value * 0.0254

    # Extract average cost
    cost_element = measure.find(".//costs/cost/cost_average_value")
    if cost_element is not None and cost_element.text:
        average_cost = float(cost_element.text) * 10.764
    return properties, average_cost
```

(a)

```python
# Modify IDF file with new material properties
def modify_idf_with_new_material(idf_file_path, properties, measure_id):
    IDF.setiddname("C:/EnergyPlusV23-1-0/Energy+.idd")
    idf = IDF(idf_file_path)

    # Add new material
    material = idf.newidfobject("MATERIAL")
    material.Name = f"NewMaterial_{measure_id}"
    material.Roughness = "MediumRough"
    material.Thickness = properties.get("Thickness")
    material.Conductivity = properties.get("Conductivity")
    material.Density = properties.get("Density")
    material.Specific_Heat = properties.get("Specific Heat")
    material.Solar_Absorptance = properties.get("Solar Absorptivity")

    # Replace wall exterior finish material with the new material
    constructions = [obj for obj in idf.idfobjects["CONSTRUCTION"]]
    extwall = next((c for c in constructions if c.Name == "EXTWALL:LIVING"), None)
    extwall.Outside_Layer = material.Name

    # Save the modified IDF file
    modified_idf_path = f"C:/NREM/Modified/S0_{measure_id}.idf"
    idf.save(modified_idf_path)
    return modified_idf_path
```

(b)

```python
# Run an EnergyPlus simulation
def run_energyplus_simulation(idf_path, output_directory):
    energyplus_executable = "C:/EnergyPlusV23-1-0/energyplus.exe"
    weather_file = "C:/NREM/Weather/Lansing_725390_TMY3.epw"
    os.makedirs(output_directory, exist_ok=True)

    # Construct the command to run the simulation
    command = [
        energyplus_executable,
        "-w", weather_file,
        "-d", output_directory,
        "-r",  # The -r flag runs the simulation
        idf_path
    ]

    # Execute command and handle errors
    try:
        subprocess.run(command, check=True)
    except subprocess.CalledProcessError as e:
        print(f"EnergyPlus simulation failed: {e}")
```

(c)

(a) Function for extracting wall exterior finish properties and pricing from the NREM database.

(b) Function for replacing baseline wall exterior finish in IDF file.

(c) Function for running EnergyPlus simulations.

Fig. 2. Sample Python codes.

Table 1
Extracted technical data of objects in the NREM database.

Building System	Technical Data	Application	Description
Envelope	R-value	Wall, roof, and floor	The measure of material's resistance to heat flow.
	Solar Absorptivity	Wall and roof	The ratio of solar energy absorbed by a surface to the total solar energy incident upon it.
	Conductivity	Wall and roof	The rate at which heat passes through a material.
	Specific Heat	Wall and roof	The amount of heat per unit mass required to raise the temperature by one degree Celsius.
	Density	Wall and roof	The mass per unit volume of a material.
	Thickness	Wall and roof	The measure of how thick a material is.
	U-value	Window	The measure of the rate of heat loss through a material.
	SHGC (Solar Heat Gain Coefficient)	Window	The fraction of incoming solar radiation that passes through a window.
HVAC	SEER (Seasonal Energy Efficiency Ratio)	Air conditioner and heat pump	The measure of cooling efficiency over a seasonal average.
	EER (Energy Efficiency Ratio)	Air conditioner and heat pump	The measure of how efficiently a cooling system will operate when the outdoor temperature is at a specific level.
	HSPF (Heating Seasonal Performance Factor)	Heat pump	The metric for measuring the heating efficiency over a heating season.
	COP (Coefficient of Performance)	Heat pump	The ratio of heating or cooling provided to electrical energy consumed.
	AFUE (Annual Fuel Utilization Efficiency)	Furnace, boiler, and direct heater	The percentage measure of heating efficiency.
	Fuel Type	Furnace, boiler, and direct heater	The type of fuel used by a heating system.
Appliance	Rated Annual Consumption	Refrigerator and dishwasher	The total energy consumption expected from the appliance over a year.
	Energy Factor	Clothes washer	The ratio of the appliance's operational efficiency to its energy consumption under standard usage conditions.
	Machine Energy	Clothes dryer	The direct energy consumption of the appliance during its operation.
	Drying Energy	Clothes dryer	The energy consumption during the drying process in appliances.
	Cooktop Energy Factor	Cooking range	The measure of how efficiently a cooktop converts energy into heat for cooking under standard usage conditions.
	Fuel Type	Clothes dryer and cooking range	The type of fuel used by appliances.
Water Heating	Rated Energy Factor	Water heater	The measure of the water heater's overall efficiency based on the amount of hot water produced per unit of fuel consumed over a typical day.
	Fuel Type	Water heater	The type of fuel used by water heater.
Lighting	Luminous Efficacy	Light bulb	The ratio of the emitted luminous flux to the power consumed.

prioritize personal investment returns. The source energy reduction and payback year is calculated using Equations (1) and (2).

$$R_{total} = \frac{E_{initial} - E_{post}}{E_{initial}} \times 100\% \tag{1}$$

where R_{total} is source energy reduction, E_{initial} is initial source energy, and E_{post} is post-retrofit source energy.

$$P = \frac{C_{initial}}{\left(E_{initial\_elec} - E_{post\_elec}\right) \times C_{elec} + \left(E_{initial\_fuel} - E_{post\_fuel}\right) \times C_{fuel}} \tag{2}$$

where P is payback year, C_{initial} is initial investment cost, $E_{\text{initial\_elec}}$ is initial annual electricity use, $E_{\text{post\_elec}}$ is post-retrofit annual electricity use, C_{elec} is electricity bill, $E_{\text{initial\_fuel}}$ is initial annual fuel use, $E_{\text{post\_fuel}}$ is post-retrofit annual fuel use, C_{fuel} is fuel bill.

