Low-Income Energy Efficiency Programs: A Multicriteria Framework for Energy Audit Software and Evaluation Methodologies for Energy Conservation Measures

A Dissertation Presented for the
Doctor of Philosophy
Degree
The University of Tennessee, Knoxville

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May 2025

DEDICATION

This dissertation is dedicated –

To the glory of my Lord and Master, Jesus Christ,
who has never left or forsaken me.

To my family and friends, especially my wife and confidante,
Hannah Elikplim Fianu,
for her presence and support

To my beloved mother and sister,
Vicentia Addy and Agnes Violet Addy,
for their strong and unwavering support through life's journey.

To a great man who showed great interest in and supported my education,
Mr. Emmanuel Alabi,
for ensuring that I enrolled in both high school and the university.

ACKNOWLEDGEMENTS

I express my deepest gratitude to my advisors and mentors, Dr. Joshua R. New, Bill Eckman, and Dr. Mini Malhotra, for their invaluable guidance and support throughout this journey. I am also very thankful to the members of my dissertation committee, Dr. Hongyu N. Zhou, Dr. Joshua S. Fu, and Dr. Chien-Fe Chen. Their insights and feedback have been instrumental in shaping this work.

I am profoundly appreciative of the funding and resources provided by the Oak Ridge National Laboratory (ORNL) Building Technologies Research and Integration Center (BTRIC), the U.S. Department of Energy (DOE), and its Office of State and Community Energy Programs (SCEP). My research benefited greatly from the opportunities to collaborate with talented individuals at ORNL, including Dr. Brett Bass and Dr. Anne Berres (all former staff), whose support significantly contributed to my accomplishments.

I would also like to acknowledge the University of Tennessee Knoxville's Bredesen Center for Interdisciplinary Research and Graduate Education and the University of Tennessee Oak Ridge Innovation Institute (UT-ORII) for their support through the Graduate Advancement and Training Education (GATE) Fellowship.

Special thanks go to the supportive staff and colleagues at the University of Tennessee, including Allie Burns, Rebecca Christ, Dr. Stephen Puplampu, and Dr. Bernard Baffuor Asare Bediako. I am also profoundly grateful to my colleagues outside the UT-ORNL community, including Dr. Yen Adams Sokama-Neuyam, Joel Neymark, Edward Quaye, Abigail and Hezekiah Samwini, John K. Ansah, and Nicholas Boafo for their unwavering support and encouragement.

The love, encouragement, and frequent interaction with my friends and family inspired me throughout this journey. Finally, I would like to thank all my collaborators for their invaluable contributions and the fruitful research discussions that enriched this work. I am immensely grateful for my meaningful experiences and notable accomplishments during my doctoral program.

ABSTRACT

The transition to more energy-efficient residential buildings, particularly in low-income households, requires innovative methodologies and tools to address the complexities of energy conservation. This thesis aims to enhance the effectiveness of residential energy audits by developing a comprehensive multi-criteria framework, demonstrating its application with existing energy audit software, and establishing a systematic methodology for evaluating the lifetimes of energy conservation measures (ECMs). The study's first objective was to develop a holistic framework that integrates over 50 factors under 14 criteria, addressing energy and non-energy considerations such as health, safety, and socio-economic impacts. The framework provides a structured approach for evaluating energy audit software, equipping stakeholders with tools to select solutions that align with the specific needs of low-income households. The second objective involved applying the framework's utility to three widely used energy audit software tools – REM/RATE, Weatherization Assistant, and TREAT. The comparative analysis highlighted each tool's strengths and limitations, such as REM/RATE's strong alignment with renewable energy modeling and WA's superior scalability features, while identifying opportunities for improvement in user-friendliness and sustainability modules. The third objective focused on developing a methodology for systematically and repeatably assessing ECM lifetimes across diverse measure types. This methodology integrates statistical techniques, manufacturer data, and field testing to produce reliable lifetime estimates. It also addresses long-term economic analyses, emphasizing the challenges of uncertainty in evaluating ECMs with lifetimes exceeding 30 years. This thesis contributes to advancing residential energy efficiency by offering tools and methodologies to streamline energy audits, enhance decision-making, and maximize the benefits of energy conservation for low-income households. The findings have implications for software developers, program administrators, and policymakers, providing actionable insights to improve energy audit processes and achieve equitable energy savings at scale.

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CHAPTER 1

INTRODUCTION AND GENERAL INFORMATION

The impact of buildings on energy consumption and greenhouse gas (GHG) emission cannot be underestimated, yet buildings also offer the most significant opportunity for energy savings and sustainability [1]. Globally, buildings, without including the construction sector, are responsible for 30% of final energy consumption and 28% of direct and indirect greenhouse gas (GHG) emissions [2], and amounted to a combined $422 billion (about $1,300 per person) in electricity bills to the average consumers in the U.S in 2021 [3]. The International Energy Agency (IEA) and the U.S. Energy Information Administration (EIA) forecast a significant increase in building sector energy consumption [4]. In its 2019 edition of the International Energy Outlook, the U.S. Energy Information Administration (EIA) predicts that energy consumption of all buildings worldwide will increase by 1.3% annually between 2018 and 2050. Before 2018, building sector energy demand rose by approximately 1.1% per annum between 2000 and 2017, chiefly driven by precipitous increases in floor area of habitable spaces and growing energy intensity of energy services [5]. This increasing trend has implications for the average household and also for low-income families in the U.S. whose energy burden (that is, the percentage of gross household income that goes into energy bills) is disproportionately higher (8.6%), three times more than for non-low-income households [6], [7]. In some cases, the energy burden can be as high as 30% when location and income are considered [6], [7].

Global efforts toward energy efficiency are falling short in the face of the rapid increase in building energy consumption. The IEA estimates that efficiency improvements need to reach an average of 4% per year by 2030 if we are to meet the global Net Zero Emissions target by 2050. This underscores the urgent need for comprehensive and effective energy efficiency solutions. [8]. Meanwhile, residential and commercial buildings form a substantial unserved market for energy efficiency [9]. Yet less than 1% of U.S. buildings are improved each year.

Several agencies in the U.S. are working toward building energy efficiency, especially for low-income households. This includes the Office of State and Community Energy Programs (SCEP), which, among other things, works to accelerate the deployment of clean energy technologies, improve the energy efficiency of low-income homes, and reduce the cost of energy associated with such households [10]. Similarly, the Building Technology Office (BTO) has a long-term goal of reducing energy use intensity (EUI) of U.S. buildings by 50% compared to the 2010 baseline and minimizing building EUI in the short-term by 30% by 2030 compared to the 2010 baseline [11]. BTO aims to achieve this by developing, demonstrating, and promoting the uptake of high-performing technologies, tools, and services. These efforts focus on making new and existing residential and commercial buildings energy efficient, affordable to purchase and operate, capable of peak performance, and conducive to occupants' health and safety conditions. This would make all homes and buildings operate at peak energy performance, affordable, and provide optimal health conditions and comfort. On the international front, the IEA proposes that digital products to reduce building sector energy consumption and GHG emissions are outstanding energy efficiency solutions. [12].

In the different goals and objectives of energy efficiency programs, there is the convergence of technology, performance, and affordability at the heart of energy efficiency solutions to meet the needs of low-income households. Meanwhile, about 50 million low-income families (44% of households) in the U.S. may not be able to afford energy efficiency improvements in their homes. Some of the energy efficiency programs being implemented to address these concerns include the Better Buildings Initiative [13], Better Climate Challenge [14] and the Energy Saver [15] programs. However, specific to low-income households is the foundational program of the SCEP, spanning over 40 years – the Weatherization Assistance Program (WAP) – which is the single most extensive residential whole-house energy efficiency program to reduce energy costs for low-income households in the U.S. through improved energy efficiency [16].

This makes research in energy efficiency solutions for low-income households a subject of grave importance if we are to meet national energy efficiency goals in the U.S.

Yet, central to most building energy efficiency programs are energy modeling or energy audit software, but the framework for developing such tools to meet the ever-evolving needs low-income family households are lacking. This study proposes and expands on a criteria framework that could be used in residential energy audits for low-income households. Energy auditors, energy efficiency program administrators, and managers, as well as energy modeling software developers, may find it helpful in developing, selecting, and improving energy audit or modeling software that addresses the energy and non-energy aspects of a residential energy audit for users and beneficiaries while meeting the core goals of energy efficiency. The framework will also provide a qualitative and quantitative description of a list of criteria in the form of a scoring model. With this model, different energy audit software can be assessed to determine their suitability for specific energy efficiency program requirements or an overall score-based capability of the tool based on an aggregate score of all criteria. This research builds on previous work [17] by the U.S. Department of Energy (DOE), wherein select energy audit tools were reviewed to support establishing a national building performance assessment and rating program.

Another aspect of this research will seek to address how to evaluate energy conservation measure (ECM) lifetimes to develop a repeatable evaluation methodology for ECM lifetimes applied in low-income, residential energy efficiency programs in the U.S. Understanding how to evaluate ECMs lifetimes is of paramount importance, and ensures accurate and reliable evaluation methodologies that can help in effective decision-making, resource allocation, and long-term planning. By including measure lifetime in the study, this research will establish a systematic and standardized approach that can be applied across a diverse range of ECMs, enabling consistent, repeatable, and informed decision-making.

1.1 Brief overview of the energy efficiency challenges in the United States

The building sector's greatest challenge is high energy consumption, as buildings account for 30% of final energy consumption [2]. In 2021, the average U.S. consumer's electricity bills amounted to $422 billion (about $1,300 per person) [3].

Buildings are also a major contributor to greenhouse gas (GHG) emissions, accounting for 28% of direct and indirect emissions [3] (29% in the U.S.) [19], with two-thirds of this emission coming from the surging electricity consumption in this sector. Remarkably, since 2000, the rate of electricity consumption in buildings outpaced carbon efficiency efforts of the power sector by a factor of five [20]. Amid the rising carbon footprint of buildings, the IEA notes the key role that technology could play in not only reducing CO_2 emissions but also improving occupant comfort. For example, using heat pumps for heating and solar thermal technologies could cut energy use by a factor of four and provide carbon-free heat to nearly 3 billion people, respectively [20].

The lack of diversification in energy efficiency saving sources is emerging as one of the challenges of energy efficiency facing the residential sector in the U.S. [21]. Traditionally, energy efficiency has focused on known areas of high consumption, such as lighting and HVAC, with little attention to plug-in equipment. Meanwhile, in California, for example, the Natural Resources Defense Council (NRDC) reports that plug-in loads make up only 12 percent of electrical efficiency programs in the state, even though two-thirds of California's residential energy consumption is attributed to plug-in equipment (see Figure 1.1) [22]. This shows that the rate at which plug-in loads are growing in residential buildings exceeds appliance efficiency standards. Existing energy efficiency programs are not vigorously pursuing and capturing these areas, leaving potential saving areas unnoticed.. Therefore, energy efficiency efforts should focus on the whole building and all systems encompassing various end-use applications – wherever there is potential to save energy.

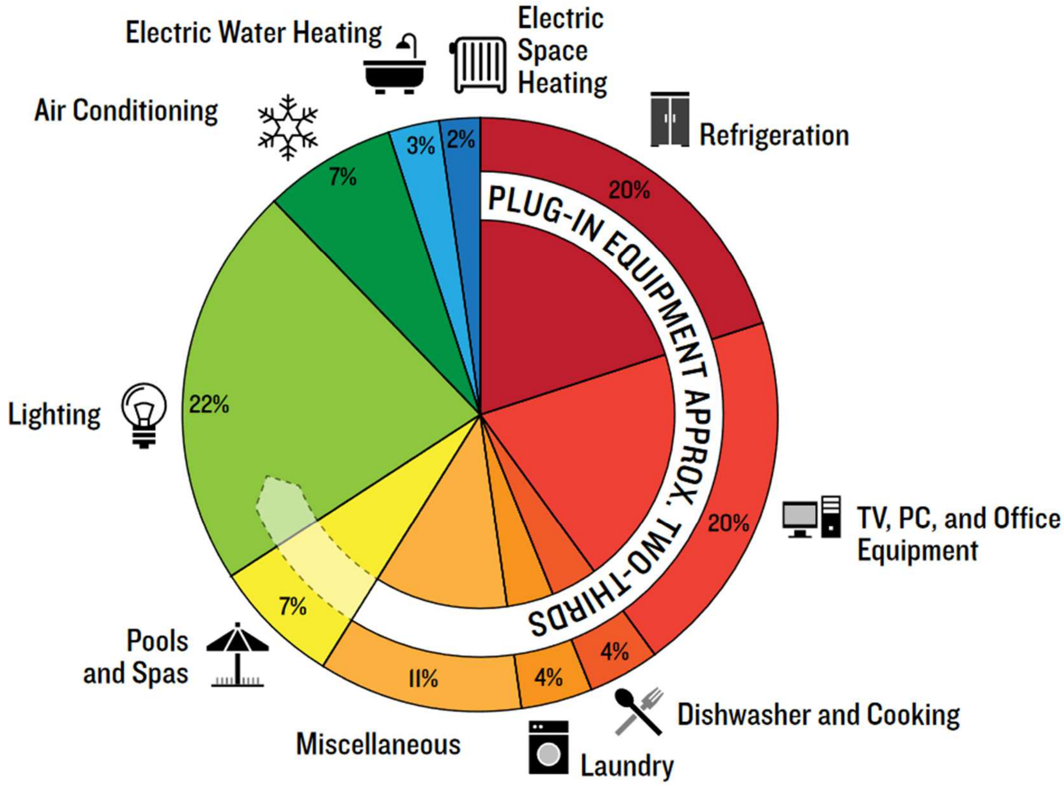

Figure 1.1 Plug-in equipment is responsible for approximately two-thirds of California's residential electricity consumption.

Another energy efficiency challenge is the lack of effort to measure or ensure the persistence or impact of savings. As governments and organizations spend millions of dollars on energy efficiency measures and retrofits, it is essential to ensure that estimated energy savings are reliable over the lifetime of installed systems to meet climate goals and for future planning purposes. In the past, the means to measure actual savings, such as using smart meters, were lacking, and decision-makers relied heavily on engineering calculations or estimates from economic analysis. The surge in smart meter data and complex data analytics tools comes with it the ability to monitor changes in building energy consumption or savings as well as observe their significance and persistence across the entire building [23]. Yet, amid recent developments in smart metering technologies to enable real-time monitoring and measurement of energy consumption/savings, little attention is being given to the post-retrofit impact of energy efficiency measures. At an MIT Energy Initiative symposium to tackle needed actions to move energy efficiency forward, "big data" was identified to play a key role in tracking energy use and monitoring which energy efficiency efforts are working [24]. This is especially important for energy efficiency programs for low-income households funded by taxpayer dollars. Program administrators must be able to measure post-retrofit savings and other forms of impact.

The seeming disconnect between building energy efficiency and GHG emissions reduction goals is attributed to the lack of effort to measure the persistence of savings as described above. Building energy efficiency has a crucial role in meeting climate goals, yet little connection is made between the two, so it is not clear how meeting the objectives of one is helping the other. The goals of energy efficiency must not only be understood in terms of reducing energy cost/consumption of building occupants or operators but also in the broader context of reducing or avoiding GHG emissions [21]. For building occupants or operators who care about positive climate action, this becomes a motivation for collective ownership of organization- or government-led energy efficiency programs to realize greater benefits.

Another concern this proposal is partly devoted to solving is energy modeling software. In a report by the U.S. Department of Energy summarizing some of the gaps and barriers to implementing residential building energy efficiency strategies, the issues identified regarding energy modeling software include (1) overprediction in older or existing homes, (2) traditional software more tailored to equipment sizing, commercial buildings, and new buildings, rather than new and existing residential buildings, and (3) not reliably predicting pre-retrofit energy use and post-retrofit energy savings [25]. Related to all of this is the limited access to energy utility data, further heightened by privacy concerns that make it convenient for utilities to deny utility data requests [25]. While this research will not attempt to solve each existing issue with energy modeling software development, primarily those applicable to buildings occupied by low-income families, the framework it proposes will provide directions that make solutions possible.

1.2 Problem Statement

Meeting the needs of low-income households requires that energy auditors or managers carry out energy audits following federal or state regulations, using energy audit software or energy modeling tools, and following standard procedures for carrying out energy audits in residential buildings, which make up about 95% of U.S. building stock and 70% of the total square footage of the building stock [26]. Interestingly, even though U.S. residential buildings are disproportionately higher than commercial (or non-residential) buildings, there have been in existence for more than two decades standard "procedures for commercial energy audit" [27] by the American Society for Heating, Refrigeration and Air-Conditioning Engineers (ASHRAE), but none tailored explicitly for residential buildings. While the laid-out procedures for commercial building energy audits may apply to residential buildings and the general goal of commercial building energy audits – reduction of energy use and associated cost – may be deemed the same for residential buildings, there is more involved in residential building energy audits than just reducing energy use and cost. The variability of residential buildings by type – single-family, multifamily, and mobile homes – and economic levels of building occupants – low-income and non-low-income – require a more nuanced approach to energy audits that sufficiently captures the complexities of different building types or occupants. Besides, carrying out energy audits, especially in residential buildings, may involve or pose non-energy concerns [28], such as health and safety concerns that need to be captured and addressed within the scope of energy audits. This is especially true for low-income households. All modern energy audits rely on energy audit software or other similar computer programs. However, there is hardly a comprehensive, well-laid-out framework for residential energy audits that energy auditors or energy managers could follow not only in selecting the most suitable software for these tasks but also in addressing some of the most pertinent energy- and non-energy-related challenges for both the auditors and the beneficiaries.

Another problem that this proposal seeks to address is the lack of understanding and viable evaluation methodologies for energy conservation measures (ECMs). Evaluating ECMs and their lifetimes is crucial in determining the effectiveness and long-term viability of energy efficiency measures. Most energy modeling software comes with default ECM lifetimes to guide energy auditors in using the software to carry out energy audits. However, ECMs are constantly evolving in their technology, application, and persistence (duration during which they yield energy savings). Therefore, energy efficiency program administrators or implementors must know how to evaluate ECMs, especially their lifetimes. However, no repeatable methodology provides a systematic and standardized approach that can be applied across various ECMs to enable consistent, reproducible, and informed decision-making.

1.3 Research Significance

The research will advance knowledge in energy efficiency and provide practical insights for stakeholders involved in low-income energy efficiency programs and policies. Specifically, this research holds immense significance in the following ways and for the following reasons:

I. **Mitigating Energy Poverty**: One of the primary drivers behind this research is the urgent need to alleviate energy poverty among low-income households. A comprehensive multicriteria framework for energy audit software selection tailored to their specific needs can significantly reduce the energy burden on vulnerable households. This, in turn, can lead to improved living conditions, reduced financial stress, and enhanced well-being for millions of individuals and families.

II. **A Novel Tool**: By providing a new framework for assessing energy audit software and methodology for evaluating lifetimes of energy conservation measures, energy modeling software developers and energy efficiency program administrators/managers will have a new approach to going about energy audits. Also, decision-makers will be able to understand better and analyze the economic viability of implementing ECMs for a well-informed decision-making process.

III. **A Whole Impact Approach**: Traditional energy assessments have often focused on the energy aspects of energy efficiency retrofits. This novel framework also considers the non-energy aspects of energy efficiency not as unintended consequences or benefits but as deliberate considerations, thereby helping to measure the full range of impacts of residential energy efficiency projects for low-income households.

IV. **Measuring and Verifying Impact**: Ensuring the persistence and impact of energy savings is a critical challenge in energy efficiency programs. This study explores the possibility of a repeatable methodology for evaluating energy conservation measures to measure and verify energy savings. Doing so ensures the reliability and accountability of energy efficiency efforts, a key aspect of achieving sustainability and demonstrating program effectiveness.

V. **Guiding Government Initiatives**: Government agencies and policymakers invest significant resources in energy efficiency programs for low-income households. This research can provide valuable guidance and evidence-based insights for designing, implementing, and evaluating such programs. Offering practical solutions and methodologies can help government initiatives achieve their energy efficiency and social equity goals more effectively.

1.4 Research Questions

To guide the research, the following fundamental research questions were explored:

- How can a comprehensive multicriteria framework for energy audit software selection be developed, and what criteria should be included to meet the specific needs of low-income households while considering both energy and non-energy factors?
- How can the developed framework be tested and demonstrated with existing software for residential energy audits to show its strengths and weaknesses?
- What methodologies can be established to evaluate the lifetimes of energy conservation measures (ECMs) in residential buildings, especially in the context of low-income households, and what are the considerations for assessing the cost-effectiveness of long-lived measures?