In Step 5, the values of source energy reduction and payback year for various top three retrofit measures under different scenarios are used to generate heatmaps for each evaluation indicator. Additionally, the top three retrofit choices for each scenario are recorded, with crosses marking differences from the baseline scenario. This cross-marked heatmap provides a clear visualization of both the variation in retrofit effectiveness and the shifts in retrofit choices across different scenarios.

3. Case study for framework demonstration

The case study was conducted at a residential neighborhood in Lansing area, Michigan, located in Climate Zone 5, characterized by cold winter and warm summer. The area comprises 63 one-story single-family houses, 121 two-story single-family houses, and 8 townhouses, each with four units. These houses were constructed between 2006 and 2023. Data from the International Residential Code (IRC), Google Maps, BS&A Online, Zillow, and International Energy Conservation Code (IECC) prototype building model were used to model three building prototypes that represent the most prevalent characteristics within the community. The geometric models were developed using 3D models from Google Maps, geometric data from BS&A Online, and architectural drawings from Zillow. The thermal models were built based on IRC requirements for the corresponding construction years, along with material data from Zillow and parameters from the IECC prototype building model. The HVAC system configurations were identified based on the system descriptions from BS&A Online and Zillow. These configurations were then modeled based on the IECC prototype building models with the same HVAC system configurations. Specific HVAC system parameters were determined using HVAC sizing function in EnergyPlus. These prototypes were built in OpenStudio (Fig. 3) and converted into IDF format for simulations under different scenarios. EPW files were downloaded from the EnergyPlus official website. Appliance energy efficiency data was collected from the NREM database, and occupant behaviors were referred to IECC prototype building model. Other data, like rebate policies and future weather data, will be detailed in the scenario descriptions. The electricity rate used in this case study is \$0.17/kWh, while the gas rate is \$0.43/m^3, based on local utility provider pricing. The site-to-source energy conversion factors, 3.167 for electricity and 1.084 for natural gas, are default values in EnergyPlus. These conversion factors are designed to represent the complete energy

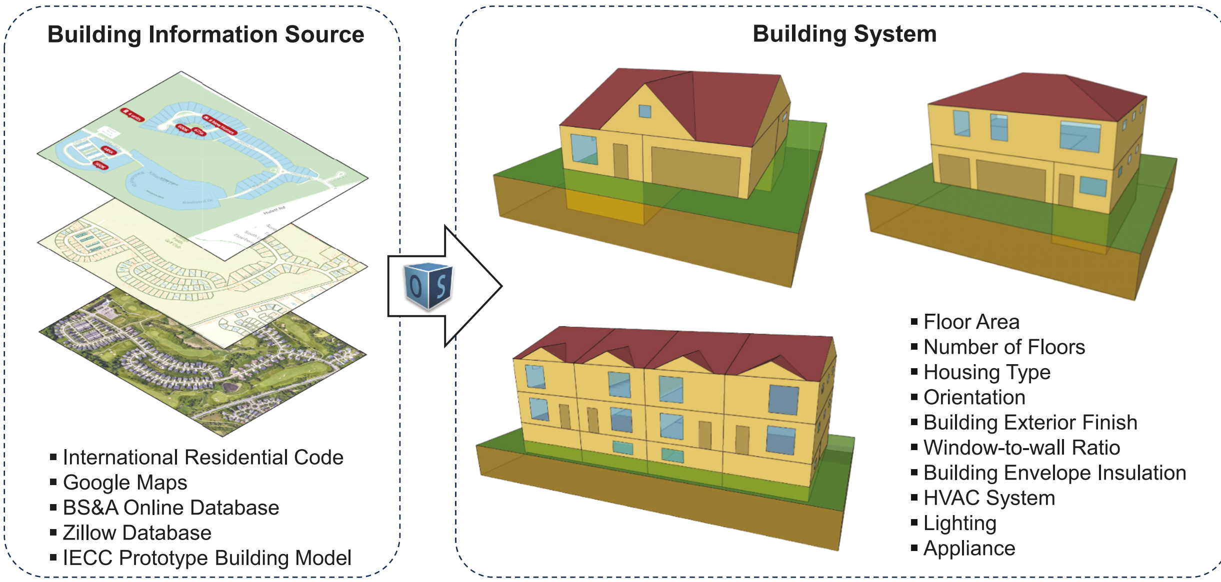

Fig. 3. Workflow to build building prototypes.

cycle, accounting for generation, transmission, and distribution losses associated with delivering energy from the source to the site.

3.1. Scenario development

The baseline scenario (S0) for this study uses the most common house type: the two-story single-family house built in 2016. The model house faces south with a footprint of 115.66 m^2 and a garage area of 59.46 m^2, representing the median areas for the 121 two-story single-family houses. The building's total floor area is 287.52 m^2, with a living area of 228.06 m^2, including the basement living area. All floors have a height of 2.74 m. The window-to-wall ratio is 15 %. The exterior walls are finished with light vinyl, and the roof is covered with light asphalt shingles. The building envelope insulation meets the 2015 IRC minimum requirements, and appliances comply with the Federal Standard 2010 requirements as recorded in the NREM database. The luminous efficacy of lighting is 45 lm/W. The house is occupied by three residents who do not open the window. The thermostat setpoint is set to 24 °C for cooling and 22 °C for heating. The power levels and schedules of appliances and lighting were referred to in the settings in IECC prototype building models.

14 control scenarios were examined to explore the effects of three major factors—building system, occupant behavior, and environment—on retrofit measures. Tested building system factors include floor area, number of floors, housing type, orientation, exterior finish, window-to-wall ratio, and energy efficiency. In the "floor area" scenario (S1), the building footprint increases by 25 %, and the conditioned floor area increases by 35 % compared to the baseline scenario (S0). In the "number of floors" scenario (S2), the building is single-story with no change in floor area. In the "housing type" scenario (S3), the building is a four-family townhouse, with the footprint increasing by 157 % and the conditioned floor area by 206 % compared to the baseline scenario (S0). In the "orientation" scenario (S4), the building faces west. In the "exterior finish" scenario (S5), the exterior walls are finished with dark vinyl, and the roof is covered with dark asphalt shingles. In the "window-to-wall ratio" scenario (S6), the ratio is 10 %. In the "energy efficiency" scenario (S7), the building envelope insulation meets the 2006 IRC minimum requirements, and appliances comply with the federal standards from 2001 to 2010 as recorded in the NREM database.