1.5 Research Goals

This research aims to develop and demonstrate a comprehensive multicriteria framework for energy audit software and evaluation methodologies for energy conservation measures tailored for low-income energy efficiency programs. To achieve this goal, the following objectives will be met:

Objective 1: Develop a comprehensive framework for residential energy audits that address low-income households' specific needs and complexities, encompassing energy and non-energy considerations.

Objective 2: Demonstrate how the framework works with existing energy audit software.

Objective 3: To establish a systematic and repeatable methodology for assessing the lifetimes of energy conservation measures (ECMs) that can be applied across diverse ECM types, focusing on their suitability for low-income households.

1.6 U.S. Department of Energy (DOE) low-income household energy efficiency targets

This work is funded by the Office of State and Community Energy Programs (SCEP), and the mission of the SCEP is to partner with state and local organizations to deploy clean energy solutions, boost regional economic development through the creation of jobs, reduction of energy costs, and pollution prevention. Foundational to SCEP's mission are programs like the Weatherization Assistance Program (WAP), which has been running for over four decades. WAP lessens the energy burden on low-income households by improving their homes' energy efficiency while prioritizing residents' health and safety. Moreover, the WAP has made weatherization improvements and upgrades possible for low-income families, helping them save an average of $372 annually. Carrying out the SCEP mission through the WAP requires using energy audit tools. This research supports the efforts of the SCEP by providing a framework that can be utilized to approve energy audit tools for use in WAP. Also, this study supports the efforts of the Oak Ridge National Laboratory (ORNL), managers of the DOE's software for WAP. This research contributes to ORNL's effort by demonstrating ways of optimizing energy savings calculations in energy audit software by analyzing the methodologies for estimating the default lifetime values of ECMs. It proposes methods for extending these default lifetime values to reflect practical use cases better and enhance the economic analyses of ECMs.

1.7 Research Scope

This research will primarily focus on low-income households in the United States, recognizing the unique challenges they face regarding energy efficiency. The scope of the study encompasses the following areas:

- Residential Building Types: The research will focus on several types of residential buildings, including single-family homes, multifamily buildings, and mobile homes, to account for the diversity of low-income housing in the U.S.

- Energy Audit Framework: Developing a comprehensive energy audit framework will involve identifying criteria addressing energy-related and non-energy factors, such as health and safety concerns.
- Evaluation of Energy Audit Software: The research will evaluate energy audit software and energy modeling tools commonly used to assess their suitability for low-income energy efficiency programs.
- ECM Evaluation Methodology: A systematic and repeatable methodology for evaluating the lifetimes of energy conservation measures (ECMs) will be developed and tested, focusing on applicability to various ECM types.
- Policy and Program Recommendations: This research's findings will inform recommendations for policymakers and energy efficiency program administrators to enhance energy efficiency programs targeting low-income households.

1.8 Organization of the Thesis

The results and information obtained from this dissertation to address the research objectives will be organized as follows:

- **Chapter 2**: a comprehensive framework for low-income household energy audit software. This chapter discusses the approach for developing a framework consisting of several criteria that can be used to assess energy audit software or to guide the development of energy audit software in the context of low-income households. Each criterion of the framework is defined and used to develop a matrix of criteria and their defining factors in qualitative and quantitative forms. The possible use cases of the framework and their limitations are discussed.
- **Chapter 3**: Testing of the Framework. This chapter presents a test of the framework developed and discussed in Chapter 2. The framework is tested against three software programs based on availability and suitability to low-income contexts. The testing results are discussed thoroughly regarding their strengths, weaknesses, and applications. These results are also summarized in a table for ease of comparison.

- **Chapter 4**: methodologies for evaluating energy conservation measures to optimize energy savings in energy efficiency calculations. This chapter is a critical review of seven methodologies employed in estimating the lifetimes of energy conservation measures. It highlights how the procedure is carried out, its advantages and disadvantages, the measures for which they can best be applied, and examples of how they have been applied.
- **Chapter 5**: a framework for extending default energy conservation measure lifetimes in energy efficiency programs. This chapter is an extension of chapter four, wherein a methodology is proposed that energy auditors or energy efficiency program managers may follow to extend the default lifetime values of ECMs, with sensitivity analyses using different scenarios and economic indicators.
- **Chapter 6**: conclusions. This chapter highlights the detailed summary of all the prior research discussed in chapters 2-5. Also, this thesis's unique contributions and impact are discussed extensively, and the recommendations for further research are highlighted.

CHAPTER 2

A MULTICRITERIA FRAMEWORK FOR ASSESSING ENERGY AUDIT SOFTWARE FOR LOW-INCOME HOUSEHOLDS IN THE UNITED STATES

This chapter proposes an expansive framework of several criteria and factors for developing and assessing energy modeling and energy audit tools. This framework is necessary for holistically meeting the needs of low-income households by addressing both energy consumption needs and the non-energy impacts of energy consumption. Springer submitted the chapter for publication in Energy Efficiency and has undergone peer review from the scientific community. It has also been presented at a major conference and a research symposium, where it received helpful feedback, which has been incorporated into this version.

Acknowledgments: The U.S. Office of State and Community Energy Program sponsored this work under contract DE-AC05-00OR22725 with UT-Battelle, LLC.

Chapter Abstract

In the United States, buildings consume 40% of primary energy, significantly contributing to greenhouse gas emissions. This issue is further compounded by the disproportionate burden placed on low-income households, spending three times more (8.6%) of their income on energy compared to non-low-income households. To meet the global net-zero emissions target by 2050, an average annual energy efficiency improvement of 4% is crucial. However, only 1% of U.S. buildings are improved annually. Recognizing the critical role of technology, agencies have implemented energy efficiency programs like the Weatherization Assistance Program (WAP), explicitly targeting low-income households. These programs rely on energy auditors who utilize software tools to assess energy performance. However, currently, there is no comprehensive framework for selecting the most suitable software for low-income housing.

This paper proposes a novel framework comprising over 50 factors organized under 14 critical criteria to assess energy audit software specifically for low-income households. This framework enables qualitative and quantitative evaluations, empowering stakeholders to make informed decisions in energy efficiency programs. The framework's originality lies in its tailored focus on the unique needs of low-income housing, offering a valuable tool for software developers and program administrators. This framework's significance is

its ability to provide a systematic approach to assessing software options, ultimately contributing to improved energy efficiency and reduced energy costs for low-income households. Moreover, the framework considers essential aspects of low-income living that are often ignored, such as the non-energy impact on health, safety, and comfort.

2.1 Introduction

The impact of buildings on energy consumption and greenhouse gas (GHG) emission cannot be underestimated, yet buildings also offer the most significant opportunity for energy savings and sustainability [1]. Globally, buildings, without including the construction sector, are responsible for 30% of final energy consumption and 28% of direct and indirect greenhouse gas (GHG) emissions [2], and amounted to a combined $232 billion in electricity bills to the average residential consumers in the U.S in 2023 [3]. The International Energy Agency (IEA) and the U.S. Energy Information Administration (EIA) forecast a significant increase in building sector energy consumption [4]. Recent analysis from the U.S. Energy Information Administration (EIA) predicts that energy consumption of all buildings in the world will increase by 1.3% annually between 2018 and 2050 [28]. Before 2018, building sector energy demand rose by approximately 1.1% per annum between 2000 and 2017, chiefly driven by precipitous increases in floor area of habitable spaces and growing energy intensity of energy services [5]. This increasing trend has implications for the average household and also for low-income families in the U.S. whose energy burden (that is, the percentage of gross household income that goes into energy bills) is disproportionately higher (8.6%), three times more than for non-low-income households [7] In some cases, the energy burden can be as high as 30% when location and income are considered [7].

It seems that global efforts toward energy efficiency are hardly enough to catch up with the increasing building energy consumption rate. The IEA estimates that efficiency improvements need to reach an average of 4% per year by 2030 if we are to meet the global Net Zero Emissions target by 2050 [8]. Meanwhile, residential and commercial buildings form a substantial unserved market for energy efficiency [9].

Several agencies in the U.S. are working toward building energy efficiency, especially for low-income households. This includes the Office of State and Community Energy Programs (SCEP), which, among other things, works to accelerate the deployment of clean energy technologies, improve the energy efficiency of low-income homes, and reduce the cost of energy associated with such households [10]. Similarly, the Building Technology Office (BTO) is working long-term to reduce the energy use intensity (EUI) of U.S. buildings by 50% compared to the 2010 baseline and to minimize building EUI in the short-term by 30% by 2030 compared to the 2010 baseline [11]. This it intends to do by developing, demonstrating, and accelerating the adoption of affordable technologies, techniques, tools, and services that enable high-performing, energy-efficient residential and commercial buildings in both new and existing markets. This would make all homes and buildings operate at peak energy performance, affordable, and provide optimal health conditions and comfort. On the international front, the IEA proposes that digital products to reduce building sector energy consumption and GHG emissions are outstanding energy efficiency solutions [12].

In the different goals and objectives of energy efficiency programs, there is the convergence of technology, performance, and affordability at the heart of energy efficiency solutions to meet the needs of low-income households. Meanwhile, about 50 million low-income families (44% of households) in the U.S. may not be able to afford energy efficiency improvements in their homes. Some of the energy efficiency programs being implemented to address these concerns include the Better Buildings Initiative [13], Better Climate Challenge [14], and the Energy Saver [15] Programs. However, specific to low-income households is the foundational program of the SCEP, spanning over 40 years – the Weatherization Assistance Program (WAP) – which is the single most extensive residential whole-house energy efficiency program to reduce energy costs for low-income households in the U.S. through improved energy efficiency [16].

Meeting the needs of low-income households requires that energy auditors or managers carry out energy audits following federal or state regulations, using energy audit software or energy modeling tools, and following standard procedures for carrying out energy audits in residential buildings, which make up about 95% of U.S. building stock and 70% of the total square footage of the building stock [26]. Interestingly, even though U.S. residential buildings are disproportionately higher than commercial (or non-residential) buildings, there have been in existence for more than two decades standard "procedures for commercial energy audit" [27] by ASHRAE, but none tailored explicitly for residential buildings. While the laid-out procedures for commercial building energy audits may apply to residential buildings and the general goal of commercial building energy audits – reduction of energy use and associated cost – may be deemed the same for residential buildings, there is more involved in residential building energy audits than just reducing energy use and cost. The variability of residential buildings by type – single-family, multifamily, and mobile homes – and economic levels of building occupants – low-income and non-low-income – require a more nuanced approach to energy audits that sufficiently captures the complexities of different building types or occupants. Besides, carrying out energy audits, especially in residential buildings, may involve or pose non-energy concerns [29], such as health and safety concerns that need to be captured and addressed within the scope of energy audits. This is especially true for low-income households. All modern energy audits rely on energy audit software or similar computer programs. However, there is hardly a comprehensive, well-laid-out framework for residential energy audits that energy auditors or energy managers could follow not only in selecting the most suitable software for these tasks but also in addressing some of the most pertinent energy—and non-energy-related challenges for both the auditors and the beneficiaries.

This study proposes and expands on a criteria framework that could be used in residential energy audits for low-income households. Energy auditors, energy efficiency program administrators, and managers, as well as energy modeling software developers, may find it helpful in developing, selecting, and improving energy audit or modeling software that addresses the energy and non-energy aspects of a residential energy audit for users and beneficiaries while meeting the core goals of energy efficiency. The framework also provides a qualitative and quantitative description of a list of criteria in the form of a scoring model. With this model, different energy audit software can be assessed to determine their suitability for specific energy efficiency program requirements or an overall score-based capability of the tool based on an aggregate score of all criteria. This research builds on previous work [17] wherein select energy audit tools were reviewed to support establishing a national building performance assessment and rating program.

2.1.1 The Energy Audit Process: An Overview

The goal of an energy audit is to identify and prioritize energy efficiency retrofits or measures which, when implemented, will lead to significant energy savings that justify the investment made – that is, yield a cost-effective, positive savings-to-investment ratio (SIR) of a specific minimum value as determined by the energy efficiency manager or relevant stakeholders involved. For example, Title 10 of the U.S. Code of Federal Regulations, Chapter II, Subchapter D, Part 440 (10 CFR 440) establishes that the weatherization assistance program scope requires a SIR greater than or equal to 1.0 [30]. Building owners or occupants gain knowledge through an energy audit to make informed decisions on managing their energy expenses and about economically viable energy efficiency improvements [31]. A good energy audit reduces energy waste, improves the health and comfort of the building occupants, and makes the home sustainable [32].

The audit process may be divided into three steps: the pre-audit, audit and post-audit [33]. Also, energy audits could be done at three distinct levels of detail based on the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) standards [34]. An ASHRAE Level 1 Audit is a preliminary audit that involves identifying no- to low-cost saving opportunities based on a high-level view of potential improvements [35]. A Level 2 Audit provides a more detailed analysis of energy costs, usage, and building characteristics, leading to generating Energy Conservation Measures (ECMs) based on matching budget against costly potential energy savings opportunities. The Level 3 Audit offers the most thorough of details and includes the most comprehensive financial and engineering analysis of recommendations for which significant capital investment is required [33], [35].

An energy audit could be done for a whole building, which is the most accurate means of identifying energy savings opportunities in the building, or could be tailored to specific systems such as lighting or heating, ventilation, and air conditioning (HVAC) systems if there is a particular energy efficiency retrofit to be considered. However, the latter could take away from the bigger picture that a whole-building approach can offer [35].

During the pre-audit process, if records of utility bills of the house to be audited are available, they are first reviewed. Typically, utility bill records for the past 12 months provide a good overview of the building's energy consumption profile not only on an aggregate scale but also on a benchmark scale such as the Energy Use Intensity or Energy Utilization Index (EUI) if the total floor area of the building is known [36].

The second step of the audit phase involves a qualified or certified energy auditor visiting the site to collect data. Data may be collected through visual inspection of buildings and key systems, photographs, site measurements, and interviews of building occupants or managers [36]. During this stage, the energy auditor knows of prevailing concerns that could not have been known by merely examining building drawings and utility bill records, such as signs of infiltration based on blower door tests and infrared imaging, insufficient insulation, or old, inefficient HVAC systems. Some valuable information that can be gathered through this process includes building occupancy and occupancy schedule, envelope construction details, capacities and ratings of HVAC systems, automation, and other building system controls. Having a checklist for this process is helpful to avoid missing important aspects of the data collection process that may necessitate returning to the site.

The ultimate step of the audit process, the post-audit, involves evaluating the site data gathered, analyzing energy and cost savings, developing and prioritizing a list of recommendations, as well as summarizing and presenting the findings through reports, graphs, and meetings [36]. The analysis often involves a breakdown of energy use in the building, cost of energy and retrofits, energy and cost savings using savings-to-investment ratios (SIRs), and simple payback. A Level 3 Audit analysis may go further to provide sub-metering analysis, detailed energy modeling, and life cycle cost analysis [33]. In some cases, facility managers may require the energy auditor to report cost analysis using specific factors such as internal rate of return (IRR) and discounted payback. Also, where there are recommended utility incentives and tax credits for ECMs, the financial analysis should capture that [35]. The analysis should consider all measure interactions and acknowledge assumptions. The final report or presentation given to decision-makers should contain sufficient information and be comprehensive enough to help them make informed decisions on energy saving and cost.

2.1.2 The Challenges of Energy Audit

While energy audits help save energy and cost in a building's operation if actions are taken upon their ECMs and installed, they are not without challenges. Implementing the ECMs from an energy audit could be expensive in some cases, but not sufficiently addressing the challenges that come with such projects could prove to be more costly eventually [37]. [38] highlights ten common problems in energy audits based on a survey of 300 energy audits. According to the study, one of the leading problems is missed improvements, which happens in about 80% of all audits. The lack of comprehensiveness of audits has often led to not considering or including essential measures such as high-efficiency HVAC and HVAC controls, high-efficiency domestic hot water, lighting power density and lighting controls, wall or roof insulation, and fenestration improvements [36]. Admittedly, energy auditors could be constrained by budget and scope regarding what improvement could be implemented. Still, regardless of what measures are economically feasible to execute, the purpose of an energy audit is to consider all improvement options from which owners, building managers, or energy efficiency program administrators can choose what to implement [38].

Another challenge concerns a weak scope of work, a problem that characterizes 77% of audits [38]. Failure to sufficiently define the scope of work could affect significant areas to cover during the implementation of ECMs, such as installation location, quantity of materials to install, confirming energy rating, and establishing testing requirements for installation materials/equipment [39]. For example, regarding quantity and location, it is crucial to get the right amount of materials needed and place them where they are required or where they could yield the estimated savings. This means that not getting the correct quantity of insulation materials for a retrofit may not produce the estimated energy savings, and the same applies to placing a replacement refrigerator close to a heat source. Energy rating concerns the equipment's wattage or efficiency rating (kWh/yr), and testing requirements apply to physically or visually inspecting equipment/materials to ensure they function as anticipated.

Additionally, 73% of the audits from the survey were found to include improvements for which the payback is longer than the period for which the installation is anticipated to last [38]. Some audits do not provide such information at all. Supplementary to this challenge is the lack of holistic, life-cycle costing based on which to choose the best of two measures for the same intended improvement and with the same simple payback [40].

Poor improvement selection is another frequent challenge of most audits (63%) [38]. Such poor selection choices could include choosing the longer of two improvement measures with different payback periods. It is not always the case that improvement selection follows logic or best practices. Sometimes, they could be influenced by other factors, such as the attractiveness of a longer-payback measure to the building owner, vendor-driven improvements to promote specific products, or energy-auditor-driven improvements to test the limits of unproven or less proven technologies.

Other problems are missing or unreasonably underestimated the cost of installation for which reason they might be chosen over a more economically viable option; poor prioritization of improvements; poor description of buildings; insufficient billing analysis; overestimation of savings or missing information on savings for recommended improvements; and poor or inadequate review such as wrong units of measurement, mismatching of equipment types and overlooked errors [38]. Figure 2.1 shows the ten most common problems of energy audits and their frequency of occurrence.

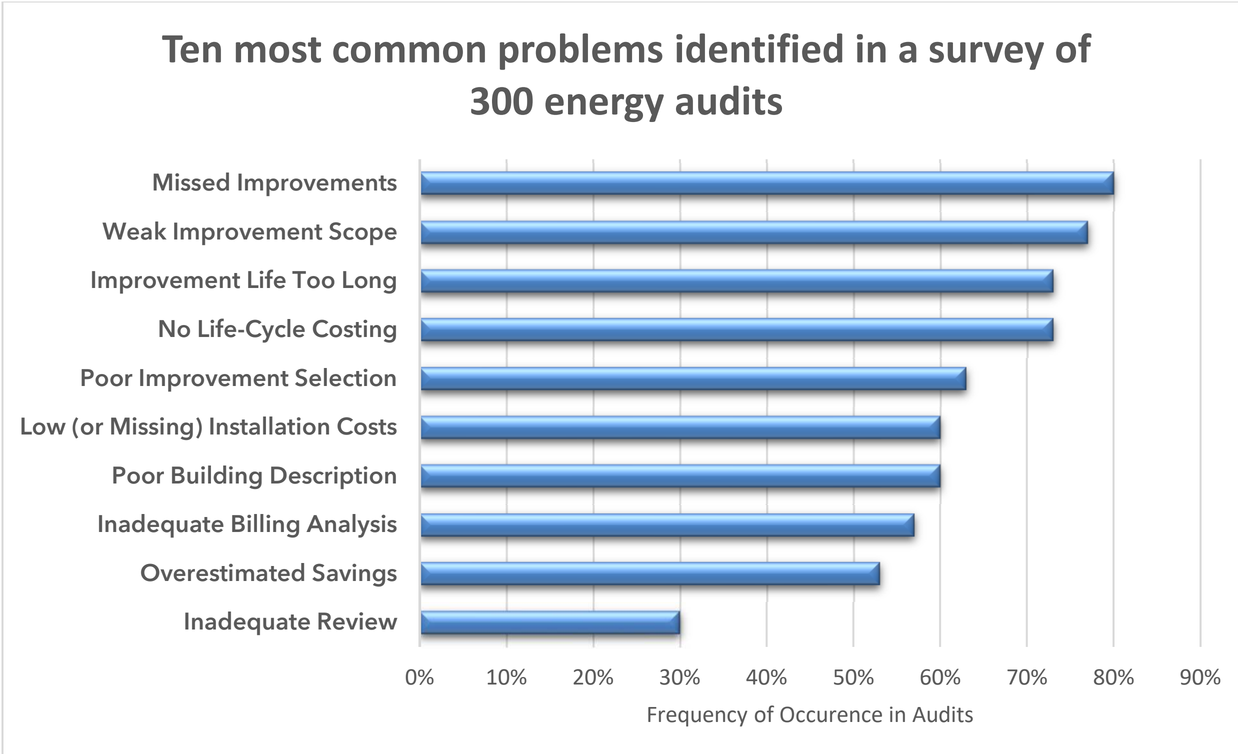

Figure 2.1 Frequency distribution of the ten most common problems identified in a survey of 300 energy audits [38]

2.1.3 The Role of Energy Audit Software

Energy audit software has a vital role in addressing most energy auditing challenges. Energy audit software is predominantly desktop, web, or cloud-based computer programs used to describe buildings, facilities, or processes, measure and analyze their energy use, and assist in identifying areas of operation where energy waste can be reduced or eliminated. An advantage of energy audit software could be the high depth of analysis and the rapid delivery of accurate, comprehensive, and cost-effective results or energy efficiency solutions [41].

Energy audit software makes data entry and processing easy by collecting, analyzing, and reporting data. It allows a variety of input methods and data types, including utility bills, pictures, building information, and metering and sensor data, to create detailed analyses of a facility or process's energy performance [42].

Typically, the engine of an energy audit software is a set of algorithms that combines building physics, local weather data, and economic parameters to simulate sophisticated building energy use as well as estimate energy efficiency measures in seconds [43]. It also generates reports that capture distinct aspects of the building's energy use and provides an action-driven, prioritized list of recommendations necessary for implementing energy efficiency retrofits [33].

Energy audit software is vital in ensuring that energy auditors are accurate and efficient in their work in a way that reduces error, saves time, and is cost-effective. Building owners, facility managers, or energy efficiency program administrators can use the reports of energy audit software to identify cost-saving opportunities and prioritize energy efficiency investments [44].

Specific to some of the challenges highlighted in this paper, energy audit software is excellent at identifying improvements that could be missed by energy auditors even when energy auditors do not specifically include such measures in their analysis [37]. Further, the energy audit software can prioritize the retrofit options based on logic rather than auditor preference to aid the selection process [45]. The economic parameters that an energy audit software will apply in retrofit prioritization and selection are more rigorous than what most energy auditors have the luxury of adding on their own [46]. Such parameters include life-cycle metrics such as savings-to-investment ratio (SIR), net present value (NPV), or return on investment (ROI), among others [47]. It is left to auditors to choose which measures to implement within budgetary provisions and constraints [48] or according to building owner, operator, or manager preference. Also, some software comes with built-in or user-added libraries for fuel cost, location-specific weather data, replacement equipment specifications, and costs, all of which are important for ease in the modeling process and for defining and strengthening the scope of work for retrofitting. Moreover, the ability of some energy audit software to provide billing analysis and calibrate energy consumption and savings against billing analysis could be useful in avoiding overestimating errors [49]. Another helpful function of energy audit software is the checks that are provided in the program to ensure that inexperienced energy auditors have a guide in the form of the acceptable range of values for building descriptors or error logs to diagnose simulation problems and ensure that the building description and results are within reasonable expectations [50]. Lastly, there is a lower likelihood that software-generated reports [51] would have human-oversight errors such as duplication errors, formatting mistakes, or mismatching errors [52].

Organization of the Framework Criteria

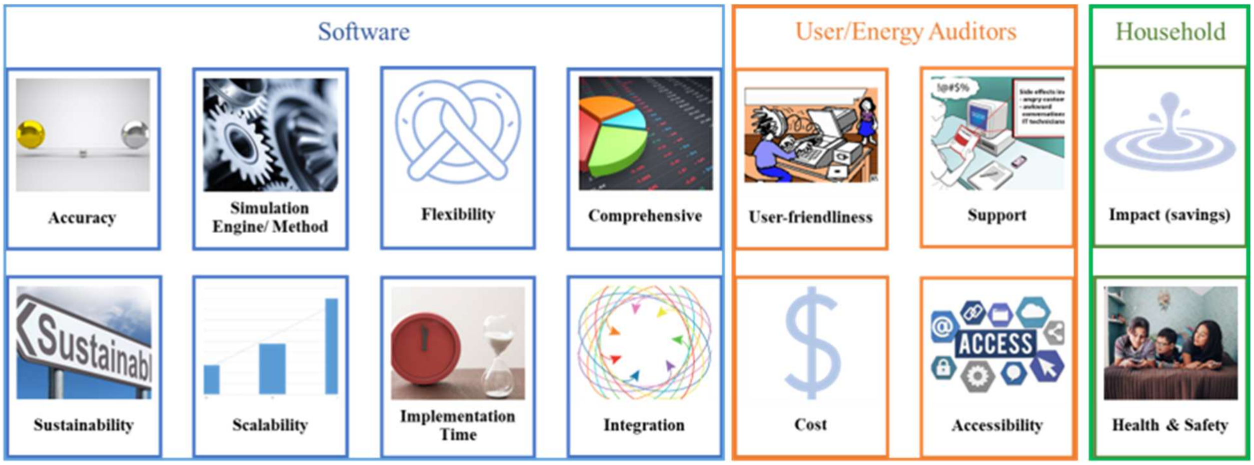

Figure 2.2 Model criteria organized into three main groups

The list of criteria that were used to develop the framework may be organized into three main groups, as shown in Figure 2.2, each with a different focus. The first group of criteria focuses on the software tool and ensures that the tool is functional and has the key features that an energy audit software should have. The second group focuses on the user and guarantees that the software is accessible and valuable to those who use it. The last group focuses on the primary beneficiaries of the energy audit – low-income households/families – and ensures that the energy audit meaningfully impacts their lives.

2.2 Defining the Criteria for the Framework

Accuracy: For building energy models generated from simulation based on building descriptors that have underlining or user-defined assumptions, defining accuracy in 'exact' terms may be such a misnomer since all computer-generated models are, at best, close estimates of actual results when validated against measured data. Variations in factors like user behavior, system settings, and specific applications can create substantial differences in energy consumption, even among similar buildings. As such, a model's energy efficiency results are best represented as a distribution, with the mean indicating expected energy demand under standard framework conditions, while the range captures deviations from those conditions. This approach allows us to identify buildings with higher energy-saving potential, contributing to more accurate energy-saving estimates. Our framework will influence accuracy by building descriptors that apply to residential buildings at the individual building scale, following computational methods that align with proven and acceptable industry standards.

A known and well-established industry standard is the American National Standards Institute (ANSI) and ASHRAE Standard 140, which provide a standard method of testing for evaluating building energy modeling (BEM) software [53]. This Standard, which provides a set of test cases and metrics to assess how well a simulation software predicts a building's energy usage compared to actual energy usage, plays a critical role in ensuring that BEM engines give accurate and repeatable test results to developers, energy auditors, energy consultants, energy engineers, and other building energy professionals. Another test procedure more aligned to residential buildings and closely mimicking the test procedures set out in ANSI/ASHRAE Standard 140 is the Building Energy Simulation Test for Existing Homes (BESTEST-EX) [54]. BESTEST-EX leverages building physics or utility bill calibration to provide test procedures that software developers can use to assess how their energy audit software performs in modeling energy use and savings in existing homes when utility bills (actual energy use) are available [54]. BESTEST-EX provides a test suite representing several cases for building physics and calibrated energy savings test procedures. In the BESTEST-EX calibration test, an energy modeling or audit software is tested against itself [55]. Also, tested software can be compared with some of the most advanced simulation engines such as EnergyPlus, SUNREL, and DOE21-1E[1], a method like ones previously developed by the National Renewable Energy Laboratory (NREL) and included in ANSI/ASHRAE Standard 140 [54]. The different cases evaluate a software's ability to model space heating loads and space cooling loads in representative heating and cooling climates, respectively, for different retrofit options [58]. It also includes combined retrofit cases for heating and cooling climates and all the input data for the other cases [57]. In BESTEST-EX, a tested energy audit software is deemed accurate if its simulation results fall within, for example, acceptance range maxima and minima, indicated by 'range' bars. Examples of how the BESTEST-EX tests work are shown in Figure 2.3 and Figure 2.4. Here, the blue and green range bars indicate that the heating tests for gas usage/savings (Figure 2.3) or cooling test for electricity usage/savings (Figure 2.4) predicted by testing three energy modeling software – EnergyPlus, Sunrel, and DOE2.1 – are within acceptable ranges in 9 different cases.

[1] SUNREL has been retired (no longer in use) and there are more updated versions of EnergyPlus and DOE-2. However, the BESTEST-EX has not seen any major update in more than a decade after its development. Regardless, the procedures employed to develop it are still relevant for modern energy audit software.

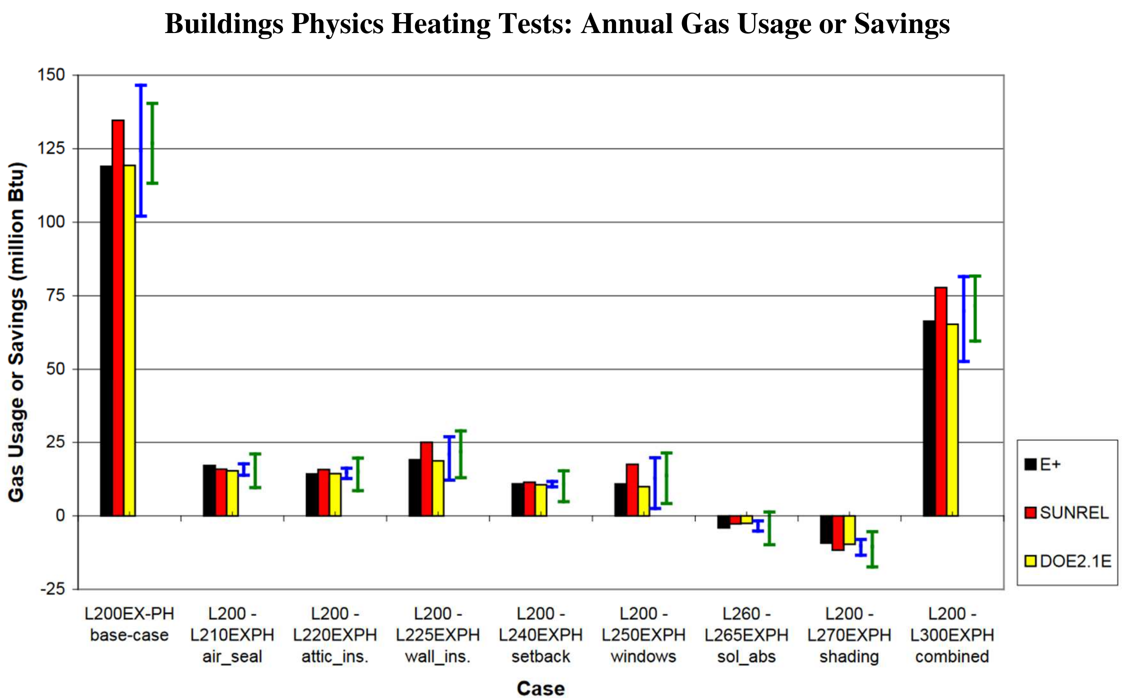

Figure 2.3 Reference simulation results and acceptance criteria of building physics heating tests[55]

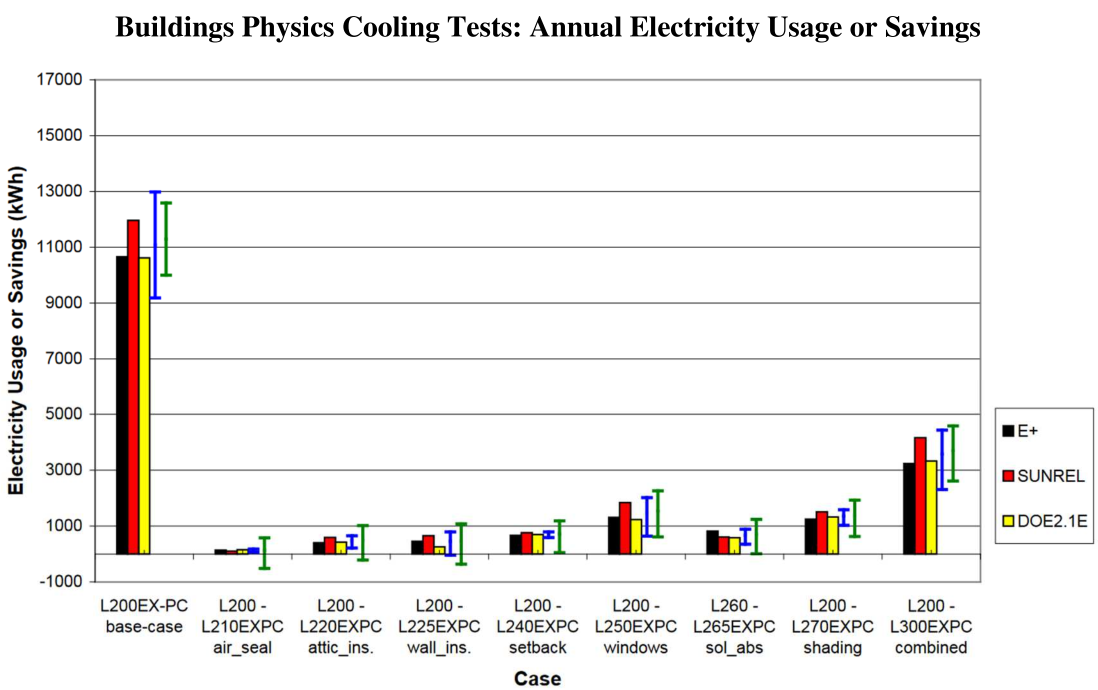

Figure 2.4 Reference simulation results and acceptance criteria of building physics cooling test [55]

Rather than a strict binary of 'accurate' or 'inaccurate,' accuracy is represented by an acceptable range. This range is defined by the specification of average deviations from the mean, ensuring tools provide meaningful results even with slight discrepancies. When software performance falls outside acceptable ranges but has negligible impacts on utility costs, this will not necessarily invalidate the tool as inaccurate. [57].

Additional procedures to ensure or improve the accuracy of energy modeling software used for energy audits, such as data validation, model calibration, and sensitivity analysis, but not discussed within the scope of our proposed framework may be found in [58].

Simulation Method/Engine: In choosing energy audit software, an equally important consideration to complement accuracy as already defined is the simulation method that is employed in its development [59]. There are three main approaches to BEM – physics-based modeling, a semi-physical or hybrid method, and a data-driven approach [60]. The physics-based method uses the principles of physics, taking the whole building as a system together with the interactions of all internal subsystems as well as external environmental factors to simulate building energy use [60]. This approach takes input from building descriptors (building geometry, lighting, water heating, HVAC, construction materials, etc.) and building operation/use (occupancy schedules, plug-loads, and controls and sensors) and combines them with local weather data, fuel type, and cost, and runs them through physical/mathematical models that could be based on thermodynamics, or mass and energy balance to determine thermal loads, system responses and energy use [61]. Physics-based models, while typically offering high accuracy, often require substantial data and computation resources to develop [62].

The semi-physical or hybrid simulation approach combines first-principle physics-based equations with statistical methods and experiment data, making it more computationally efficient and flexible for evaluating energy retrofits across building systems [63]. This method can balance the high accuracy of physics-based models and the efficiency of data-driven approaches. Still, it may present practical limitations, such as vague model naming conventions and a lack of unified software solutions, which can hinder widespread adoption [64].

The data-driven approach relies primarily on statistical methods, which can produce valuable results with significantly less data and at lower time and monetary costs [65]. Although the accuracy of data-driven models may not match that of detailed physical simulations, they are often effective for applications where rapid assessment is needed [66]Minor accuracy losses do not significantly affect outcomes, particularly when factoring in unpredictable variables like user behavior.

Each approach has its advantages depending on the goals of the energy audit. Physics-based models may be ideal for highly detailed and rigorous simulations. In contrast, data-driven models may be more suitable for quicker, cost-effective assessments, especially when evaluating buildings with varied user behaviors.

Flexibility: Software is not designed to address all problems, but it can often be adapted to address new challenges as they arise. Therefore, minor changes to the issues they were initially designed to solve do not necessarily render the software obsolete or unusable. This adaptability ensures the software remains relevant and valuable in a dynamic environment. [67]. Flexibility in software engineering relates to the software's ability to function normally despite uncertainty in input values or changes in assumptions, goals, and processes [68]. Flexible software provides a variety of ways in which the software can be used [69], in addition to being run on different platforms. Software flexibility allows the tool to be customized to fit individual cases or scenarios' specific needs and circumstances [70]. In our framework, flexibility in energy audit software would include making the tool customizable and allowing users to input their data and assumptions, such as the type of HVAC system, the age of the appliances, or the local climate. This flexibility empowers users to tailor the software to their needs and circumstances.

Comprehensive: There are diverse types of energy that can be used in buildings. The primary energy types are electricity and natural gas, especially in commercial buildings, even though other fuel types include fossil fuels (coal, natural gas, or fuel oil) and renewable energy sources (photovoltaic technology, bioenergy, geothermal, and wind energy). These energy types could also be used to meet the energy needs of buildings that are close together, such as on university campuses or in a city, through a district energy system [71]. Buildings use energy for various purposes, such as lighting, refrigeration, ventilation, space cooling and heating, computer operation, cooking, and water heating [72]. The energy utilized for each application can vary depending on building type, location, and usage patterns [73]. To improve energy efficiency and reduce costs, building owners and operators should identify and optimize energy consumption for each use [74]. Therefore, it is crucial to comprehensively understand how buildings use energy to optimize it for specific use cases. According to our framework, comprehensive energy audit software should be able to capture and account for the different fuel types used in a building and how they are used. Figure 2.5 shows how energy use might be distributed in a residential building by fuel type. According to our proposed framework, the ability to capture and the extent to which an energy audit software can account for these variations in energy use determines its comprehensiveness.