Tested occupant behavior factors include appliance usage, window opening behavior, and thermostat settings. In the "appliance usage" scenario (S8), the use of the dishwasher, clothes washer, and clothes dryer doubles, and hot water usage also doubles. In the "window opening behavior" scenario (S9), windows are opened to 1/3 of their total area. In the "thermostat settings" scenario (S10), the cooling setpoint is 26 °C, and the heating setpoint is 20 °C.

Environment factors refer to political and natural environment factors, including rebate policies, utility rates, location, and global warming. In the "policy" scenario (S11), a rebate policy, encompassing Home Efficiency Rebates (Section 50121) and Home Electrification and Appliance Rebates (Section 50122) of the Inflation Reduction Act (IRA) [44], is implemented. This policy provides rebates for energy-saving measures that meet efficiency requirements. In the "utility rates" scenario (S12), utility rates increase 5 % per year. In the "location" scenario (S13), the site is moved to Des Moines, Iowa, which is in the same climate zone as the baseline scenario (S0) but has higher summer temperatures and more solar radiation year-round. In the "global warming" scenario (S14), CNRM-ESM2-1 Future Typical Meteorological Year (fTMY) weather file for Des Moines from 2040 to 2059 [45] is used. Because future climate data for Lansing is unavailable, Des Moines' future climate data is used instead. The "global warming" scenario (S14) is compared to the "location" scenario (S13) rather than the baseline scenario (S0). Table 2 presents the parameters of the baseline scenario (S0) and modified parameters for the 14 control scenarios.

3.2. Retrofit measures and evaluations

The tested retrofit measures involve the retrofitting for building envelope, HVAC, appliance, lighting, and water heating. Building envelope measures include retrofitting wall exterior finish, roof exterior finish, roof insulation, windows, wall sheathing, and wall wood studs. HVAC measures involve upgrading the air conditioner, furnace, and installing heat pump. Appliance measures include upgrading refrigerator, dishwasher, clothes washer, clothes dryer, and cooking range. Lighting measures involve upgrading light bulbs. Water heating measures include upgrading to a more energy-efficient water heater or one that utilizes a different energy source.

Two evaluation indicators were selected in this study. Source energy reduction percentage is used to evaluate the environmental benefits of retrofit, while payback year is used to assess the cost-effectiveness of retrofit measure by considering the investment and site energy cost savings.

Table 2
Baseline and modified parameters for different scenarios.

Category	Parameter	Baseline value	Modified value
Building System	Footprint [m^2]	115.66	S1:144.58 S3:297.28
	Conditioned Floor Area [m^2]	234.58	S1: 316.68 S3: 717.21
	Number of Floors	2	S2: 1
	Housing Type	Two-story Single Family House	S2: One-story Single Family House S3: Four-unit Townhome
	Orientation	South	S4: West
	Exterior Finish	Wall Light Vinyl/ Roof Light Asphalt Shingles	S5: Wall Dark Vinyl/Roof Dark Asphalt Shingles
	Window-to-wall Ratio	15 %	S6: 10 %
	Vintage	2016	S7: 2006
	Window U-value [W/(m^2·K)]	1.82	S7: 1.99
	Door U-value [W/(m^2·K)]	2.84	–
	Floor R-value [m^2·K/W]	5.28	–
	Ceiling R-value [m^2·K/W]	8.63	S7: 6.69
	Basement Wall R-value [m^2·K/W]	2.64	S7: 1.76
	Wall R-value [m^2·K/W]	3.52	S7: 3.35
	Air Conditioner COP	3	S7: 3
	Furnace AFUE	80 %	S7: 78 %
	Refrigerator Energy Factor [m^3/kWh]	0.45	–
	Dishwasher Rated Annual Consumption [kWh]	324	S7: 474
	Clothes Washer Modified Energy Factor [m^3/kWh-cycle]	3.57×10^{-2}	S7: 1.44×10^{-2}
	Clothes dryer Drying Energy [kWh/load] / Machine Energy [kWh/load]	3.81 / 0.23	–
	Water Heater Rated Energy Factor	0.82	–
	Lighting [lm/W]	45	S7: 15
Occupant Behaviors	Appliance Usage	Power level and schedule based on IECC prototype model	S8: Double the power level
	Window Opening Behavior	No	S9: Yes
	Thermostat Settings	Cooling 24℃ / Heating 22℃	S10: Cooling 26℃ / Heating 20℃
Environment	Rebate Policy	No	S11: Yes
	Utility Rate	No change every year	S12: Increase 5 % per year
	Weather Variability	Lansing, MI	S13: Des Moines, IA
	Climate Change	Lansing 1973–2005 Historical Weather File	S13: Des Moines 1973–2005 Historical Weather File S14: Des Moines 2040–2059 Futural Weather File

3.3. Results by source energy reduction

Fig. 4 overviews the source energy reductions by retrofit measures across different scenarios. The horizontal axis indicates scenarios where S0 serves as the reference for evaluating S1–13 and S13 serves as the reference for S14. The vertical axis indicates the retrofit subjects with a sequence number assigned to rank the source energy reduction. For example, "Wall sheathing 1" represents the specific wall sheathing retrofit measure with the greatest source energy reduction; "Window 3" represents the window retrofit measure with the third most optimal source energy reduction. Most retrofit measures display the top three options, but some measures yield fewer savings than the three, thus only providing the rank for the available options. The color bar on the right side of the heatmap transitions from light yellow to deep blue, correspondingly signifying the source energy reduction percentage from 0 % to 10 %. The grey diagonal stripes indicate that the retrofit measure applied in the scenario is not able to reduce source energy. Crosses within certain cells indicate that the retrofit measures corresponding to those cells are different from those in the baseline S0 scenario. For example, the cross in the cell corresponding to "window 1" retrofit measures under "number of floors" (S2) scenario means that the optimal window retrofit measure in this scenario differs from the baseline scenario (S0).

Overall, the results indicate that furnace retrofit has outstanding performance and robustness. The performance only slightly decreases in "appliance usage" (S8) and "global warming" (S14), but it still surpasses other retrofit measures. There is no significant difference in performance among the top three furnace retrofit measures, and the retrofit selection remains consistent across different scenarios.

3.3.1. Robustness of retrofit measures by source energy reduction

For building envelope retrofits, the top three measures for wall exterior finish and roof exterior finish have very limited and similar energy savings. Their rankings, based on source energy reduction capacity, are easily influenced by building system, occupant behavior, and environmental factors. Additionally, the top three window retrofit choices are highly susceptible to various factors: in building systems, all factors except floor area (S1) affect the top three choices. Among occupant behavior factors, both appliance usage (S8) and window opening behavior (S9) influence the top three window retrofit options. In environmental factors, global warming (S14) impacts the selection of the top three window retrofits. Other retrofit measures' top three choices remain unaffected by changes in building system, occupant behavior, and environmental factors.

In building systems, the number of floors (S2) and window-to-wall ratio (S6) significantly influence the energy reduction performance of building envelope retrofits. Housing type (S3) and energy efficiency (S7) notably impact the performance of retrofits across building envelope, HVAC, and appliances. Among occupant behavior factors, appliance usage (S8) and window opening behavior (S9) significantly affect energy reduction in building envelope, HVAC, and appliance retrofits. Environmental factors such as location and global warming notably influence the energy reduction performance of HVAC upgrades.

3.3.2. Performance of retrofit measures by source energy reduction

In building envelope retrofits, the impact of upgrading wall exterior finish, roof exterior finish, and roof insulation on source energy is negligible, with a maximum reduction of 1.5 % across all scenarios. Optimal window retrofits can achieve reductions of 1.6 % to 4.6 %, with the smallest reduction in the "number of floors" (S2) and the largest in the "orientation" (S4). Wall sheathing upgrades can lower source energy by 0.5 % to 3.9 %, with the minimal reduction in the "number of floors" (S2) and the maximum in the "window-to-wall ratio" (S6). Among building envelope measures, wall wood stud retrofits are the most efficient, reducing source energy by 3.0 % to 4.0 % in the "housing type" (S3), "appliance usage" (S8), and "window opening behavior" (S9), and

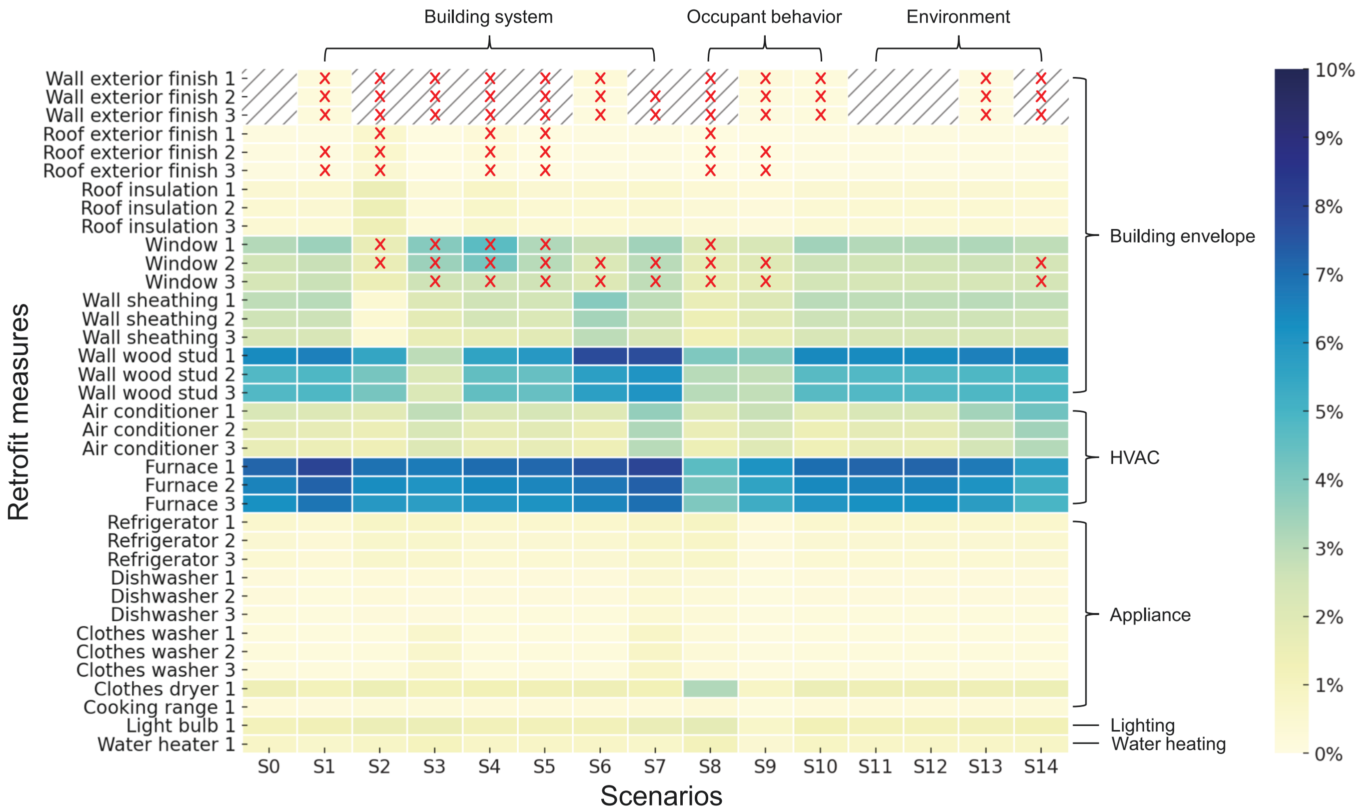