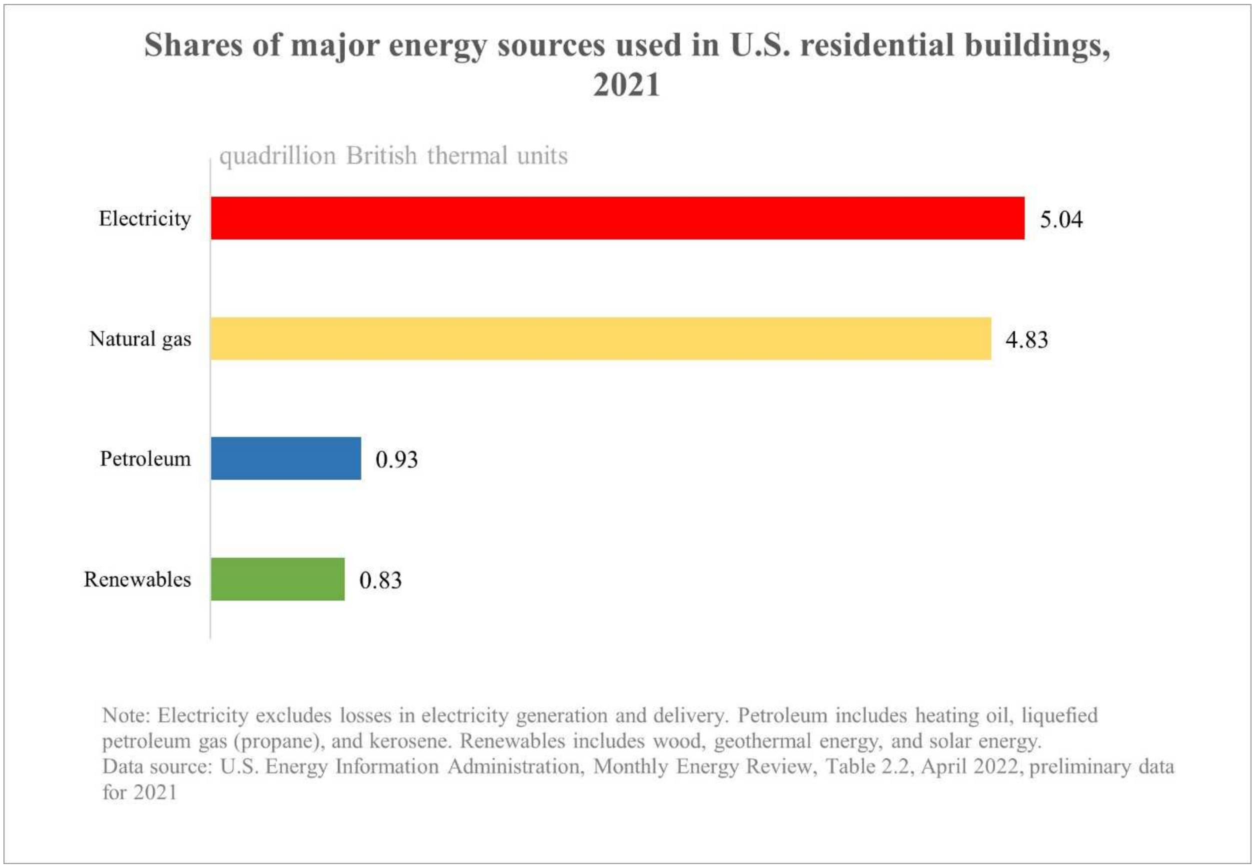

Figure 2.5 Distribution of energy used in commercial buildings by energy type (2021) [75]

Integration: Integration of software assesses how different software programs could be combined into one system so that the various programs can share one database [76]. Software integration must allow the different components to communicate with each other to increase efficiency [77]. Some software enables integration on different systems through Application Programming Interfaces (APIs), which can make cross-platform access possible [78]. In our proposed framework, energy audit software integration will be assessed by how well the tool integrates with other energy-saving systems, renewable technologies, and other programs such as home automation systems and utility rebates – a model that has been proven to lead to significant energy and cost savings [79]. Consequently, our proposed framework recognizes that energy audit software must include such functions.

Scalability: Software scalability determines how the software can withstand expansion in its capacity to handle increased data volumes and user demands without compromising performance [80]. In scalability testing, factors that are often considered include response time (time between a user's request and the application's response), resource usage (memory and bandwidth consumption), and throughput (number of requests processed within per unit time [81]. Further scalability metrics are highlighted in [82]. Only an extensive scalability test will be able to address the factors raised [83]. For energy audit software, scalability is crucial in assessing how easily it can be expanded to support a more significant number of households and whether it can be used in different geographic locations or run on various hardware and software. However, a considerable scalability challenge lies in efficiently gathering the correct data to serve many households. Identifying or developing software that requires minimal, easy-to-gather data while still providing reliable results could greatly enhance scalability. Such a solution would reduce the burden of data handling, allowing energy audits to reach a larger audience more effectively.

Sustainability: This criterion must not be confused with sustainability in software development, which measures the impact of development, deployment, and usage of the software on the environment, humans, society, and the economy [84], or Green Software System defined in terms of the energy consumption and associated carbon footprint and resource utilization of software use on the environment [85]. According to our framework, this criterion will, however, measure whether the energy audit tool promotes sustainable energy practices and supports the transition to renewable energy sources [86]. This is in line with Title 10 of the U.S. Code of Federal Regulations, Chapter II, Subchapter D, Part 440 (10 CFR 440.1), which establishes the scope and purpose of the weatherization assistance program not only to increase the energy efficiency of homes occupied by people in the low-income bracket but also to provide them with renewable energy technologies or systems [30]. Conventional energy audits have focused on efficiency measures to reduce energy consumption and associated costs [87] without exploring how renewable energy technologies such as solar PV systems and solar hot water systems or options could contribute to energy efficiency goals. However, this criterion seeks to reexamine that. Another aspect of this criterion will be to assess how energy use or savings are quantified in terms of GHG emissions [88] contribution or prevention not only in conventional metrics such as tons of CO_2e but in relatable terms such as the emissions contributed or avoided by the equivalent of a certain number of cars, trucks or ships. Furthermore, as used in our framework, sustainability will consider the social cost of carbon whereby a dollar estimate is given of the economic cost or damage of what an unabated CO_2 emission into the atmosphere would have been [89]. Providing such metrics could significantly motivate individuals and organizations to act on matters that would have been ignored.

Implementation time: About 50 million low-income U.S. households (44% of U.S. households) [90] and about 38.6 million are eligible for weatherization under WAP. Yet, only about 100,000 homes (less than 1% of U.S. buildings) are weatherized yearly under the Weatherization Assistance Program [90]. The low annual rate of weatherization is mainly due to funding and administrative constraints, as well as a lack of streamlined processes to facilitate the speed and scale of weatherization [91]. At this rate, it would take approximately 386 years to weatherize the remaining homes that qualify for weatherization assistance. For this reason, implementation time is one of the most crucial consideration factors in our framework for low-income households. The implementation time includes data acquisition, input, report output, and scope generation. Data acquisition is facilitated by an audit checklist comprehensive enough to guide an energy audit's walkthrough and data acquisition phase. An energy audit software should have or generate such a checklist. The implementation time is also enhanced (reduced) by the ease with which gathered data is fed into the software. Input is made easier when the software has clear and concise labeling, making it easy for users to understand what data is required in each field. Also, adding in-built data validation would ensure that the correct data type or format is entered to avoid errors. Where the wrong data is input, an inline error message should help users quickly identify and correct such errors. An intuitive and organized user interface would provide users with a clear data flow and make navigation easier. Other factors of easy data input, such as keyboard shortcuts, multi-language support, screen optimization, and contextual help, such as tooltips, are essential but have been included in a criterion named user-friendliness to avoid redundancy.

After data gathering and input come report output (ECMs) and scope generation. The outputs directly relate to how fast the computer can process and generate results from the local CPU or receive them from remote servers. In our framework, we will consider the execution time of an energy audit software from when a building that has been characterized is run through the simulation engine to when the results are ready. The importance of the implementation time is that it helps to determine the number of homes that can be analyzed within a specified time. An efficient energy audit software should minimize processing times, but equally critical is the reduction of data complexity and the amount of data required. This focus on essential data would enable energy auditors to complete audits more quickly and accurately, expanding the number of homes that can be audited in a given period. For a fair assessment, using one set of building characteristics for all software tools is vital for easy comparison. Regardless, the authors acknowledge that extenuating circumstances could impact implementation time but have little to do with a tested software's capability or the energy auditor's competence, even when the same software is tested iteratively under the same experimental conditions [92].

User-friendliness: User-friendliness in software shows whether the tool is easy to use and understand for users with limited technical expertise. A software's design is informed by its purpose and users. To provide the best user experience, developers must stay connected with the software users through research and feedback. [93] provides a taxonomy of factors to consider when designing applications with user-friendly interfaces and defines them. The relevant aspects of [93]'s taxonomy adopted for our framework includes speed, ease of use, aesthetic appeal, responsiveness, efficiency, and smartness. Others are plugins, security features, error control, updates, and support.

Support: Software must come with adequate support [94], such as user manuals, customer service, and training materials that address how to install, launch, and use the tool [95]. Support must be given through online and offline means [93]. Online support [96] includes Frequently Asked Questions (FAQs) and answers, submitting support tickets, phone communication for technical and business support, online chat, video calls and webinars, remote connection, and emails. Offline support could come in the form of a "Getting Started" manual, user guide, and training sessions. Responses to requests for support must be prompt and exhaustive to ensure customer satisfaction. Beyond the support developers give to enhance user experience, users' requirements play a crucial role in software development, as user needs are constantly evolving [97]. Therefore, part of the support should also be tailored to provide a continuous feedback loop whereby users can share their experiences and needs [98].

Cost: The criterion of cost in our framework measures the affordability of the tool for users or beneficiaries. Different software would have various pricing models [99]. Regarding energy audit software in the U.S., most software developed or sponsored by government bodies and agencies is free to download and use. These types of software may be available to the public for expert and untrained users at no cost. There is other government-agency-approved software that is paid for by government bodies for use by expert users in carrying out agency-funded tasks in a Business-to-Business (B2B) transaction [100]. Other cost models which are explored under this criterion include software licensing [101] with or without maintenance fees or subscription-based models such as software as a service (SaaS) [102] with options that include metered usage payment, active user counts, or freemium models – that is, a free trial for a limited period or a free version with basic, limited functionalities [103].

Accessibility: Accessible software works for all people regardless of hardware, software, geographic location, language of the user, or physical ability or disability [104]. Our criterion of accessibility would address the concerns of whether, for example, the tool would be accessible to rural households or energy auditors who go to work in remote places with limited internet access or other technological barriers. Also, our definition of accessibility goes beyond having electronic access to the tool; it also measures how a person can use what is available. For example, if a person has a physical or neuromuscular disorder that poses limitations in fine motor control so that such a person would instead use the keyboard rather than the mouse, will all the functionalities of the software still be accessible from a keyboard [104]? Moreover, does the choice of colors make it easier for those with color blindness to access the software [105]? Addressing disability concerns should also factor in those with hearing, cognitive, and speech disabilities.

Impact: According to our framework, the impact of an energy audit software would be measured by whether it is achieving what it was built for. For other types of software, the impact is measured by the number of active users, customer acquisition rate, monthly recurring revenue, customer satisfaction, product engagement, or deliverables met [106]. In our framework, the impact of energy audit software on low-income households would be ascertained by whether the tool leads to significant energy savings and cost reductions for households. Also, non-energy impacts (NEIs) could be considered, such as operations and maintenance savings, occupant comfort, occupant productivity, property value improvement, and lower debt, among others [107]. While NEIs are undoubtedly useful, some are hard to quantify [108], and their immediate benefits may not be readily ascertained as a basis for software selection or scoring. Therefore, NEIs will not be included in our framework except those related to health and safety, which are discussed in the criterion named "Health and Safety (Indoor air quality)."

Health and Safety (Indoor air quality): This criterion discusses the health and safety aspect of NEI that stems from energy-audit-based retrofit, focusing on the occupant [109]. We consider that energy audit software should provide building occupants with greater control of the building, reduce unwanted temperature variations, and improve indoor air quality, among others [110]. However, the health and safety aspects of energy audits for building occupants should not come as unintended benefits; energy audit software should be intentionally designed to address such concerns. This could be implemented by including a checklist that checks for symptoms often associated with building-related health concerns [111]. Additionally, observation checklists could be used to observe or evaluate the presence of lead, moisture and mold, radon, formaldehyde and volatile organic compounds (VOCs), pest infestation, and safety hazards, bearing in mind the nature of the occupants—elderly, disabled, children, etc.

2.3 Chapter Summary

In this research, we proposed an expanded framework of factors that should be considered in energy audit software approved for energy efficiency programs, particularly for low-income households. The framework includes more than 50 factors organized under 14 assessment criteria and can be used to score different energy audit software to determine their suitability for specific energy efficiency programs. The proposed framework can contribute to developing more effective energy audit software for low-income households, which can reduce energy consumption and costs and contribute to the global net zero emissions target by 2050. The framework also recognizes the importance of sustainability and the social cost of carbon in energy efficiency solutions for low-income households.

CHAPTER 3

EVALUATING ENERGY AUDIT SOFTWARE FOR LOW-INCOME HOUSEHOLDS: A COMPARATIVE ANALYSIS OF THREE SOFTWARE USING A MULTICRITERIA FRAMEWORK

This chapter demonstrates the applicability of the proposed framework in Chapter 2 by evaluating three energy audit software tools against a slightly updated version of the framework criteria. The comparative analysis revealed that while each software tool has distinct strengths and limitations, the framework effectively highlights its suitability for specific contexts and identifies areas for improvement. This chapter is an article in preparation for submission to a journal.

Acknowledgments: This work was sponsored by the U. S. Department of Energy's Office of State and Community Energy Program under contract DE-AC05-00OR22725 with UT-Battelle, LLC.

Chapter Abstract

Energy audit software is critical in identifying energy-saving opportunities within residential buildings. Yet, limited research has explored the effectiveness of these tools specifically for low-income households, where health, safety, and cost considerations are paramount. This study introduces a novel, multi-criteria framework to assess the suitability of energy audit software for low-income residential applications. The framework evaluates software tools across 14 criteria categorized as software-focused, user-focused, and household-focused, with over 50 assessment points designed to capture both quantitative and qualitative aspects of performance. Three widely used software tools – REM/RATE, Weatherization Assistant (WA), and Targeted Retrofit Analysis Tool (TREAT) – were evaluated to identify strengths, limitations, and areas for improvement specific to low-income contexts. Findings reveal distinct trade-offs among the tools: REM/RATE excels in compliance with established energy standards and renewable energy modeling but lacks health and safety assessments; WA demonstrates superior scalability and health and safety checks yet falls short in sustainability features; TREAT provides a balanced user experience but is limited in energy standard compliance and renewable energy integration. The results stress the need for future software enhancements, including improved health and safety modules, renewable energy and emissions metrics integration, and customizable features for diverse building and household types. By establishing a comprehensive,

adaptable framework for evaluating energy audit tools, this study contributes to energy policy and software development. It supports more effective energy audits that meet the specific needs of low-income households.

3.1 Introduction

Buildings are major contributors to global energy consumption and greenhouse gas emissions, with residential and commercial buildings in the United States accounting for about 40% of primary energy use and related emissions [112] – a trend that continues to rise [113]. Low-income households face a disproportionately high energy burden, averaging 8.6% of income, which is nearly three times that of non-low-income households [114]. Addressing this inequity through energy efficiency improvements is essential, as reducing energy use by an average of 4% per year over this decade is required to achieve global net-zero targets by 2050 [115]. Currently, however, fewer than 1% of U.S. buildings undergo efficiency upgrades annually [112].

Energy audits are instrumental in enhancing the energy efficiency of residential buildings, particularly for low-income households [116]. Recognizing this, government agencies have implemented energy efficiency programs such as the Weatherization Assistance Program (WAP), the largest residential energy efficiency initiative in the U.S., which aims specifically to reduce energy costs for low-income households [90].

Software tools have become vital in conducting effective energy audits. These tools allow auditors to assess building energy performance, identify potential savings, and recommend cost-effective upgrades [117]. These tools streamline data collection, analysis, and reporting, enabling auditors to deliver more reliable, comprehensive assessments [118]. By simulating building energy use and evaluating potential savings from different retrofits, energy audit software provides detailed insights for homeowners and program administrators.

Within many energy efficiency initiatives, energy auditors must follow designated audit procedures and use approved software tools [119]. However, a well-defined, comprehensive framework for selecting the most suitable software – particularly for low-income households – has been lacking. This study addresses this gap by developing an expanded criteria framework for determining energy audit software within programs targeting low-income communities.

Our research compares three widely used energy audit tools – REM/RATE, Weatherization Assistant (WA), and Targeted Retrofit Analysis Tool (TREAT) – using a novel multi-criteria framework to assess each tool's suitability for applications in low-income households. By evaluating these tools against comprehensive criteria, we aim to identify the strengths and weaknesses of each option, provide recommendations to improve energy audit software for low-income applications, offer guidance to energy efficiency program administrators in tool selection, and inform software developers on enhancing existing tools or creating new ones tailored to low-income households.

This study is significant for its potential to contribute to more effective energy efficiency programs for low-income households. By refining software selection and development, we can improve the reliability and thoroughness of energy audits, leading to more impactful energy savings and cost reductions for vulnerable populations. Our research aligns with broader goals of reducing energy poverty, enhancing housing quality, and advancing climate change mitigation efforts through building energy efficiency.

3.1.1 Brief Overview of Tools

REM/RATE, developed by NORESCO Energy Service Company, is widely used by Home Energy Rating System (HERS) providers for home rating and energy analysis [120]. Weatherization Assistant is a suite of four audit tools created by Oak Ridge National Laboratory and is specifically designed for the Department of Energy's Weatherization Assistance Program [121]. TREAT, developed by Performance Systems Development, is a versatile tool energy professionals use for building energy modeling and analysis [122].

3.1.2 Multi-Criteria Framework for Evaluating Energy Audit Software

The multi-criteria framework developed for this study introduces an extensive range of factors relevant to energy audits for low-income households. Organized into three categories – software-focused criteria, user-focused criteria, and household-focused criteria – the framework comprises 14 assessment criteria, as shown in Figure 3.1.

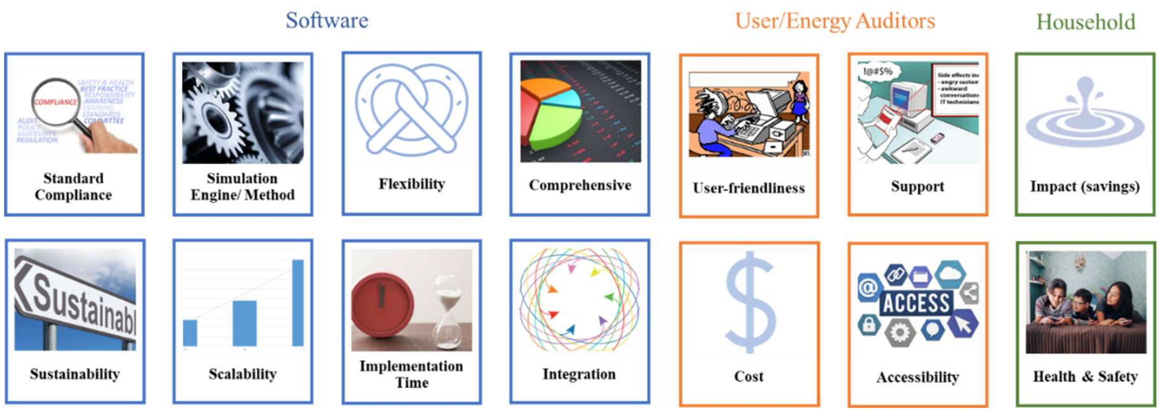

Figure 3.1 Organization of Framework Criteria (Updated with Standard Compliance)

The software-focused criteria primarily address the technical capabilities of each software tool. Standard Compliance evaluates the software's ability to meet specific residential energy efficiency standards, including ANSI/ASHRAE 90.2 [123], RESNET 301 [124], and IECC codes [125]. The purpose of the standard compliance criterion is to assess the software's reliability in energy-use predictions and savings estimates. Simulation Method/Engine reviews the computational approach (whether physics-based, hybrid, or data-driven) and assesses whether it utilizes a state-of-the-art, open-source, or proprietary engine. Flexibility considers the software's adaptability across diverse building types and responsiveness to varied data inputs. Comprehensiveness assesses the range of energy systems and conservation measures that the software can model, including fuel types, renewable resources, and end-use energy distribution. Integration evaluates the software's compatibility with other tools and systems, such as home automation platforms, utility rebate programs, and renewable energy technologies. Scalability examines the software's capacity to handle multiple projects and more extensive datasets and its compatibility with different types of hardware. Sustainability assesses the software's capability to include renewable energy options, quantify environmental impacts such as greenhouse gas emissions, and provide metrics such as net-zero energy analyses. Finally, Implementation Time evaluates the efficiency of the audit process through features such as a well-designed user interface, audit checklist availability, and data validation functionalities.

The user-focused criteria assess usability, accessibility, and affordability. User-friendliness examines the ease of installation, navigation, and general usability of the software across various devices, considering factors like keyboard shortcuts, readable fonts, clear icons, and intuitive menu layouts. Support evaluates the availability and quality of user assistance through manuals, training materials, and channels for user feedback. Accessibility reviews the software’s functionality in both online and offline modes, its compatibility with assistive technologies, and the availability of features specifically designed for users with disabilities. Cost considers the affordability of the software for a range of users, examining options such as free trials, subscription pricing, and any pricing structures accessible to non-commercial users.

The household-focused criteria measure the software's capacity to generate impactful and safe outcomes for low-income households. Impact (Savings) assesses the software's accuracy in predicting energy and cost savings, focusing on its ability to achieve results within an acceptable margin of error. Health and Safety evaluates the software’s inclusion of checklists for identifying common hazards (such as mold, moisture, lead, and radon) and its consideration for specific safety needs of vulnerable populations, including the elderly, disabled, and children.

Each criterion is divided into specific factors and subfactors, totaling over 50 distinct assessment points. This comprehensive design enables a nuanced evaluation of each software tool’s strengths and limitations. The framework incorporates qualitative and quantitative assessment methods: the qualitative component offers detailed descriptions of each criterion and its associated factors. In contrast, the quantitative component assigns scores to factors and subfactors based on their relevance in assessing software suitability for low-income household energy audits. This multi-criteria approach expands traditional software evaluation by integrating factors especially important to low-income communities, including health and safety considerations, accessibility features, and options for affordable renewable energy.

Table 3.1,Table 3.2 and Table 3.3 summarize the qualitative framework for the software-focused, user-focused, and household-focused criteria.

Table 3.1 Outline of measuring factors in the qualitative framework for software-focused criteria

Software-focused Criteria (Part A)			
Standard Compliance (STC)	Simulation Method/ Engine (SME)	Flexibility (FLEX)	Comprehensiveness (COM)
1. Meets ANSI/ASHRAE 90.2 or RESNET 301 2. Meets BESTEST-EX reference simulation results and acceptance criteria 3. Meets IECC Codes	1. Simulation Method A. Physics-based B. Hybrid method C. Data-driven 2. Engine A. Known open-source state-of-the-art engine. B. Proprietary	1. Allows customization of data input and assumptions	1. Accounts for different fuel types 2. Accounts for renewable energy resources 3. Provides end-use energy distribution
Software-focused Criteria (Part B)			
Integration (INT)	Scalability (SCAL)	Sustainability (SUS)	Implementation Time (TIME)
1. Integrates with home automation systems. 2. Integrates with utility rebates.	1. Support many building types 2. Supports multi-building aggregation 3. Runs on different	1. Explore renewable energy technologies. 2. Quantifies energy usage in terms of GHG emissions/savings.	1. Provides an audit checklist to facilitate data gathering. 2. Clear and concise labeling to help users

3. Integrates with renewable energy technologies	software/ hardware	3. GHS emission/savings metrics are relatable. 4. Provides net-zero energy/emission analysis 5. Estimates the social cost of carbon.	understand required data input fields. 3. In-built data validation to ensure the correct data type and format is entered. 4. Inline error message to identify and correct errors 5. Intuitive user interface

Table 3.2 Outline of measuring factors in the qualitative framework for user-focused criteria

User-focused Criteria			
User-friendliness (USE)	Support (SUP)	Accessibility (ASB)	Cost (COST)
1. Installing and uninstalling was fast and easy. A. Yes B. No C. N/A (for web or cloud-based applications) 2. The application provides keyboard shortcuts. 3. Navigating pages and input fields is possible using the tab key 4. The choice of design colors is appealing and poses no problem to the eye	1. The software comes with a user manual. 2. Training materials (videos and webinars) are provided/available for use of the software. 3. Provides support through emails, online chats, FAQs and answers, or contact number 4. There is a means to provide feedback to developers	1. Software Availability A. Online mode only B. Offline mode only C. Offline and online modes 2. All software features are available from a keyboard. 3. Features and reports are accessible to	1. Software is free to users with full features in a non-B2B transaction 2. Paid software A. Has a limited free-trial version with full features. B. Has free version with limited features with no time restrictions C. Has a limited free-trial version

5. Font type and size are readable. 6. Icons and shapes are understandable. 7. No issues with viewing the tool on different devices (laptop, tablet, desktop) 8. Running the application does not affect using other activities. 9. It is easier to select items from menus. 10. It is easier to search for information. 11. Could use the application without referring to user guide often. 12. The application works well with [external] mouse and keyboard 13. Software does not crash during use. 14. Software comes with regular updates and bug fixes		people with disabilities	with limited features. D. Has no free trial version

Table 3.3 Outline of measuring factors in the qualitative framework for household-focused criteria

Household-focused Criteria	
Impact (savings) (IMP)	Health and Safety (HS)
1. ECMs generated by software lead to energy and cost savings, that is A. Significantly lower than predicted (more than 25% less	1. Software has checklists to inspect general *health hazards* such as mold, moisture, lead, radon, etc. 2. Software helps to inspect safety concerns related to *injury prevention.*

B. Around what was predicted (within a 25% margin of error) C. Significantly above what was predicted (more than 25% higher)	*3.* Software checks the safety of the *elderly, disabled and children.* 4. Software checks safety related to the *structural integrity of the building.* 5. Software checks safety related to *fire and electrical safety*

3.2 Methodology

This study uses a comparative analysis approach to evaluate three widely used energy audit software tools – REM/RATE, Weatherization Assistant (WA), and TREAT – based on a novel multi-criteria framework explicitly developed to assess their suitability for low-income household applications. The research methodology involves a series of structured steps, which include framework development, nomenclature and structure definition, software selection, software testing, data analysis, and a comprehensive comparative assessment.

3.2.1 Framework Development

The multi-criteria framework developed for this study integrates a broad set of factors essential for evaluating energy audit software for low-income households. The framework comprises 14 assessment criteria, further divided into specific factors and subfactors to yield over 50 individual assessment points. Each criterion is organized into three main groups – software-focused, user-focused, and household-focused – providing a comprehensive structure for assessing software capabilities and limitations.

The framework incorporates both qualitative and quantitative methods. The qualitative component provides in-depth descriptions of each criterion and its associated factors, enabling a detailed evaluation of software performance. The quantitative scoring system assigns numerical values to each factor and subfactor based on relative importance. It allows for an overall assessment of each software tool's suitability for low-income household applications. This scoring system was designed to offer a systematic, objective approach to evaluating energy audit software, particularly for applications within low-income households.

3.2.2 Nomenclature and Structure

The framework is organized hierarchically, with each criterion (C) divided into factors (F) and, where relevant, further subdivided into subfactors (SF). Each criterion is represented by an abbreviated code of two, three, or four letters, as shown in Tables 4, 5, and 6. The criteria codes include:

1. **Standard Compliance** (STC)
2. **Simulation Methods/Engine** (SME)
3. **Flexibility** (FLEX)
4. **Comprehensiveness** (COM)
5. **Integration** (INT)
6. **Scalability** (SCAL)
7. **Sustainability** (SUS)
8. **Implementation Time** (TIME)
9. **User-friendliness** (USE)
10. **Support** (SUP)
11. **Accessibility** (ASB)
12. **Cost** (COST)
13. **Impact** (IMP)
14. **Health and Safety** (HS)

In the quantitative framework, each factor within a criterion is numbered sequentially, and subfactors, where present, are identified with letters of the alphabet, reflecting the same hierarchy used in the qualitative descriptions in Table 3.1, Table 3.2 and Table 3.3. For instance, STC-1 denotes the first factor under Standard Compliance, while SME-2-B represents subfactor B under the second factor of Simulation Methods/Engine.

Error! Not a valid bookmark self-reference.,Table 3.5 and

Table 3.6 illustrate the scoring systems for software-focused, user-focused, and household-focused criteria, respectively. Each criterion in these tables has a designated maximum score, indicating its importance in the context of low-income household energy audits. Points are then distributed among factors and subfactors, with binary subfactors receiving full points for “yes” responses and zero for “no.” At the same time, multi-level factors allocate points according to levels of compliance or capability.

The total score for each criterion is derived by summing the points for its associated factors and subfactors, and the overall score for each software tool is calculated by aggregating the scores across all 14 criteria. This point-based quantitative scoring system enables a comprehensive, objective evaluation of the software tools, facilitating comparisons and highlighting areas of relative strength and weakness in each tool's suitability for low-income household energy audits.

Table 3.4 Scoring System of Software-focused Criteria

Software-focused Criteria (Part A)							
Standard Compliance (STC) = 11		Simulation Method/ Engine (SME) = 8		Flexibility (FLEX) = 5		Comprehensiveness (COM) = 9	
STC-1	5	SME-1-A	5	FLEX-1	3	COM-1	3
STC-2	2	SME-1-B	4	FLEX-2	2	COM-2	3
STC-3	4	SME-1-C	3			COM-3	3
		SME-2-A	3				
		SME-2-B	2				
Software-focused Criteria (Part B)							
Integration (INT) = 8		Scalability (SCAL) = 11		Sustainability (SUS) = 11		Implementation Time (TIME) = 11	
INT-1	2	SCAL-1	5	SUS-1	3	TIME-1	2
INT-2	2	SCAL-2	3	SUS-2	2	TIME-2	2
INT-3	4	SCAL-3	3	SUS-3	2	TIME-3	3
				SUS-4	2	TIME-4	3
				SUS-5	2	TIME-5	1

Table 3.5 Scoring System of User-focused Criteria

User- or Energy-Auditor-focused Criteria

User-friendliness (USE) = 23		Support (SUP) = 14		Accessibility (ASB) = 7		Cost (COST) = 9	
USE-1	3	SUP-1	5	ASB-1-A	2	COST-1	5
USE-2	1	SUP-2	3	ASB-1-B	1	COST-2-A	4
USE-3	1	SUP-3	4	ASB-1-C	3	COST-2-B	3
USE-4	2	SUP-4	2	ASB-2	2	COST-2-C	2
USE-5	2			ASB-3	2	COST-2-D	1
USE-6	1						
USE-7	1						
USE-8	1						
USE-9	1						
USE-10	2						
USE-11	2						
USE-12	1						
USE-13	2						
USE-14	3						

Table 3.6 Scoring System of Household-focused Criteria

Household-focused Criteria			
Impact (savings) (IMP) = 22		Health and Safety (HS) = 10	
IMP-1-A	5	HS-1	2
IMP-1-B	10	HS-2	2
IMP-1-C	7	HS-3	2
		HS-4	2
		HS-5	2

3.2.3 Software Selection

Several critical criteria guided the selection process for energy audit software in this study to ensure the tools chosen were applicable and relevant to low-income households. Key considerations included the software's ability to accurately assess residential building energy performance, its accessibility – favoring free tools or those with free trials – and its suitability for evaluating residential buildings commonly occupied by low-income families, such as single-family homes, manufactured housing, and multifamily units.

The initial pool of potential energy analysis software included options like Home Energy Saver (HES) Pro, Home Energy Yardstick, eQuest®, OptiMiser®, TREAT, EnergyGauge®, REM/Rate™ Desktop, and the Weatherization Assistant suite. After a thorough review, three software tools were ultimately selected for evaluation: REM/RATE™, TREAT, and Weatherization Assistant. This selection focused on their specific effectiveness for analyzing residential building types relevant to low-income households and aligns with the DOE-approved (US Department of Energy) tools recommended for the Weatherization Assistance Program, as outlined in the Weatherization Program Notice (WPN 19-4), Attachment 3 [126].

While these three tools were chosen to align with the study's objectives, the authors acknowledge that other suitable software might also meet the criteria. However, they were not included due to limitations in awareness or availability. This selection does not imply an endorsement of these tools as the universal optimal choice for energy audits. Instead, it reflects a deliberate, focused scope to allow for an in-depth, manageable comparative analysis that meets the research objectives.

3.2.4 Software Testing

The software testing phase involves a hands-on evaluation of REM/RATE, WA, and TREAT using the developed multi-criteria framework, focusing on the most pertinent criteria for assessing these tools in the context of low-income household applications. Each software tool undergoes a systematic series of tests to evaluate performance across the framework's criteria. This process begins with installing and configuring each software tool on compatible systems, then inputting standardized building data representing a typical low-income household to ensure consistent platform benchmarking. The systematic testing process provides a rigorous evaluation of each tool's performance.

Subsequent tests include running simulations and energy audits in each tool to assess functionality, comprehensiveness, and reliability, focusing on evaluating user interface design, ease of use, and overall user experience. Each tool's integration with other relevant systems and databases and its ability to scale to different building scenarios are examined. In addition, the time required to complete a full energy audit is evaluated for efficiency. Available documentation, support resources, and training materials are reviewed to gauge the support each tool offers users.

While the initial methodology intended to gather quantitative data on simulation runtimes, energy savings predictions, and cost estimates, some elements—particularly simulation runtime and energy savings predictions—could not be thoroughly tested. Observations and detailed notes were recorded for each criterion and subfactor where applicable, ensuring a comprehensive qualitative analysis of each software's strengths and limitations.

3.2.5 Data Analysis

After completing the testing phase, the collected data is systematically analyzed to evaluate the performance of each software tool across the framework's criteria. This analysis involves compiling both qualitative observations and quantitative data and then organizing this information by criterion for each software tool. Each criterion and subfactor is scored based on the predefined scoring system within the quantitative framework, enabling the calculation of aggregate scores for each main criterion and an overall score for each software tool.

The analysis identifies each tool's strengths and weaknesses by examining performance across different criteria, allowing for a comparative assessment of the tools to highlight notable differences or similarities. Additionally, the analysis examines the effect of particular features or limitations on each tool's overall suitability for low-income household energy audits. This phase is designed to deliver an objective, comprehensive assessment of each software tool's capabilities and limitations in meeting the unique needs of low-income households.

3.2.6 Comparative Assessment

The final stage of the methodology involves a comparative assessment of REM/RATE, WA, and TREAT, using the analyzed data to evaluate each software tool's relative performance. This assessment ranks the tools based on overall scores, identifying the best-performing tool for each criterion. The comparative analysis highlights each tool's strengths and weaknesses in meeting the specific needs of low-income household energy audits. Trade-offs between criteria, such as standard compliance versus implementation time or comprehensiveness versus user-friendliness, are evaluated to understand each tool's balance of features.

Implications of the findings are considered for energy efficiency program administrators, auditors, and low-income households, emphasizing practical outcomes for each user group. Standardized building data and predefined criteria enhance the objectivity and consistency of the evaluation, minimizing bias and ensuring a fair comparison. The methodology also notes potential limitations, such as the inability to test all scenarios and the possible effects of future software updates.

Through this comprehensive approach, the study offers insights into the capabilities and limitations of current energy audit software for low-income households. The findings guide software developers, energy efficiency program administrators, and policymakers, helping them improve and select tools well-suited to energy efficiency needs within low-income communities.

3.3 Results and Analysis

The comparative analysis of REM/RATE, Weatherization Assistant (WA), and TREAT revealed significant differences in performance and suitability for low-income household energy audits. Each software demonstrated strengths and weaknesses across various categories, influencing their effectiveness for specific aspects of energy audits. **Error! Not a valid bookmark self-reference.** presents the total scores for each software across all criteria.

Table 3.7 Overall Performance Scores of REM/RATE, Weatherization Assistant, and TREAT

Criteria	**REM/RATE**		**WA**		**TREAT**	
Total Score	**90**		**90**		**83**	
General Information						
Vendor	Noresco™		ORNL		PSD Consulting	
Targeted User	HERS service providers		States and local weatherization agencies		Varied	
Primary Use	Home rating and home energy analysis/ weatherization		To perform energy audit in support of DOE's WAP		Energy analysis and building modeling	
Availability	Available to the general public for use/purchase		Only available to States and local weatherization agents		Available to the general public for use/purchase	
Standard Compliance	**11**		**1**		**2**	
ASHRAE 90.2 or RESNET 301	Yes	5	No	0	No	0
BESTEST-EX	Yes	2	Partially	1	Yes	2
IECC Code	Yes	4	No	0	No	0
Simulation Method/Engine	**8**		**7**		**8**	
Simulation Method	Building Physics	5	Building Physics	5	Building Physics	5
Simulation Engine	NREL Engine (E+)	3	Proprietary (for NEAT and MHEA) and DOE-2 for MulTEA	2	SUNREL	3
Flexibility	**5**		**5**		**4**	
Customization	Yes	3	Yes	3	Yes	3
Assumption	Yes	2	Yes	2	Partially	1
Comprehensiveness	**9**		**6**		**6**	
Variety of fuel types	Yes	3	Yes	3	Yes	3
Renewable energy resources	Yes	3	No	0	No	0
End-use energy distribution	Yes	3	Yes	3	Yes	3
Integration	**4**		**0**		**0**	
Home automation systems	No		No		No	
Utility rebates	No		No		No	
Renewable energy technologies	Yes	4	No	0	No	0

Table 3.7 (cont'd)

Scalability	**5**		**8**		**8**	
Supports many building types	Yes	5	Yes	5	Yes	5
Multi-building aggregation	No	0	No	0	Yes	3
Runs on different systems	No	0	Yes	3	No	0
Sustainability	**3**		**0**		**0**	
Explores RETs	No	0	No	0	No	0
Quantifies energy in GHG	Partially	1	No	0	No	0
Provides relatable GHG metrics	No	0	No	0	No	0
Provides net-zero energy analysis	Yes	2	No	0	No	0
Estimates the social cost of carbon	No	0	No		No	
Implementation time	**9**		**11**		**9**	
Provides audit checklist	No	0	Yes	2	No	0
Clear and concise labeling	Yes	2	Yes	2	Yes	2
Inbuilt data validation	Yes	3	Yes	3	Yes	3
Inline error message	Yes	3	Yes	3	Yes	3
Intuitive user interface	Yes	1	Yes	1	Yes	1
User-friendliness	**18**		**20**		**19**	
Ease of installation	Yes	3	Yes	3	Yes	3
Keyboard shortcuts	No	0	Yes	1	Yes	1
Ease of navigation	Yes	1	Yes	1	Yes	1
Design colors and visual appeal	Partially	1	Yes	2	Partially	1
Font readability	Yes	2	Yes	2	Yes	2
Intuitive icons/shapes	Yes	1	Yes	1	Yes	1
Device/screen compatibility/responsiveness of application	Yes	1	No	0	Yes	1
Non-interference of application	No	0	Yes	1	Yes	1
Ease of menu selection	Yes	1	Yes	1	Yes	1
Search function	No	0	No	0	No	0
Ease of application use	Yes	2	Yes	2	Yes	2
External hardware compatibility	Yes	1	Yes	1	Limited	1
Application stability	Yes	2	Yes	2	Yes	2
Updates and bug fixes	Yes	3	Yes	3	Yes	3
User support	**14**		**14**		**14**	
User manual	Yes	5	Yes	5	Yes	5
Training materials	Yes	3	Yes	3	Yes	3
Phone or Online support	Yes	4	Yes	4	Yes	4
Customer feedback	Yes	2	Yes	2	Yes	2

Table 3.7 (cont'd)

Accessibility	**2**		**3**		**2**	
Software availability	Offline	1	Online	2	Offline	1
Accessibility of features	Limited	1	Limited	1	Limited	1
Disability-friendly	No	0	No	0	No	0
Cost	**2**		**5**		**4**	
Free to user	No	0	Yes	5	No	0
Not free but has:						
A. Free-trial with full features	No	0	No	0	Yes	4
B. Free version with limited features	No	0	No	0	No	0
C. Free-trial with limited features	Yes	2	No	0	No	0
D. Free-trial version	No	0	No	0	No	0
Impact (savings)						
Actual savings < predicted (more than 25% less)						
Actual savings close to the predicted						
Actual savings > predicted (more than 25% higher)						
Health and Safety	**0**		**10**		**7**	
Health hazard (mold, moisture, lead, etc.) inspection checklist	No	0	Yes	2	Yes	2
Injury prevention checklist	No	0	Yes	2	Yes	2
Safety of the elderly, disabled, and children	No	0	Yes	2	Partially	1
Structural integrity safety	No	0	Yes	2	Partially	1
Fire and electrical safety	No	0	Yes	2	Partially	1