Fig. 4. Source energy reduction heatmap. (Grey diagonal stripes indicate the retrofit measure does not reduce energy and red crosses show selection differences from the baseline S0). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

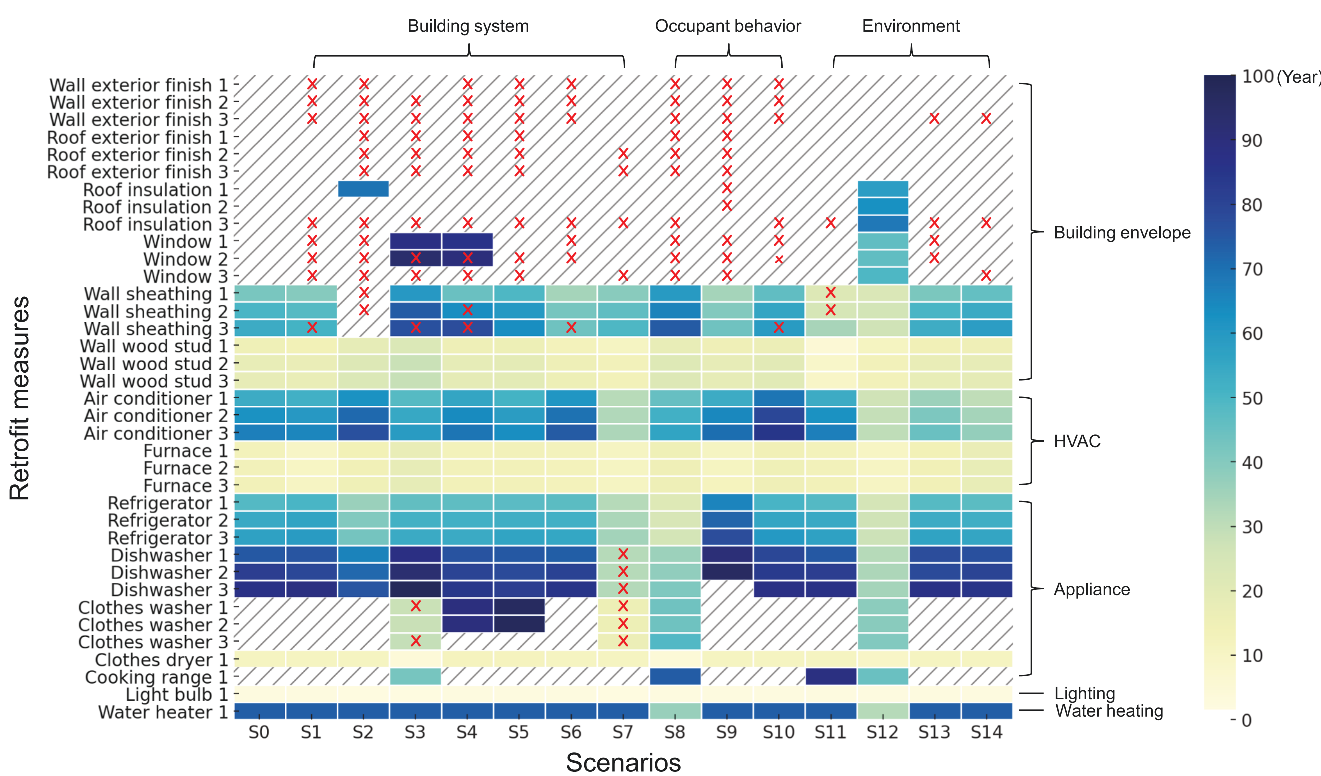

Fig. 5. Payback year heatmap. (Grey diagonal stripes indicate that the retrofit measure has a payback year exceeding a century and red crosses show selection differences from the baseline S0). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

achieving reductions of 5.5 % to 7.7 % in other scenarios.

In HVAC upgrades, furnace upgrades are more effective than air conditioner improvements. Optimal air conditioner retrofits can save 1.9 % to 4.3 % of source energy, with the lowest reduction in the "number of floors" (S2) and the highest in the "global warming" (S14). Optimal furnace retrofits can reduce source energy by up to 8.0 %, with the highest savings in the "floor area" (S1) and "energy efficiency" (S7), and the lowest at 4.7 % in the "appliance usage" (S8).

In appliance upgrades, only the clothes dryer measures achieve notable source energy reductions. Other measures reduce energy by less than 1.0 %. Clothes dryer upgrades can save up to 3.2 % in the "appliance usage" (S8). Upgrades to light bulbs and water heaters have limited impact, reducing energy by no more than 2.0 %.

For retrofit measures with negligible energy savings, the top three options exhibit only slight differences in energy reduction. For measures with slight energy savings: the top three window retrofit options differ by up to 2.0 %, the top three wall sheathing retrofit options differ by less than 1.0 %, and the top three air conditioner retrofit options differ by up to 1.0 %. For measures with moderate energy savings: the top three wall wood stud retrofit options differ by up to 1.7 %, and top three furnace retrofit options by up to 1.1 %. For clothes dryer, cooking range, light bulb, and water heater retrofits, there is only one option available that achieves energy savings.

3.4. Results by payback year

Fig. 5 overviews the payback year by retrofit measures across different scenarios. The color bar on the right side of the heatmap transitions from light yellow to deep blue, correspondingly signifying the payback year from 0 to 100 years. The grey diagonal stripes indicate that the retrofit measure has a payback year exceeding a century. Other aspects of the payback year heatmap (Fig. 5) are identical to those of the source energy reduction heatmap (Fig. 4).

Overall, the results indicate that light bulb upgrading demonstrates optimal performance and robustness in payback year. Additionally, the retrofit measures for the clothes dryer, furnace, and wall wood stud also show acceptable performance with the payback year less than 20 years mostly. The retrofit selections remain consistent across all scenarios.