3.3.1 Detailed Analysis by Criteria

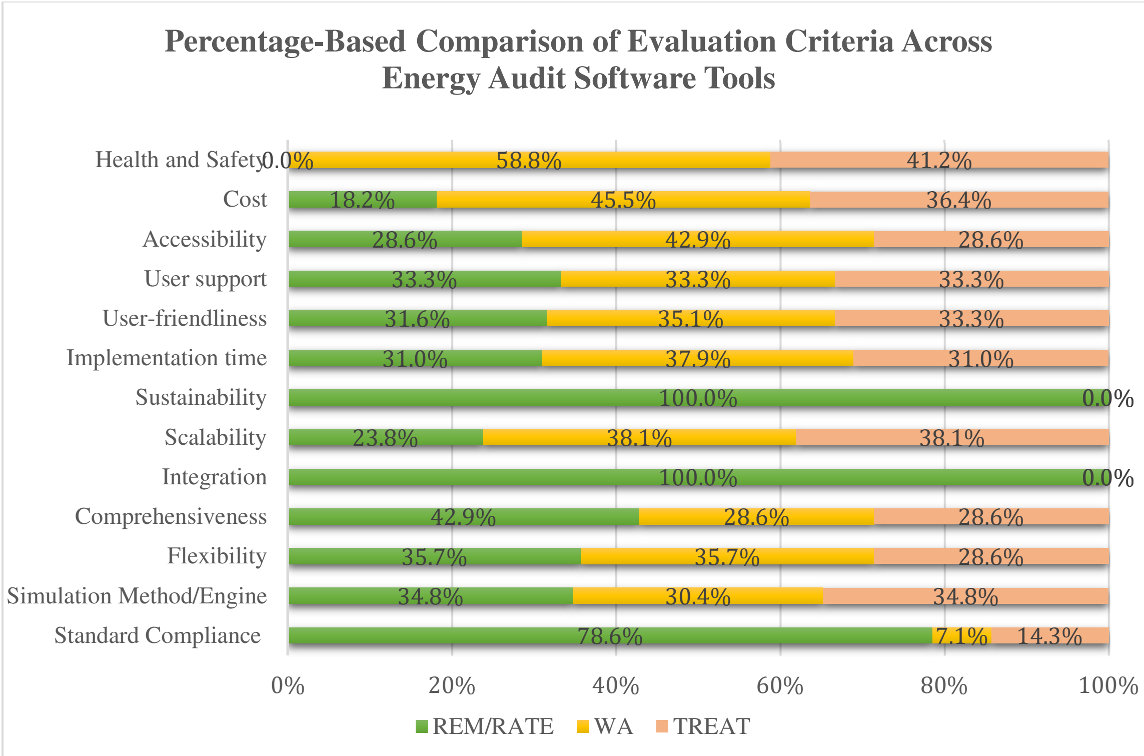

Figure 3.2 Percentage-Based Comparison of Evaluation Criteria Across Energy Audit Software Tools

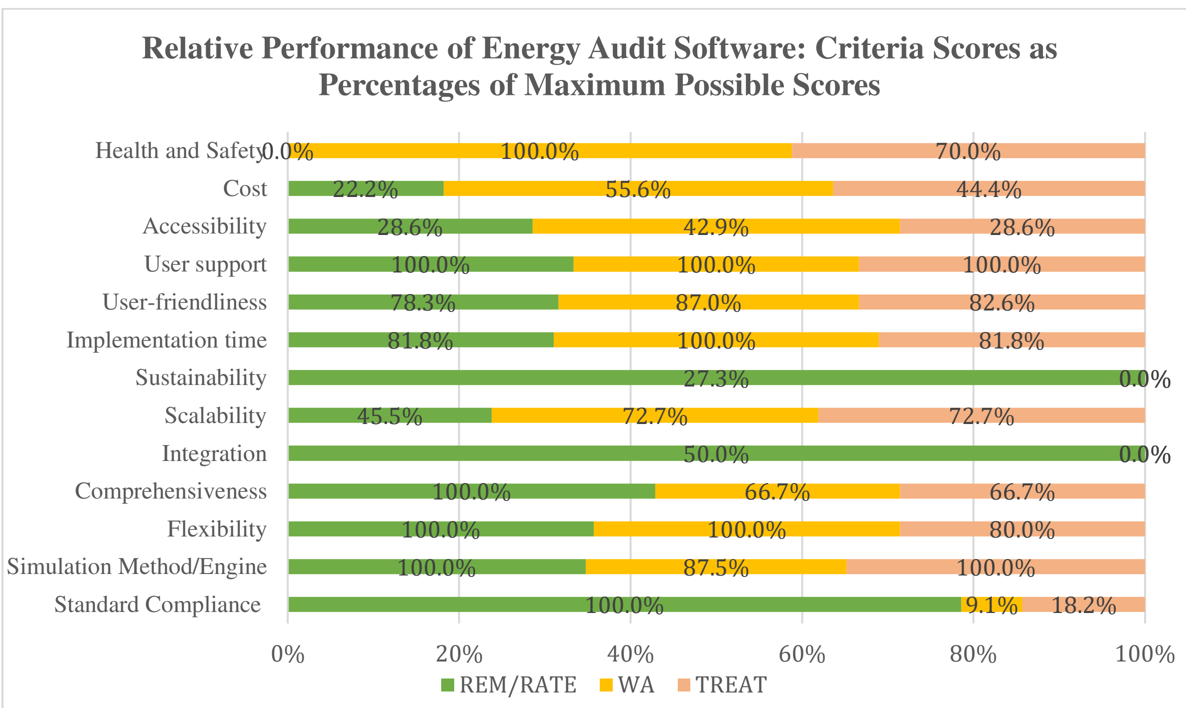

Figure 3.3 Relative Performance of Energy Audit Software: Criteria Scores as Percentages of Maximum Possible Scores

Software-focused Criteria

Standard Compliance (STC): None of the software tools fully comply with ASHRAE 90.2, but REM/RATE distinguishes itself with adherence to RESNET Standard 301, which supports Home Energy Rating System (HERS) scores and aligns with the IECC's Energy Rating Index (ERI). This compliance enhances REM/RATE's suitability for energy rating and modeling. WA and TREAT do not meet RESNET or IECC standards, limiting their use in contexts requiring these compliance metrics. REM/RATE and TREAT demonstrated full compliance with BESTEST-EX, thanks to their reliance on recognized engines like EnergyPlus and SUNREL. Using DOE-2 for MulTEA and the Variable-Based Degree Days (VBDD) method for NEAT and MHEA, WA showed partial BESTEST-EX compliance, as its monthly simulation output lacks the analytical depth of hourly engines. While there are ongoing efforts to transition WA to the EnergyPlus engine to enhance the reliability of modeling calculation and enable it to provide Home Energy Scores [127], it was not considered in our analysis as it has not yet been implemented fully.

Simulation Method/Engine (SME): All three tools use building physics-based simulation methods, but their engines vary. REM/RATE, with the EnergyPlus engine developed by NREL, and TREAT, which uses SUNREL, achieved high scores. WA scored slightly lower due to its reliance on DOE-2 for MulTEA and the VBDD method for NEAT and MHEA, which utilizes monthly rather than hourly simulations, reducing precision.

Flexibility (FLEX): REM/RATE and WA are equally flexible because they allow utility rate customization and adjustable assumptions. TREAT scored slightly lower because it restricts some default assumptions, which users cannot modify.

Comprehensiveness (COM): REM/RATE leads in comprehensiveness by including renewable energy resources, such as photovoltaic systems, in its modeling. This sets it apart from WA and TREAT, which do not account for renewable technologies, limiting their applicability for audits focusing on sustainability. All three tools accommodate various fuel types and end-use energy distributions.

Integration (INT): REM/RATE is the only tool offering integration with renewable energy technologies, enabling it to model systems like solar PV panels in energy consumption calculations. WA and TREAT lack integration capabilities with renewable technologies, home automation systems, or utility rebate programs. While all tools assess energy efficiency and potential savings, the utility rebate integration feature evaluates whether the software connects with specific rebate programs applicable to the audited home. Additionally, while all three software tools support thermostat modeling as part of standard energy audit functions, thermostats were not included in this integration assessment to avoid scoring inconsistencies.

Scalability (SCAL): WA and TREAT outperform REM/RATE in scalability. WA, a web-based tool, is compatible with multiple operating systems, while TREAT supports multi-building aggregation, enabling models of scattered buildings to be a single entity. REM/RATE and TREAT, desktop applications designed for Windows, require virtualization or emulation to run on other systems. All three tools support various building types, including single-family homes, manufactured homes, and multi-family buildings.

Sustainability (SUS): REM/RATE is the only tool scoring in sustainability, enabling net-zero energy analysis. This feature, absent in WA and TREAT, sets REM/RATE apart as it supports renewable energy calculations and net-zero assessments, aligning it with sustainability objectives.

Implementation Time (TIME): WA excels in implementation time due to its built-in audit checklist, streamlining the audit process. REM/RATE and TREAT offer similar time efficiency but lack this checklist feature, placing them slightly behind WA.

User-focused Criteria

User-friendliness (USE): TREAT was noted for its user-friendly interface and device compatibility, while WA's web-based format simplifies access as it doesn't require installation. REM/RATE provides a well-organized layout but is slightly less intuitive due to its color scheme and lack of keyboard shortcuts. All three tools are designed with ease of use in mind and perform comparably in aspects like installation ease, font readability, and intuitive icons. However, none of the software includes a search function, which could further improve user navigation.

Support (SUP): All three software performed equally in user support. Each software tool provides substantial support options, including comprehensive user manuals, training resources like webinars and tutorial videos, and online or phone support. All tools also enable users to submit feedback directly to developers, maintaining a channel for user input and continuous improvement.

Accessibility (ASB): WA scored slightly higher in inaccessibility due to its online accessibility. This allows it to be accessed from any internet-connected device, giving it an advantage over REM/RATE and TREAT, offline desktop applications with specific system requirements. However, none of the tools include disability-friendly features like screen readers or magnification, limiting broader accessibility for users with particular needs.

Cost (COST): WA, free to Weatherization Assistance Program participants, is the most cost-effective option. TREAT follows with a 30-day free trial with full features, while REM/RATE provides a 14-day limited trial.

Household-focused Criteria

Impact (IMP): The effect of savings generated by the software tools cannot be evaluated without conducting actual audits, implementing the recommended measures, and verifying the results over time. As a result, all three software tools are unscored in this category, highlighting the need for further empirical testing.

Health and Safety (HS): WA excels in addressing health and safety concerns by incorporating a comprehensive audit checklist that covers critical issues such as mold, moisture, lead, fire hazards, and injury prevention. This makes it particularly well-suited for low-income households facing heightened risks. TREAT provides partial coverage in health and safety areas but lacks the depth found in WA's tools. In contrast, REM/RATE does not address health and safety considerations, indicating a significant gap in its suitability for applications focused on the well-being of occupants, especially vulnerable populations like the elderly, disabled, or children.

3.4 Discussion of Findings

3.4.1 Strengths and Weaknesses

The analysis of the software tools reveals distinct strengths and weaknesses for each in the context of energy audits for low-income households.

REM/RATE excels in standard compliance, demonstrating superior alignment with RESNET Standard 301. Its high level of comprehensiveness, particularly in accounting for renewable energy technologies, further enhances its capabilities. Including sustainability features, such as net-zero energy analysis, positions REM/RATE as a strong option for audits requiring detailed energy evaluations. However, its scalability is limited due to lacking multi-building aggregation capabilities and compatibility across multiple platforms. Moreover, REM/RATE does not adequately address health and safety considerations, which are critical in low-income household energy audits.

Weatherization Assistant (WA) is well-suited for large-scale auditing programs, benefiting from superior scalability and efficient implementation processes. Its integration of a comprehensive health and safety audit tool, coupled with its availability free of charge for weatherization agencies, enhances its applicability for low-income households. Nonetheless, WA's limited compliance with widely recognized energy standards and lack of integration with renewable energy technologies or sustainability features diminish its utility for programs that heavily focus on energy conservation and emissions reduction.

TREAT balances user-friendliness and scalability, offering a flexible, user-centric interface. It includes features for multi-building aggregation, making it suitable for auditors managing complex projects. While TREAT provides moderate health and safety features, it does not achieve the same level of comprehensiveness as WA. Like WA, TREAT lacks compliance with essential energy standards and does not support integrating renewable energy technologies, limiting its application in audits that prioritize sustainability.

3.4.2 Implications for Low-Income Household Energy Audits

The findings from this comparative analysis offer valuable insights for selecting and developing energy audit software, particularly within the context of low-income households. Practical energy audit tools for these settings must strike a balance among critical factors, including reliable energy consumption assessments, adherence to industry standards, and the integration of renewable energy technologies. Additionally, they should prioritize practical considerations such as health and safety, scalability for diverse building types, and user accessibility to maximize their utility across various contexts.

Audit software must go beyond standard energy modeling for low-income households, where health and safety issues intersect with energy efficiency challenges. Essential features include comprehensive health and safety checks – for mold, lead, fire hazards, and structural integrity –ensuring that energy-saving measures do not compromise residents' well-being. Software designed for large-scale, multi-building programs also benefits from being flexible and scalable, allowing ease of use across various building types and regions while aligning with local energy codes and rebate programs.

Cost considerations are crucial as well. Access to affordable or free software can significantly influence the feasibility of implementing energy-saving measures in programs targeting low-income households. Publicly funded initiatives and organizations with limited budgets benefit from tools that offer robust features without high costs, helping ensure that energy audits and related improvements are accessible to low-income households.

Energy audit software development should prioritize sustainability features, such as modeling renewable technologies and assessing net-zero energy potential. As global energy policies increasingly emphasize carbon reduction and energy efficiency, audit tools will need to integrate metrics that quantify greenhouse gas emissions and support calculations of the social cost of carbon. By addressing these needs, future software developments can more effectively contribute to reduced energy consumption, improved living conditions, and lower energy costs in low-income households while supporting broader environmental goals.

3.5 Effectiveness of the Multi-Criteria Framework in Evaluating Energy Audit Software

The multi-criteria framework used in this study proved to be a robust tool for evaluating energy audit software across measures particularly relevant to low-income household energy audits. By assessing the software on a wide array of criteria – encompassing technical aspects, user accessibility, and specific household needs – the framework provided a comprehensive, multi-faceted comparison highlighting each tool's strengths and limitations. While generally effective, the framework revealed several strengths and areas where refinements could enhance its application.

3.5.1 Strengths of the Framework

The primary strength of the multi-criteria framework lies in its comprehensive scope. By evaluating a broad spectrum of categories, including standard compliance, simulation methods, scalability, cost, and health and safety, the framework captured essential aspects relevant to conducting energy audits in diverse settings. This inclusive approach ensured that the evaluation did not focus overly on a single dimension but considered each software tool's overall utility. For instance, including user-centered criteria like user-friendliness and support added a practical dimension, highlighting usability factors that could directly impact auditor efficiency and effectiveness in the field.

The framework’s quantitative scoring system also offered an objective basis for comparing tools. Assigning scores to individual criteria provided a data-driven approach to identifying clear performance differentials among software packages, allowing for a structured and consistent comparison. The flexibility of incorporating weighting factors was beneficial, enabling prioritization of criteria critical to low-income household audits, such as health and safety features and cost-effectiveness.

3.5.2 Weaknesses of the Framework

Despite its strengths, the multi-criteria framework also exhibited some limitations. A primary challenge was that not all criteria held the same relevance across different software applications, yet they were often weighted similarly. This could have led to an evaluation where less impactful aspects, such as interface design elements, contributed equally to the overall score as critical factors like standard compliance or health and safety. Although some weighting adjustments were made to mitigate this, future framework improvements would benefit from a more nuanced weighting system that reflects each criterion's varying importance based on the software's intended use.

Another limitation was the framework's inability to assess the real-world impact of recommended measures without actual implementation and sufficient time to measure or quantify their outcomes. While the framework did include metrics to evaluate post-implementation results, it could not fully capture them within this study's time limit, as measuring outcomes like actual energy savings, improvements in household safety, and enhanced living conditions require data collection well after audit recommendation implementation. Including these outcome-based metrics in future evaluations would provide a more comprehensive understanding of each tool's long-term practical effectiveness, especially in supporting energy conservation and improving living standards in low-income settings.

3.5.3 Recommendations for Improving Energy Audit Software for Low-Income Households

Based on the comparative evaluation of energy audit software and the unique needs of low-income households, the following recommendations aim to enhance these tools' technical capabilities and practical applicability in settings where health, safety, cost-effectiveness, and energy efficiency are critical.

I. Enhance Health and Safety Features

Given the heightened health and safety risks for low-income households, future energy audit software should prioritize comprehensive health and safety assessments. Incorporating detailed checklists for identifying potential hazards – such as mold, moisture, lead, fire, and structural risks – would significantly improve the value of these tools. Moreover, considering specific needs for vulnerable populations, including the elderly, disabled, and children, within the auditing process would support safer, healthier environments in low-income homes.

II. Integrate Renewable Energy and Sustainability Features

In line with global energy efficiency and sustainability goals, energy audit software should include features that model renewable energy technologies (RETs). Tools that evaluate the feasibility and benefits of solar panels, wind turbines, and energy storage systems can make clean energy more accessible for low-income households. Additionally, features estimating greenhouse gas (GHG) emissions and enabling net-zero energy analysis would allow the software to address immediate and long-term energy costs while meeting policy-driven carbon reduction targets.

III. Improve Customization and Flexibility

Customization options enable auditors to account for local variations in utility rates, climate, and building characteristics, tailoring analyses to specific household conditions. This flexibility is essential for low-income settings, where unique energy challenges may not align with default software configurations. Enhancing user-friendly interfaces for adjusting assumptions and input parameters would allow even less experienced auditors to personalize assessments confidently and effectively.

IV. Prioritize Scalability and Multi-Building Support

Auditing programs serving low-income households often target multiple buildings, particularly in public or subsidized housing. Software with multi-building aggregation features efficiently analyzes scattered sites, saving time and resources. In addition, web-based platforms compatible with various operating systems and devices (e.g., Windows, macOS, tablets, smartphones) would enhance accessibility and scalability for auditors working in diverse environments.

V. Ensure Cost-Effectiveness and Accessibility

Energy audit software affordability is critical for low-income communities and the agencies serving them. Developers should consider offering free or low-cost versions for public agencies or nonprofits that perform audits in these contexts. Options like free trials with full features, limited versions for basic audits, or discounted licenses for public-sector use would encourage broader adoption in resource-constrained settings. Additionally, making tools accessible online, with minimal system requirements, would further expand their reach.

VI. Improve Usability and User Support

User-friendly design and robust support options would make energy audit software more accessible, especially for auditors with limited technical expertise. Simplifying the user interface, including intuitive design elements, and providing tutorials, webinars, and technical documentation could support broader, more efficient use. In-built data validation, real-time error checking, and checklist features would streamline the process, reducing errors and supporting auditors in conducting thorough assessments.

VII. Incorporate Metrics for Real-World Impact

In addition to technical precision, energy audit software should help auditors and households understand the real-world impact of recommended measures. Including metrics for cost savings, energy reduction percentages, and payback periods allows users to assess tangible benefits, while estimates of environmental impact (e.g., GHG reduction) offer broader insights into sustainability. Such impact metrics are essential for decision-making for low-income households, where cost savings directly affect financial stability.

VIII. Regular Updates to Meet Evolving Standards and Needs

As energy codes, regulations, and technologies evolve, software should be regularly updated to remain relevant and practical. Maintaining compliance with the latest standards (e.g., ASHRAE, IECC codes) and supporting emerging technologies is essential for long-term utility. Developers should also actively solicit feedback from users in low-income contexts to understand and address specific needs. Incorporating this feedback into software updates ensures that it remains a practical, effective tool in promoting energy efficiency and well-being in low-income households.

3.6 Chapter Summary

This study conducted a comprehensive evaluation of energy audit software to assess their suitability for use in low-income household contexts, where health, safety, cost-effectiveness, and energy efficiency are paramount. By applying a multi-criteria framework that included technical, user-focused, and household-specific criteria, we were able to provide a detailed analysis of the capabilities and limitations of three widely used energy audit tools: REM/RATE, Weatherization Assistant (WA), and TREAT.

The analysis revealed that each software has distinct strengths and weaknesses relative to the needs of low-income households. REM/RATE demonstrated strong alignment with recognized energy standards and supports renewable energy modeling, making it a practical choice for programs prioritizing sustainability. However, its limited health and safety features and scalability restrictions reduce its applicability to low-income settings. WA, by contrast, excelled in scalability and health and safety assessments, making it particularly suited for large-scale, multi-building audits where the well-being of occupants is a priority. However, its lack of renewable energy features and limited compliance with industry standards may restrict its utility in initiatives targeting energy efficiency and emissions reductions. TREAT balanced usability and scalability, featuring moderate health and safety tools and multi-building support. Yet, it lacked standard compliance and renewable energy capabilities, limiting its effectiveness in sustainability-focused projects.

The multi-criteria framework used in this study proved effective in providing a holistic comparison. Yet, it highlighted areas where energy audit software could be further developed to meet the specific demands of low-income household audits. For example, future framework enhancements could incorporate post-implementation metrics to assess real-world outcomes like energy savings, health and safety improvements, and user satisfaction over time. Furthermore, the absence of renewable energy and GHG emissions assessment capabilities in most tools points to a need for software that aligns with emerging global energy policies and carbon reduction goals.