3.4.1. Robustness of retrofit measures by payback year

All factors except utility rates in Scenario 12 impact the top three options of building envelope retrofits. Housing type in Scenario 3 and energy efficiency in Scenario 7 affect the top three options of appliance upgrades. The top three options for wall wood stud retrofit, HVAC upgrade, and refrigerator upgrade are unaffected by building systems, occupant behavior, or environmental factors.

Several factors within the building system influence the payback year of various upgrades. Specifically, the number of floors (S2), housing type (S3), and energy efficiency (S7) slightly affect the financial return period for building envelope retrofits, HVAC upgrades, and appliance upgrades. Occupant behavior and environmental factors also play significant roles. For building envelope retrofits, the payback year is influenced by appliance usage (S8), rebate policy (S11), and utility rates (S12). For HVAC upgrades, the payback year is affected by appliance usage (S8), thermostat settings (S10), utility rates (S12), location (S13), and global warming (S14). Appliance usage (S8), window opening behavior (S9), and utility rates (S12) impact the payback year of appliance upgrades. Finally, appliance usage (S8) and utility rates (S12) influence the payback year of water heater replacements.

3.4.2. Performance of retrofit measures by payback year

In building envelope retrofit measures, retrofitting wall exterior finish, roof exterior finish, and roof insulation rarely pay back within a century in most scenarios. However, roof insulation pays back in 70 years in the "number of floors" (S2) and in 58 years in the "utility rates" (S12). Retrofitting windows only proves financially viable in the "housing type" (S3), "orientation" (S4), and "utility rates" (S12), with a minimum payback of 88, 86, and 46 years, respectively. Optimal wall sheathing retrofit payback years vary by scenario. Paybacks of 40–50 years in the "floor area" (S1), "orientation" (S4), "exterior finish" (S5), "thermostat settings" (S10), "location" (S13), and "global warming" (S14) are similar to the baseline (S0). The "housing type" (S3) and "appliance usage" (S8) increase payback to 60 years, while the "number of floors" (S2) exceeds a century. The "window-to-wall ratio" (S6) and "window opening behavior" (S9) have a payback of 34 years, whereas the "rebate policy" (S11) and "utility rates" (S12) lower it to 22 years. In most scenarios, optimal wall wood stud retrofits have 10–20 year s of payback. This is 23 years in the "housing type" (S3) and five years in the "rebate policy" (S11).

In HVAC upgrades, the payback years for optimal air conditioner improvements vary by scenarios. In the "floor area" (S1), "orientation" (S4), "exterior finish" (S5), "window opening behavior" (S9), and "rebate policy" (S11), paybacks are around 50–60 years, similar to the baseline (S0). In the "number of floors" (S2), "housing type" (S6), and "thermostat settings" (S10), they extend to 60–70 years. Conversely, in the "housing type" (S3) and "appliance usage" (S8), paybacks shorten to 40–50 years, and in the "energy efficiency" (S7), "location" (S13), and "global warming" (S14), they reduce further to 30–40 years. The shortest payback is 27 years in the "utility rates" (S12). Furnace improvement in all scenarios has 10–20 year s of payback.

In appliance upgrades, payback years vary significantly across scenarios. Typically, optimal upgrades for refrigerators, dishwashers, and clothes dryers have payback years of 46–50 years, 74–79 years, and 11 years, respectively. In most scenarios, the payback for clothes washers and cooking ranges exceeds a century. In the "number of floors" (S2) and "energy efficiency" (S7), paybacks for refrigerators and dishwashers shorten to 36 and 66 years. In the "housing type" (S3), the payback for dishwashers extends to 88 years, while paybacks for clothes washers, clothes dryers, and cooking ranges shorten to 28, 4, and 43 years. In the "energy efficiency" (S7), paybacks reduce to 32 years for refrigerators, 32 years for dishwashers, and 16 years for clothes washers. In the "appliance usage" (S8), paybacks shorten to 22 years for refrigerators, 36 years for dishwashers, 44 years for clothes washers, four years for clothes dryers, and 74 years for cooking ranges. The "window opening behavior" (S9) extends paybacks to 65 years for refrigerators and 91 years for dishwashers. Under the "utility rates" (S12), paybacks shorten to 25 years for refrigerators, 32 years for dishwashers, 39 years for clothes washers, nine years for clothes dryers, and 45 years for cooking ranges.

Replacing light bulbs offers a payback of less than two years across all scenarios. Water heater retrofits generally have a 74-year payback, except for 37 years in the "appliance usage" (S8) and 32 years in the "utility rates" (S12).

The top three retrofit measures show significant differences in payback year. Wall sheathing, refrigerator, and dishwasher retrofits have a gap of up to 13 years, while air conditioner retrofits exhibit the largest gap of up to 17 years. Wall wood stud retrofits have a smaller gap of up to five years. Furnace retrofits have the smallest gap in one year. Clothes washer retrofits have a gap of up to two years. These variances emphasize the need to carefully choose retrofit options for optimal economic and energy-saving outcomes.

3.5. Summary of case findings

Table 3 shows the number of identical top three measures selected across S0–S14 using different indicators. The top three choices for air conditioner, furnace, and refrigerator remain consistent across different indicators. For dishwasher upgrades, the top three choices vary by indicator only in the "energy efficiency" (S7), while remaining uniform across indicators in all other scenarios. For clothes dryer, cooking range, light bulb, and water heater retrofits, when keeping other parameters constant (e.g., maintaining the same capacity for clothes dryers and the

Table 3
Number of identical retrofit measures selected across the 15 scenarios using different indicators.

Category	Retrofit object	Number
Envelope	Wall exterior finish	1
	Roof exterior finish	0
	Roof insulation	0
	Window	2
	Wall sheathing	0
	Wall wood stud	0
HVAC	Air conditioner	15
	Furnace	15
Appliance	Refrigerator	15
	Dishwasher	14
	Clothes washer	0
	Clothes dryer	15
	Cooking range	15
Lighting	Light bulb	15
Water heating	Water heater	15

same fuel type for cooking ranges), there is typically only one upgrade option available, with no alternative choices. For building envelope retrofit measures, the top three choices differ by indicator within the same scenarios.