Several recommendations have emerged from this analysis. Energy audit software for low-income households would benefit from enhanced health and safety assessments, renewable energy and sustainability features, greater flexibility in customization, multi-building support, cost-effective options, improved usability, and real-world impact metrics. Implementing these enhancements would make the software more adaptable, comprehensive, and accessible, supporting auditors, agencies, and households in achieving meaningful energy savings and quality-of-life improvements.

This study underscores tailored energy audit software's critical role in advancing energy efficiency and environmental sustainability within low-income communities. By addressing the unique challenges these households face, improved energy audit tools can potentially drive substantial benefits – not only in terms of energy and cost savings but also in fostering safer, healthier living conditions. Future software development should prioritize integrating the recommended features to enhance the effectiveness and impact of energy audits, supporting broader objectives of social equity, environmental responsibility, and economic resilience in low-income settings.

CHAPTER 4

OPTIMIZING ENERGY SAVINGS CALCULATIONS: A COMPREHENSIVE REVIEW OF MEASURE LIFETIME ESTIMATION FOR ENERGY CONSERVATION MEASURES

This chapter evaluates seven methodologies for estimating the lifetimes of energy conservation measures: Survival Analysis, Manufacturer's Data, Industry Standard, Field Survey, Accelerated Life Test, Modeling and Simulation, and Expert Judgement. The study employs a critical review methodology to describe each methodology and its strengths, weaknesses, and applications. The study revealed that while each methodology provides a plausible means of evaluating measure lifetimes, the specific context in which measure lifetimes need to be estimated may inform which methodology to use, and also notes that external circumstances may affect measure lifetimes. This chapter is under review for publication in Renewable and Sustainable Energy Reviews.

Acknowledgments: This work was sponsored by the U. S. Department of Energy's Office of State and Community Energy Program under contract DE-AC05-00OR22725 with UT-Battelle, LLC.

Chapter Abstract

Achieving significant energy savings through Energy Conservation Measures (ECMs) hinges on accurate estimations of ECM or measure lifetimes. Measure lifetime underpins economic analyses and guides decisions for program implementation. This study presents a comprehensive review of measure lifetime estimation, exploring a diverse set of methodologies and their applicability. The limitations and importance of context-specific data selection are highlighted by delving into traditional approaches like manufacture data and industry standards. Valuable insights from field surveys and testing are examined while acknowledging their time constraints. Accelerated life tests (ALTs) are presented as a faster alternative, with a caveat regarding their real-world applicability. Statistical techniques such as data-driven modeling and simulation offer efficient and potentially more accurate predictions and can explore scenario planning to empower informed decision-making around measure selection, replacement schedules, and overall energy management strategies. Expert judgement also plays a vital role, particularly for novel technologies or situation with limited data. However, the elicitation processes must be carefully considered to minimize bias and ensure reliability. Additionally, the study acknowledges the factors

that could affect lifetime estimates by highlighting the critical influence of environmental factors and the necessity of project-specific considerations when selecting data sources. Furthermore, the study offers statistical techniques like the Weibull distribution for deriving representative lifetime values from diverse data sources, fostering consistency and enhancing the accuracy of energy savings calculations. The approaches given in this study enable reliable economic and energy savings analyses, leading to more informed decision-making and maximizing the impact of ECM implementation.

4.1 Introduction

Energy conservation is a critical component of environmental control policy and is paramount in addressing climate change and ensuring long-term energy security. Asif [128] underscores the role of energy conservation and management in the sustainable energy transition, particularly in the building sector. Energy Conservation Measures (ECMs) are the cornerstone of efficiency programs, offering significant potential to reduce energy consumption, greenhouse gas (GHG) emissions, and associated costs while maintaining service levels. These reductions translate into enhancing social, economic, and environmental benefits, aligning with program goals [129].

The long-term effectiveness, financial viability, and successful implementation of ECMs hinge on accurately assessing their expected lifetime [130], energy delivery duration, and cost savings. This lifespan can vary dramatically, from months for filter replacements to decades for building envelope upgrades [131]. Accurately assessing ECM lifetimes is crucial for several reasons. First, it allows robust lifecycle cost (LCC) analyses for determining the cost-effectiveness of ECMs, the economic basis upon which one ECM is purchased, implemented, or prioritized over the other [132]. By factoring in the upfront costs, operational savings, and maintenance expenses of ECMs over their lifetimes, LCC analyses could be used to assess the economic attractiveness of ECMs [133]. Second, accurate lifetime estimates facilitate comparisons between different ECM options [134], empowering decision-makers to take action regarding prioritizing interventions with the most enduring benefits, program design and evaluation, program approval, goal setting, or demand forecasting, among others. Third, ECM lifetime estimates are essential in addressing stakeholder needs. Different stakeholders have varying interests in ECMS. For example, federal, state, and local agencies are concerned with cost-effective implementation [135], utilities focus on avoiding energy and capacity costs, consumers prioritize reduced energy bills [136], and society seeks to minimize GHG emissions and health impacts associated with energy production [137]. Measure lifetime evaluation caters to these diverse needs.

Accurate ECM lifetime estimates are essential for optimizing lifecycle cost analyses, comparing retrofit options, and prioritizing investments. However, current methodologies for evaluating ECM lifetimes may lack consistency and comprehensiveness. This study addresses this gap by providing a critical review of the field.

Specifically, this review will define and differentiate key terms related to ECM lifetimes, ensuring clear communication and understanding across stakeholder groups. This study also examines the factors influencing ECM lifetimes, such as material degradation, usage patterns, maintenance practices, and environmental factors. Finally, the study reviews seven established methodologies for estimating ECM lifetimes. This analysis details each method's implementation process, advantages, limitations, and appropriate applications.

This review provides a comprehensive overview to equip stakeholders with the knowledge necessary to select and implement the most effective ECM lifetime evaluation methodology for their needs.

4.2 Definition of Measure Lifetime

To understand measure lifetimes, it is essential to understand what measures (ECMs) are. ECMs could be equipment such as an energy-efficient refrigerator, a building envelope installation such as windows and doors, automation devices such as thermostats and lighting controls, or an operational practice (occupant behavior changes and education) such as fully shutting the door.

ECM lifetimes may be defined in many ways. One way of defining measure lifetime is in terms of what is known as the effective useful life (EUL) [138]. The EUL is the estimated length of time during which ECMs are expected to remain in effect and still have the potential to yield electricity or energy savings [139]. Hoffman et al. [140] define EUL as the median length of time an installed measure performs its function and yields energy savings. Another way of looking at the median length of time is to think of it in terms of the period for which half of the measures of the same kind will remain in use and half will have stopped functioning for a given sample installation [141]. By defining EUL this way, both functioning and non-functional installations are recognized, unlike the so-called age-at-replacement definition, which is based on opinion surveys and ignores the population of equipment still in use [142].

Without understanding the definition of EUL in the preceding paragraph, it would seem that the lifetime of specific categories of measures, such as building envelope or insulation measures, are not adequately captured. These measures do not stop functioning as some electrical/mechanical equipment or baseload appliances do but reduce their expected functionality due to infiltration, leakage, or degradation. The concept of measure lifetime can become increasingly intricate for such measures, as multiple factors influence it [143], such as the current infrastructure in which the measure is installed, the quality of the measure, and evolving technology standards. The lifetimes of retrofits may differ based on these factors and might not consistently adhere to the conventional concept of EUL.

To clarify the scope of the EUL definition, two components are provided: the technical life and measure persistence. The technical life refers to the average length of time that the measure is operational [140]. It is based on engineering tests under standard operating conditions. Therefore, any unfavorable condition or unrecommended use of the measure, such as those related to climate, maintenance, and installation, could affect its technical life [131]. Measure persistence measures the actual time that the ECMs last [144], considering numerous factors. The factors affecting measure persistence vary depending on the building type or primary use. [141] provides some of the frequently encountered factors, as summarized in Table 4.1 below.

Table 4.1 Factors Influencing Measure Persistence [141]

Residential Sector Programs and Measures	**Commercial and Industrial Sector Programs and Measures**
1. Changes in ownership **2.** Maintenance practices **3.** Changes in equipment use **4.** Behavioral changes **5.** Occupancy changes **6.** Inappropriate installation of equipment **7.** Manufacturer performance estimates which do not reflect in-field operating conditions.	**1.** Business turnover **2.** Remodeling **3.** Varying maintenance **4.** Operating hours and conditions **5.** Inappropriate installation of equipment **6.** Manufacturer performance estimates that do not reflect in-field operating conditions

Since the factors above affect the measure lifetime and the savings that could be derived from the measures, this introduces another consideration known as savings persistence. *Savings persistence* has to do with measure performance and how it changes over the measure lifetime [140], reflecting both a decrease ("decay" or "degradation) and an increase in savings. Goldberg et al. [145] define savings persistence as the percent change in expected savings due to changed operating hours, human behavior and interaction factors, and/or degradation in equipment efficiency relative to the baseline efficiency option. While measure and savings persistence may appear to be the same in that both consider changes in savings, they are not [146]; the latter quantifies the percentage of change in savings.

Notwithstanding the nuances of the EUL definition, some ECMs may not fit in any of the components of EUL, such as educating building occupants about lifestyle and behavioral changes that directly impact energy consumption, have measurable savings, and are cost-effective. Encouraging behavioral ECMs, such as turning off lights when not in use, utilizing natural daylighting when possible, adjusting thermostat settings for optimal comfort and energy savings, or unplugging appliances and electronics that are not in use, may not have an easy lifetime estimate that could be used in lifecycle costing as justification for an energy efficiency investment, but work best when implemented together with active (or technological) ECMs.

A term known as the remaining useful life (RUL) applies to measures that must be retrofitted or replaced. The RUL is an assumption of how many more years the existing unit to be retrofitted or replaced would have lasted. The RUL is the amount of time left for an equipment or installation to perform its valuable functions before it is no longer effective [147]. The RUL is generally assumed to be a third of its EUL [148].

Another term used to describe measure lifetime is the "service life," which the International Organization for Standardization (ISO) defines as the period after installation during which a facility or its components meet or exceed the performance requirements [149]. There are several related terms to this which provide a more precise definition of measure lifetime. One such precise and widely used definition is the reference service life (RSL), which is the service life of a product (measure) under a specified or reference set of in-use conditions. As noted by ISO, the reference in-use conditions could be based on data gathered through equipment testing or recorded from actual performance or service life data. RSL may become the basis for estimating the service life of the same measure under different in-use conditions, otherwise known as the Estimated Service Life (ESL). Some factors that determine the RSL of a measure are indoor and outdoor environments, predicted maintenance, and the product's design, among others [150]. Three main approaches are recognized to estimate the RSL of a building component [150]. The first approach is rooted in engineering principles, focusing on structural integrity and material fatigue over time. The second approach considers factors such as component quality, design level, work execution, and environmental conditions to modify the RSL to provide an ESL. The third approach relies on empirical data, which, while accurate, can be resource-intensive.

4.3 Methodologies for Estimating Measure Lifetime – Explanation, Strengths, Weaknesses, and Applications

Several methodologies for estimating measure lifetimes exist, but no single, universally accepted methodology exists. Instead, researchers draw from a diverse toolbox of methodologies, each offering unique strengths and limitations. These sources include statistical analyses, interviews, manufacturer specifications, industry standards, field surveys, accelerated aging tests, computer simulations, and expert opinions. Often, these methods work in tandem, with data from one source strengthening the validity of estimates derived from another. For instance, field surveys may incorporate expert judgment, survival studies may combine manufacturer data with field observations, and expert opinions may rely on industry standards and assumptions.

4.3.1 Survival Studies or Survival Analysis

Survival studies, among various statistical methods available, are commonly utilized to estimate the anticipated lifespan of events (measures) [151]. Depending on whether researchers derive new insights from existing data or utilize published survival studies in their investigations, these studies can serve as either primary or secondary data sources.

Survival analysis, also known as time-to-event analysis, is a stochastic model based on probability theory and statistical methods [152] that model the relationship between inputs and outputs using mathematical functions that best fit the given data [153]. Researchers across fields, including health and the sciences, leverage survival functions to predict survival probabilities and assess covariate impacts. Even though survival analysis has been widely applied in clinical research and epidemiology, there are diverse fields

[154] exploring the utility of survival analysis. A few of the fields where survival analysis has been utilized include the insurance industry for estimating when a claim might be expected or when a policy might become invalid [155], [156], in asset management for calculating depreciation and value of an asset [157], or in engineering for estimating the reliability of an equipment or installation to know when maintenance or replacement might be due [158]. As with most statistical methods, survival studies are data-driven and rely heavily on the availability of data and the nature of the data [159].

Survival analysis offers several advantages, with one notable benefit being the utilization of parametric models, such as the Weibull distribution. In this statistical framework, the distribution of probability variables is explicitly defined, and assumptions are made about the parameters governing the data [160]. These parameters encapsulate essential characteristics of the distribution. Unlike non-parametric methods, which make minimal assumptions, parametric models exhibit high efficiency and flexibility, adapting to various scenarios. They allow precise estimation of parameters, even when dealing with relatively small sample sizes – a practical advantage in scenarios where large samples are unattainable or resource-intensive [160].

While these models offer precision, their reliance on strong assumptions warrants careful consideration during application. A crucial challenge is selecting the most appropriate probability distribution for accurate survival data modeling. Misspecification of the distribution can lead to spurious inferences and unreliable results. Researchers must meticulously evaluate the underlying assumptions of candidate distributions and ensure alignment with the characteristics of the observed survival times [161].

In the context of ECM lifetime, survival analysis has been applied to analyze the time-to-failure or degradation patterns across different product groups or categories of measures, integrating various types and characteristics of lifetime data. To estimate the lifetimes of residential appliances (central air-conditioners, heat pumps, furnaces, boilers, water heaters, room air-conditioners, refrigerators, and freezers), Lutz et al. [162] leveraged a unique dataset combining national survey data in a survival analysis. This data included historical shipment information from appliance manufacturers and in-use appliance stock data obtained from the U.S. Energy Information Agency's Residential Energy Consumption Survey (RECS 1990-2005) and the Census Bureau's American Housing Survey (AHS 1991-2007). The U.S. Department of Energy (DOE) has embraced the methodology described by Lutz et al. (2011) for the lifetime estimation of appliances. This is reflected in DOE's utilization of the approach within multiple technical support documents (TSDs) about various household appliances [163]. Furthering the application of survival analysis, Northeast Utilities conducted a measure retention study in 2001 to refine the estimated lifetimes of interventions within their residential weatherization program [164]. The study surveyed 849 households to collect data on installing and removing specific measures, including CFL bulbs, torchiers, refrigerators, faucet aerators, low-flow showerheads, water heater wraps, and furnaces. The data were then analyzed using various survival function models to determine their lifespans.

4.3.2 Manufacturers' Data

Manufacturers' data come in many forms and may span different phases of a product's life cycle, including conceptualization, requirements analysis (what the product needs to achieve), design and engineering, production, operation, maintenance, and disposal [165]. However, this study is interested in the phases of the product lifecycle: operation, maintenance, and disposal, all of which help estimate the product's useful life.

A few ways product manufacturers provide helpful life data for their products are environmental product declaration (EPD) documents or warranty sheets. Manufacturer lifetime data are based on life test data, which assume that the minimum design life of a component of the product should be the same as the useful life of the product [166]. Life testing, where components are stressed to simulate real-world use and predict failure rates, is an essential tool for manufacturers because the failure rates can be used to determine the critical lifetime prediction design parameters and, subsequently, to provide warranty or guarantee on products or product components [166]. A shortcoming of this methodology is that life tests often occur under controlled environments while products encounter varied stresses during actual use.

Manufacturers of specific products may formulate other methodologies to ascertain the anticipated lifespans of their products. An illustrative instance pertains to LED products, wherein manufacturers consistently derive projections of product longevity based on the duration required for LED products to diminish to 70% of their initial lumen output after specified hours of use [167]. For example, an L70 LED rated at 25,000 hours signifies that the LED will maintain at least 70% of its original brightness for 25,000 hours of operation [168]. However, while lumen intensity provides a reasonable benchmark for LED lifetime, it neglects the potential for failure in other critical components, especially those that power the LEDs, which can significantly impact its overall useful life.

While manufacturer data may not be directly utilized as the sole source for lifetime estimation, it is a valuable foundation for more robust methodologies. Manufacturer data is often integrated with other techniques, such as survival functions, clustering analysis, and data regression, to enhance the reliability of lifetime estimates. For instance, research by Lawrence Berkeley National Laboratory (LBNL) on appliance lifetime estimation [162] and Technical Support Documents (TSDs) by the U.S. Department of Energy [169] employed manufacturer data as a springboard for further analysis. This practice elevates manufacturer data to the status of primary data within the context of these studies.

4.3.3 Industry Standard

Industry-standard lifetime data for energy conservation measures originates from stakeholder groups or professional organizations with specialized knowledge and vested interests in specific industries. These organizations establish industry standards, which the U.S. Department of Energy (DOE) defines as the widely accepted practices or specifications adhered to by industry members [170]. Developing these standards typically involves a rigorous, systematic process to ensure validity and reliability. Industry standards are crucial benchmarks and reference points for professionals when deciding energy conservation measures. Notably, numerous U.S. organizations contribute to developing these valuable standards.

Examples of U.S. Organizations Developing Industry Standards include**:**

- **American National Standards Institute (ANSI):** ANSI administers and coordinates the U.S. private sector's standardization system. While it doesn't develop standards, it assesses and approves standards created by other organizations [172]. This role is crucial in ensuring consistency and national recognition of industry standards.

- **The American Society of Heating, Refrigeration, and Air-Conditioning Engineers (ASHRAE):** ASHRAE is a prominent organization that develops industry standards specifically targeted towards building systems, energy efficiency, indoor air quality, refrigeration, and sustainability within the HVAC&R industry [171]. Their standards are vital in promoting energy-efficient practices within the built environment.

- **The National Institute of Standards and Technology (NIST):** NIST, a part of the U.S. Department of Commerce, provides crucial support for the development and use of standards across various sectors [172]. While not directly developing industry standards for energy conservation measures, NIST's role in promoting standardization practices benefits various industries seeking to establish reliable benchmarks.

While industry standards developed through rigorous scientific methods offer a reliable source for EUL data, other stakeholder groups may also contribute valuable insights. These groups may utilize methodologies that differ from the established, repeatable approaches mentioned earlier. Despite potential limitations in their methodology, these stakeholder-driven standards can yield surprisingly accurate results, often aligning with estimates from more established sources.

For instance, a Massachusetts study interviewed contractors to gather information on the EUL of commercial gas heaters [167]. The study focused on when equipment reached the end of its useful life due to age or unreliability rather than simple breakage.

This approach yielded a mean estimate of 19 years and a median of 18 years, closely matching the prevailing EUL of 18 years for commercial furnaces listed in the Massachusetts Technical Reference Manual [173]. The contractor estimates were notably lower than the 25-year EUL provided for commercial boilers in the same document.

This example highlights the potential value of considering stakeholder input, even when their methodologies differ from established standards. The study also reveals the factors influencing early equipment replacement decisions, with equipment age (67%), high repair costs (53%), safety concerns (27%), and reduced performance (13%) being the most prominent reasons cited by contractors.

Utilizing industry-standard lifetime data for energy conservation measures offers several compelling advantages. Firstly, established standards can significantly reduce the time and resources required to estimate measure lifetimes [174]. This is particularly beneficial when dealing with a multitude of measures, as pre-defined values eliminate the need and cost [130] for extensive individual assessments. Secondly, standardized data contributes to cost efficiency by minimizing the need for specialized testing or complex data collection procedures [175]. Furthermore, industry standards promote increased productivity by streamlining the process of estimating measure lifetimes, allowing researchers and professionals to dedicate their expertise to other vital aspects of energy conservation initiatives.

Beyond these practical benefits, industry standards serve as a foundation for regulation within an industry. Establishing a common set of reference point standards helps ensure consistency in how measure lifetimes are defined and evaluated [176]. This fosters transparency within the industry, allowing stakeholders to understand expected equipment lifespans clearly.

Industry standards constitute valuable sources of secondary information on measure lifetimes for various energy efficiency studies, including cost-effectiveness studies and energy audits. A prominent example is the ASHRAE suite of resources, including the HVAC Service Life Database and the ASHRAE Handbook – HVAC Applications [177]. These resources provide readily available reference points for the expected lifespans of various HVAC units.