For source energy reduction, wall wood stud and furnace retrofits outperform others, with furnace retrofits showing smaller differences across the top three options and greater consistency across scenarios. For payback year, light bulb upgrades show optimal performance and robustness, while clothes dryer, furnace, and wall wood stud retrofits also perform well, with satisfactory payback periods and consistent results across scenarios. Additionally, the top three choices for air conditioner, furnace, and refrigerator remain consistent across different indicators. The furnace retrofit stands out as the most effective and robust measure, simultaneously achieving exceptional source energy reduction, an acceptable payback year, and stable performance with consistent selection across various scenarios.

4. Discussions

4.1. Implications for framework application

This framework utilizes retrofit data from the NREM database, while other research often relies on retrofit measures derived from various local retrofit projects, market analyses, government laws, and building codes [46,47]. The advantage of using NREM data lies in its integration of multiple DOE databases into a unified, national resource. This integration provides a consistently updated and expanded repository of performance parameters and costs for residential retrofit technologies, ensuring a comprehensive, standardized dataset that enhances the reproducibility and scalability of research findings.

Recent research exploring optimal building retrofit solutions has considered occupant factors, such as optimizing retrofit plans to minimize thermal discomfort [48] and evaluating the performance of retrofit measures under stochastic human behavior [49]. These studies have typically used occupant factors as one of the criteria for selecting optimal retrofit measures or as a parameter in building energy modeling. Our study delves more specifically into how occupant behavior influences the selection and performance of optimal retrofit measures, highlighting the importance of incorporating behavioral patterns into the decision-making process for building retrofits.

Recent research has shown that global warming impacts the selection of optimal building envelope retrofit measures [50], aligning with the conclusions of this case study. Additionally, Ascione et al. indicate that climate change has a slighter effect on total energy and financial indicators than expected due to a balance between its positive impact on heating demand and negative impact on cooling demand [49]. In this study, comparisons between “location” (S13) and “global warming” (S14) reveal that with global warming, air conditioner retrofits become more efficient, while furnace retrofits become less efficient. This is because increased cooling demand makes air conditioner retrofits more effective in reducing energy consumption, whereas decreased heating demand makes furnace retrofits less effective. Other retrofit measures remain largely unchanged in efficiency, as the overall energy demand remains stable, keeping their energy reduction contributions consistent.

When comparing the selection and performance of various retrofit measures across different scenarios, using a modified heatmap effectively showcases the selection variability and performance difference of each measure across different scenarios. Additionally, it clearly illustrates the influence of each factor within a scenario on the performance of different retrofit measures. This method facilitates a nuanced insight of the performance and robustness of retrofit measures, assessing their broad applicability across diverse scenarios.

This framework has limitations due to the absence of renewable energy retrofit data, such as installing photovoltaic (PV) panels, in the NREM database. As a result, the assessment of energy conservation and investment potential for retrofit measures may be understated. For instance, the environmental and economic benefits of heat pumps could be underestimated if the electricity used is generated from fossil fuels.

4.2. Implications for energy retrofit practices

4.2.1. Retrofit robustness

When evaluating the source energy reduction performance and payback year of energy retrofits, housing type, energy efficiency, and appliance usage emerge as the most influential factors. These three parameters can be used as primary criteria for categorizing buildings in large-scale retrofit assessments. Housing type affects the thermal dynamics and energy usage patterns of a building, impacting the effectiveness of retrofits across various categories such as building envelope, HVAC, appliances, lighting, and water heating. Similarly, the vintage of a building reflects its inherent energy efficiency, with older buildings typically having poorer insulation and outdated systems that benefit more from upgrades. Appliance usage affects the overall energy demand, thereby influencing the relative impact of different retrofit measures. For example, in buildings with high appliance usage, the energy savings from appliance upgrades are more significant, making these upgrades more cost-effective compared to other measures such as building envelope and HVAC retrofits. Conversely, in buildings with low appliance usage, the potential for energy savings from appliance upgrades is smaller, and other measures like improving insulation or upgrading HVAC systems may offer more substantial benefits. Therefore, considering housing type, vintage, and appliance usage is crucial for accurately assessing the potential source energy reductions and financial viability of different retrofit measures.

The optimal choices for building envelope retrofit measures are more susceptible to change across different scenarios compared to HVAC, appliance, lighting, water heating retrofits. Building system factors significantly impact a building’s thermal performance then shifting the optimal solutions of building envelope retrofit. For example, building orientation influences the solar radiation transferred through windows. To maintain indoor thermal comfort, solar radiation should stay within certain levels. Different orientations require different windows with corresponding Solar Heat Gain Coefficient (SHGC) values to achieve the same comfort level. Thus, the window choices differ when building orientation changes. Additionally, building system factors directly influence building envelope retrofit costs. For example, a larger window-to-wall ratio increases window area, requiring more investment and affecting the payback year of window retrofits.

Occupant behavior and environmental factors can significantly impact the optimal choices for building envelope retrofits. For example, frequent use of appliances increases internal heat gains, which can diminish the benefits of higher-grade insulation. Investing in higher levels of insulation might be less prioritized because retaining more heat could lead to overheating. Instead, it may be more cost-effective to focus on moderate insulation levels that balance heat retention and dissipation. Similarly, in hot climates, excessive insulation can trap unwanted heat, leading to overheating, so less insulation might be more appropriate. Thus, the optimal choice of insulation varies depending on the environmental conditions.

4.2.2. Retrofit performance

The modifications to the wall and roof exterior finishes, as well as the upgrades to roof insulation, do not significantly reduce source energy. These investments are not cost-effective. In the prototype building, the attic is unconditioned. The unconditioned attic limits the impact of improved roof insulation on the overall thermal performance of the building. The wall exterior finish is light vinyl, and the roof finish is light asphalt shingles. The lack of noticeable source energy reduction may be due to the light materials used, which already have reflective properties that minimize heat absorption. Consequently, these retrofits offer marginal improvement over the existing setup, making the investment challenging to rationalize.

Window retrofits reduce source energy in most cases, particularly in scenarios with shared walls or specific building orientations. In buildings with shared walls, heat loss is reduced, amplifying the impact of window retrofits and accelerating payback. In west-facing buildings, the greater solar heat gain compared to south-facing ones enhances the efficiency of window retrofits and shortens the payback year.

Improving the insulation of wall wood studs reduces more source energy and results in a shorter payback year compared to enhancing wall sheathing insulation. Both measures benefit from rebate policies and increased utility rates, which can shorten their payback years. The source energy reduction performance and investment payback year of both measures are significantly influenced by various factors, including building system, occupant behavior, and environmental conditions. The building system influences how heat circulates and escapes, thereby affecting the impact of wall insulation improvements. For instance, a building with a high window-to-wall ratio may experience significant heat loss through the windows. While improved wall insulation can help reduce this loss, it may not be as effective as in a scenario with a low window-to-wall ratio. Occupant behavior, such as window opening behavior, directly impacts the effectiveness of wall insulation retrofits. Frequently opening windows during cold months allows warm indoor air to escape, increasing heat loss. Similarly, opening windows during warm months lets hot outdoor air in, increasing heat gain. These behaviors counteract the thermal barrier provided by wall insulation, thereby reducing its overall benefits in maintaining a stable indoor temperature and decreasing energy consumption. Environmental factors like different regional weather and global warming play a crucial role as well. For example, in colder weather, buildings benefit more from improved wall insulation, as it retains indoor heat more effectively than in warmer weather.

HVAC systems show effective results and investment returns across all scenarios. Furnace upgrades outperform air conditioner improvements due to the community's location in Climate Zone 5, where prolonged and cold winters create a greater demand for heating than cooling. Additionally, none of the heat pump measures, including air source heat pumps, ground source heat pumps, and mini-split heat pumps, achieve significant source energy reduction and investment returns. This is due to the lack of renewable energy retrofit measures in the database. Heat pumps use electricity for cooling and heating, more electricity consumes more source energy. Coupled with the high cost of heat pumps, even with rebate policies, there is no investment return for heat pump systems without renewable energy integration.

Appliance upgrades have minimal source energy reduction effects. However, in townhomes, with high appliance usage, or when utility bills increase annually, these upgrades can still offer an acceptable return on investment.

In the lighting system, replacing light bulbs with energy-efficient ones has limited source energy reduction effects. However, the cost is recovered within two years in all scenarios, making it a worthwhile retrofit measure.

Water heating systems have limited source energy reduction performance and long payback years. Like HVAC systems, due to the lack of renewable energy measures, using heat pumps alone for domestic hot water results in higher source energy and investment with no return.

4.2.3. Indicator selection

When assessing energy retrofits that show obvious energy conservation benefits, such as those implemented on windows, wall sheathing, wall wood studs, air conditioners, furnaces, and light bulbs, the optimal choices may vary depending on the evaluation indicator, like source energy reduction and payback year.

For building envelope retrofits, although material costs per unit do not vary greatly, the total investment can range from a few thousand to tens of thousands of dollars when considering the entire building. Both energy saving effect and investment costs significantly affect the payback year, making it difficult to achieve the same results when selecting optimal measures based on source energy reduction and payback year.

For air conditioner and furnace upgrades, the top three options remain the same for both indicators. Each 0.29 increase in the Seasonal Energy Efficiency Ratio (SEER) of a central air conditioner adds only $100 to the investment. Similarly, each 0.25 increase in the Annual Fuel Utilization Efficiency (AFUE) of a natural gas furnace adds less than $200. These small investment increments mean that the primary factor affecting the payback year is energy savings, not investment cost. Therefore, for HVAC equipment, the top three choices are consistent across different evaluation indicators.

The limited number of appliance upgrade options typically results in the same top three choices regardless of the evaluation indicator used. These top three options offer similar energy savings and have comparable payback year, with the energy savings generally being modest and the payback year lengthy. Therefore, the differences among the top three choices are minimal, making it practical to focus on other features, such as refrigerator capacity or washing machine water usage, rather than solely on energy efficiency and economic metrics.

5. Conclusion

This study proposes a framework for identifying optimal and robust energy retrofit solutions at the community level. The framework consists of five key steps: scenario model development, integration of the NREM retrofit database, energy performance simulations, cost-benefit aggregation, and selection of retrofit solutions. Each step enhances the framework's robustness by incorporating the diversity of building features, occupant behaviors, environmental conditions, retrofit measures, and evaluation methods. A case study in southern Michigan of the United States, demonstrates the framework's effectiveness, revealing that furnace retrofits stand out as the most effective and robust measure, simultaneously achieving 4.7 %–8.0 % source energy reduction, 10–20 years payback period, and stable performance with consistent selection across various scenarios. The framework proves effective as the case study conclusions are reasonable and align with other research findings, indicating its potential for broader application in evaluating and optimizing community-scale residential building energy retrofits.

Despite its strengths, this framework has some limitations. First, the absence of renewable energy retrofit data, such as PV installations in the NREM database, may understate the benefits of measures like heat pumps. Additionally, using payback year as a metric does not account for the time value of money; employing discounted payback period or net present value would allow for a more accurate assessment of long-term financial viability. Finally, comparing multiple separate indicators could make the results less straightforward.

Future work could expand the framework by incorporating renewable energy options and developing a composite metric that integrates environmental impact, economic viability, and robustness into a single score, offering a clearer and more comprehensive assessment of retrofit performance.

CRediT authorship contribution statement

Lei Shu: Writing – review & editing, Writing – original draft, Visualization, Methodology, Data curation, Conceptualization. **Tianzhen Hong:** Supervision, Methodology. **Kaiyu Sun:** Validation, Resources. **Dong Zhao:** Writing – review & editing, Visualization, Supervision, Funding acquisition, Conceptualization.

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.

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Data availability

Data will be made available on request.

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