In addition to standardized data, information from non-standardization bodies can also be beneficial. Trade organizations, such as the Air-Conditioning, Heating, and Refrigeration Institute (AHRI) and the National Association of Home Builders (NAHB), often research and compile data on equipment lifespans. For instance, a comprehensive telephone survey by the NAHB's Economics Group, encompassing manufacturers, trade associations, and researchers, yielded valuable data on the life expectancies of various home components [178].

4.3.4 Field Survey/Testing

Field surveys or testing involve gathering real-world data on the use and performance of equipment or installations. This data can then be used to infer or predict how similar equipment or installations would perform in other settings [179]. When existing data proves inadequate, field surveys emerge as a powerful tool for gathering primary information [180].

Several methods exist for collecting data in a field survey or test. One method involves in-person interviews or survey instruments (questionnaires). These two – interviews and questionnaires – may be combined through a hybrid approach where a self-administered questionnaire (e.g., paper-based) may be left with the respondent after a brief introductory interview [181]. Field surveys could also employ remote data collection, eliminating the need for being physically present. In both cases, either interviews, questionnaires, or both (hybrid) may be used. While field surveys are plausible means of estimating measure lifetimes, they can be enhanced by incorporating after-warranty failure data [182]. This approach can provide a more accurate estimation of lifetime distribution. However, the reliability of predicting long-term performance may decrease if data is collected too early in the test [183]. Lawless, Kalbfleisch, and Blumenthal [184] Highlight the challenges in collecting and analyzing field reliability data, including missing information and reporting delays. These insights underscore the need for a comprehensive and meticulous approach to field surveys, including reviewing and analyzing historical data alongside the collected survey information. This would ensure that valid conclusions are drawn.

The hybrid approach can be cost-effective while potentially boosting response rates. The choice between in-person and remote data collection methods depends on several factors. In-person surveys, like interviews, can lead to higher data quality as the interviewer can clarify questions and reduce misunderstandings. However, logistical costs associated with travel and personnel can be high, and interviewer bias may influence responses [185]. Remote surveys, on the other hand, offer advantages like reaching geographically dispersed samples and lower costs [186]. They also allow respondents to complete surveys at their convenience. However, these methods may require specific technologies and can be susceptible to technical issues on the respondents' end.

Field surveys and testing have played a critical role in estimating the lifetimes and effectiveness of energy conservation measures (ECMs). McRae et al. [130] surveyed experts to estimate the average lifespan of various ECMs in the Pacific Northwest, highlighting the importance of such data for utility conservation programs. Suter and Shammin [67] conducted a field experiment demonstrating significant reductions in natural gas consumption with attic insulation, an example of an ECM intervention. Similarly, Ternes et al. [188] tested an advanced ECM selection technique, providing valuable data for cost-effectiveness analysis of utility investments in residential gas conservation programs. These studies demonstrate how field research has been utilized to understand ECM performance, lifespan, and program improvements.

4.3.5 Accelerated Life Test

Accelerated life tests (ALT) are an essential tool in estimating the lifespan of various products, with applications in many fields, including software reliability [189], seed vigor [190], paper quality [191], and photovoltaic (PV) module performance [192]. These tests involve subjecting materials to harsh conditions, such as high temperature and humidity, to simulate the effects of long-term use in a short period [193]. It achieves this by simulating real-world wear and tear through controlled stresses and intensified conditions that accelerate their degradation [194]. For energy conservation measures, these stresses might translate to extreme temperatures for insulation materials or voltage fluctuations for power management systems. The methods used in these tests vary depending on the material. Still, they generally involve stress-accelerated aging [195] relationships to estimate how long the material will last under regular use. The results of these tests can provide valuable information on the quality, durability, and reliability of energy conservation measures and are often used for type approval testing, safety testing, and service life prediction [196].

ALT offers several advantages over traditional testing methods when estimating the lifetime of ECMs. While conventional life testing involves monitoring products under normal operating conditions for extended periods, ALT condenses this process, leading to faster failure times. This translates to significant savings in time and resources [197]. ALTs are also valuable for predicting potential failure modes in products that might take years to emerge under regular use, allowing for early design improvements and ensuring long-term reliability [198]. By leveraging diverse model and data analysis techniques, including physics-of-failure (PoF) and mechanistic approaches, alongside advanced Bayesian analysis methods [199], ALT emerges as a vital tool in identifying materials or components prone to degradation under particular stresses, thereby facilitating enhanced product design and prolonged lifetime [200].

However, it is essential to note that ALT also has limitations. The stresses applied in ALT may not perfectly replicate real-world conditions. This can lead to underestimation or overestimation of the actual lifespan depending on the specific product and the chosen stresses [201]. This is particularly true for temperature stresses, which can accelerate failure mechanisms not observed in field life, necessitating a multiple-stress model [202] and optimal decision variables [203] in ALT to improve accuracy. Moreover, ALT is limited in requiring clearly defined failure modes to test hypotheses and reliability prediction [204]. However, for products that degrade gradually without a clear point of failure, ALT may be less suitable. Accelerated Degradation Testing (ADT) can be more effective in such cases, as it predicts long-term performance and reliability without actual failures [205]. Caruso and Dasgupta [206] caution that the effectiveness of ALT or the accuracy of lifetime estimation through ALT depends on the chosen statistical models and analysis and interpretation of data [207]. Therefore, lifetime estimates from ALT are as good as the models and interpretations used.

ALT has been applied to predict how long insulation materials last in buildings by understanding how they maintain thermal resistance over time, thereby ensuring energy efficiency in buildings [208]. Several studies have explored ALT for estimating the lifetimes of LED components under the impact of elevated temperatures and voltage fluctuations [209]. ALT has also been applied to simulate years of weathering in window components through exposure to intense UV radiation, high temperatures, and humidity cycles [210]. This helped to predict how well window coating and seals would perform in terms of insulation and solar heat gain coefficient (SHGC) over time [211], thereby estimating their lifetimes under operating conditions.

4.3.6 Modeling and Simulation

Modeling and simulation, as data-driven approaches, play a crucial role in predicting equipment lifetimes. They leverage statistical techniques to extract valuable insights from large datasets. Bahn et al. and Qudrat-Ullah [212], [213] demonstrate the broader use of data-driven models in energy systems – moreover, Seyedhosseini et al. [214] highlight the effectiveness of data-driven methodologies in predicting the remaining useful life (RUL) of ECMs. Further examples of modeling and simulation include using Clustering techniques to group ECMs with similar characteristics, facilitating the identification of patterns and trends in their lifespan [215]. Additionally, regression models can be constructed to predict RUL based on operational data such as energy consumption patterns and environmental factors. These techniques can be further integrated with regression models to predict the RUL of system components based on operational data, such as energy consumption patterns and environmental factors [216].

Various sources can provide data for measure lifetime prediction models. Manufacturer specifications, historical performance data from implemented ECMs, and accelerated life tests are all valuable sources [217], [218]Warranty information, Mean Time Between Failures (MTBF) from field deployments, and degradation data from controlled experiments can also be valuable inputs.

As with all data-driven models, the modeling and simulation approach may offer a more efficient and potentially more accurate alternative to real-world testing by combining multiple algorithms to enhance the prediction's robustness and accuracy [219]. This methodology allows scenario planning by simulating various operating conditions and environmental factors, providing valuable insights into the lifespan under diverse use cases [220]. Accurate lifespan estimates from models can also empower informed decision-making regarding ECM selection, replacement schedules, and overall energy management strategies [174].

However, some possible drawbacks of the modeling and simulation approach include data gaps, inconsistencies, or errors, which can significantly impact the reliability of the estimates since the accuracy of model predictions heavily relies on the quality of input data [221]. Also, models can become complex, especially when considering multiple interacting factors, requiring specialized expertise to build and interpret [222]. This complexity is further compounded by the need to integrate various data and knowledge sources and manage uncertainty [223]. While machine learning models can be trained to generalize well across diverse conditions, their performance can still be limited in drastically different contexts [224].

Numerous studies have demonstrated the practical applications of data-driven modeling and simulation in estimating the measure lifetimes. Trappey et al. [225]

developed a lifespan forecasting approach for power transformers, while Musallam et al. [226] presented a method for estimating the RUL of power electronics. Zhe, Ghaoyou, and Qjan [227] focused on real-time RUL prediction for core components of mechanical and electrical equipment, achieving high accuracy.

4.3.7 Expert Judgement

Expert judgment is a methodology that involves eliciting knowledge from qualified professionals with extensive experience and credibility in a specific field [228]. In addition to having the requisite background in the subject area, they must be recognized by their peers or those seeking answers from them [229]. In estimating measure lifetimes, these experts would deeply understand the technologies, their installation practices, and the factors influencing their degradation over time. Their judgment becomes valuable data for decision-making when historical data might be limited or the technology is relatively new [230]. The Delphi technique, which involves a structured group process, is a valuable tool for eliciting and combining expert opinions [231]; it can also be used to improve the reliability of estimates obtained from a consensus of experts [232].

As mentioned in the preceding paragraph, expert judgment is a valuable tool when historical data is limited or technology is new, as it can provide insights into potential risks and impacts [233]. For instance, historical data might not be available when implementing a cutting-edge, energy-efficient window design. Experts can leverage their experience with similar technologies and materials to estimate the expected lifespan. Furthermore, expert judgment leads to the incorporation of diverse knowledge [234]. A single expert might possess significant knowledge, but a group can offer an even richer picture. By bringing together experts from various backgrounds, one can consider factors affecting measure lifetimes. Expert judgment also allows for incorporating uncertainties and adapting estimates in the light of emerging technologies or unforeseen circumstances, which make it challenging to predict measure lifetimes solely based on historical data [235].

Expert judgment, however, is not immune to bias and subjectivity, as it can be influenced by the same cognitive, perceptual, and motivational biases as laypeople since experts may struggle to go beyond the limits of their observable expertise [236]. The "bias blind spot" further complicates matters, as individuals tend to recognize bias in others but not themselves [237]. Also, even within a field, there can be varying levels of expertise [238]. This inconsistency is not necessarily due to a lack of knowledge, as experts may be able to focus on relevant information and exhibit greater consistency and consensus [239]. To improve the accuracy of expert advice, it is recommended to use broadly defined expert groups, structured question protocols, and feedback [228]. Moreover, if the process of eliciting expert judgment isn't well documented, it can be challenging to understand the rationale behind the estimates [236], [240]. This lack of transparency can make it challenging to assess the reliability of the results. Another drawback of this methodology is that consulting with experts can be time-consuming and expensive [241]. This is particularly true in complex fields such as business data analytics, where the need for expertise is high [242].

Expert judgments have been utilized in various ways to estimate and measure lifetimes. Katenbacher and Attari [243] and Jaber, Mamlook, and Awad [244] highlight the role of expert heuristics and knowledge-based systems in improving energy literacy and evaluating residential energy consumption programs. Expert elicitation has provided valuable insights into future energy technologies, trajectories, and prospects [245]. However, the effectiveness of these methods can be influenced by factors such as survey design, expert selection, and confidence levels, which need to be carefully considered in the estimation process [245].

Table 4.2 Summary of Measure Lifetime Estimation Methodologies

Methodology	**Description**	**Advantages**	**Drawbacks**	**Applications**	**Other Considerations**
Survival Analysis	Analyzes historical data (e.g., failure times) to	- Uses statistical models for	- Requires careful selection of	- Estimating the remaining useful life	- Requires expertise in statistical modeling.

	estimate lifespans and predict failure patterns.	precise estimation. - Applicable to various data formats (e.g., censored data).	probability distributions.	(RUL) of equipment. - Analyzing degradation patterns.	
Manufacturer Data	Provides starting point for lifetime estimates based on manufacturer specification	- readily available. - Often used as a starting point.	- May not reflect real-world operating conditions. - Limited to specific product lines.	- Initial estimates - Comparisons with industry standards.	- Should be used cautiously - Integrate with other techniques for better accuracy
Industry Standards	Provides reliable benchmarks for measure lifetimes developed by professional organizations.	- Provides reliable data. - Offers a standard reference - Saves time and resources.	- May not capture all factors affecting lifespan. - Limited to specific industries or regions.	- Initial estimates - Project planning	- Consider applicability to specific project contexts. - Consider incorporating stakeholder input
Field Surveys/Testing	Gathers real-world data on equipment performance through interviews, questionnaires, or in-person/remote surveys.	- Provides insights into actual operating conditions. - Can be combined with after-warranty failure data.	- Time-consuming and resource-intensive. - May be subject to respondent bias.	- Valuable for new technologies - Improving existing estimates by validating manufacturer data and industry standards. - Gather data for the project. - Understand user experience	- Carefully design survey instruments and sampling methods. - Can be enhanced by after-warranty failure data.

Accelerated Life Tests (ALTs)	Simulate long-term wear and tear quickly by stressing materials under harsh conditions.	- Saves time and resources. - Predicts potential failure modes.	- May not perfectly replicate real-world conditions. - Requires expertise to design and interpret results. - Limited applicability for complex systems	- Estimating RUL for new technologies. - Comparing options - Evaluating the impact of extreme conditions.	- Ensure test conditions reflect realistic use case scenarios.
Data-Driven Modeling & Simulation	Utilizes statistical techniques and large datasets to predict lifetimes.	- Efficient and potentially more accurate than other methods. - Enables scenario planning for various conditions.	- Relies heavily on data quality. - Models can become complex - May require specialized expertise.	- Optimizing ECM selection, replacement schedules, and energy management strategies. - Identifying trends and patterns in historical data.	- Carefully select data sources and validate model assumptions. - Machine learning models may not generalize well in new contexts.
Expert Judgment	Elicits knowledge from qualified professionals with extensive experience in the field.	- Valuable when historical data is limited, or technology is new. - Incorporates diverse knowledge and perspectives.	- Prone to bias and subjectivity. - Requires careful design of the elicitation process.	- Estimating lifetimes for new technologies. - Filling gaps in incomplete data sets.	- Expertise level and selection process are essential. - Utilize structured techniques (e.g., Delphi method) to minimize bias.

4.4 Measure Lifetime Data Sources and Examples

Obrecht et al. [248] identifies several data sources for obtaining RSL data for ECMs. These sources can be categorized into three main groups. The first group is industry standards and guidelines**,** such as Product Category Rules (PCR) and Environmental Product Declaration (EPD) documents, which provide standardized data for specific product categories. Additionally, existing applicable standards often define service life expectations for ECMs within a particular industry or region. The second group comprises manufacturer information and client requirements. Product and manufacturer information, including technical specifications and installation manuals, can offer insights into expected ECM lifetimes. Client requirements and current practices specific to a project may also inform service life assumptions. The third group includes databases and literature**.** Publicly available national or commercial databases on building components and materials can be valuable resources. Research publications from industry groups and scientific communities can provide data and insights on ECM lifetimes. Furthermore, LCA software packages for building design may include conventional service life data for various building components.

Appendix A provides step-by-step instructions on utilizing two measure lifetime data sources: an online database for PCR/EPD documents of certain products and a public database of HVAC service life maintained by ASHRAE.

4.5 Other Considerations

4.5.1 Factors Affecting Service Lives of Measures

Accurate estimates of measure service lives are essential for reliable economic and energy savings calculations. However, several factors can influence the actual functional life of an ECM compared to its estimated service life or warranty period.

While manufacturer warranties provide a minimum service life guarantee, ECMs may often function for extended periods. These additional years of functionality can be considered as a "persistence allowance" when estimating overall service life [141]. The

EPD framework may not offer standardized methods for examining the service life decay of specific ECMs, such as the decline in thermal performance of insulation materials over time[246]. For example, Lee, Lim, and Salleh [247] identify factors like dust accumulation, moisture, corrosion, and oxide films that can reduce the effectiveness of radiant barriers. Similarly, other ECM categories may experience degradation due to environmental factors or lack of maintenance.

Therefore, it is essential to consider the specific environment where ECMs are installed when estimating service lives rather than relying solely on the provided data sources.

4.5.2 Deriving Representative Lifetime Values for ECMs

Varied data sources often yield different lifetime values for the same measure. Various statistical techniques can be employed to address this challenge and establish a single, representative value. A prominent method is the Weibull distribution, known for its adaptability and effectiveness with limited data samples [248]. A comprehensive study by Lawrence Berkeley National Laboratory [162] exemplifies the application of this approach to estimate the service life of appliances (e.g., refrigerators).

Similarly, Technical Support Documents (TSDs) associated with specific appliances reference this methodology. For instance, TSDs for lighting systems or HVAC equipment might utilize statistical analysis of large datasets to derive representative lifetime values that account for inherent data variability. By adopting these statistical approaches, comprehensive datasets can be harnessed to establish unified and reliable lifetime values for ECMs, enhancing the accuracy of energy savings calculations.

4.6 Chapter Summary

Accurate estimation of measure lifetimes is fundamental for reliable economic and energy savings calculations when implementing Energy Conservation Measures (ECMs). This review explored a diverse set of methodologies for measure lifetime estimation, each offering unique advantages and considerations.

Survival analysis as a methodology has applications in many fields when estimating failure times, and manufacturer data provides valuable starting points, but it may not fully capture real-world conditions. Field surveys and testing offer detailed insights but can be time-consuming. Accelerated life tests (ALTs) present a faster alternative, although their accelerated aging process might not perfectly mimic real-world wear and tear.

Data-driven modeling and simulation emerged as powerful tools for measure lifetime estimation. These methods leverage statistical techniques and large datasets to deliver efficient, potentially more accurate predictions. They also empower scenario planning by simulating various conditions and informing decisions on ECM selection, replacement schedules, and overall energy management strategies. However, data quality remains paramount for model accuracy, and complex models might require specialized expertise.

Expert judgment plays a complementary role, mainly when historical data is limited or technology is new. Experts bring valuable insights and diverse knowledge, allowing for adaptation to uncertainties and emerging technologies. However, careful design of the elicitation process is crucial to minimizing bias and ensuring reliable estimates.

Beyond estimated service life or warranty periods, the review emphasized the importance of considering additional factors. A "persistence allowance" can account for extra years of functionality, while environmental factors where ECMs are installed can significantly impact their lifespan. This highlights the need to move beyond generic data sources and choose information relevant to the specific ECM under evaluation and the project context. Understanding the underlying assumptions and methodologies used to generate the service life information is also helpful. In cases where limited data is available, combining information from multiple sources and applying engineering judgment can be necessary to establish a reliable lifetime estimate.

In conclusion, a comprehensive approach that combines various methodologies is recommended for accurate measure estimation. Careful consideration of data quality, environmental factors, statistical techniques, and the project's specific context is essential for reliable economic and energy savings analyses. Ultimately, this leads to more informed decision-making regarding ECM implementation.

CHAPTER 5

ECONOMIC ANALYSIS FOR MEASURE LIFETIMES EXCEEDING 30 YEARS

This chapter builds upon the previous chapter and provides a scenario-based economic analysis of long-lived measures (i.e., measures with a lifetime beyond 30 years). Using the Weatherization Assistance Program (WAP) maximum default measure lifetime, currently 30 years, the study demonstrated a methodology to estimate post-thirty-year economic projection. It analyzed different scenarios of how extending the measure lifetime would impact the savings-to-investment ratio (SIR). This chapter is being prepared as an article for submission to a journal.

Acknowledgments: This work was sponsored by the U. S. Department of Energy's Office of State and Community Energy Program under contract DE-AC05-00OR22725 with UT-Battelle, LLC.

Chapter Abstract

Extending the default lifetimes of Energy Conservation Measures (ECMs) in energy efficiency programs to reflect their longevity presents opportunities to enhance energy savings and improve cost-effectiveness in energy efficiency programs. Measure lifetime directly influences economic analyses, including savings-to-investment ratios (SIRs), and is a critical parameter for prioritizing ECMs and allocating program resources. This study explores methodologies for assessing the economic viability of ECMs with lifetimes exceeding 30 years, focusing on projecting fuel price indices (FPIs), applying discount rates, and conducting sensitivity analyses. Through a detailed evaluation of extrapolation techniques, this study highlights the challenges associated with uncertainties in long-term projections, such as reliance on averaged escalation rates for extended FPIs and the compounded effects of discounting. Comparative analyses reveal the diminishing marginal benefits of extending ECM lifetimes, where the percent increase in SIR slows as measure lifetimes exceed 40, 50, or even 100 years. By addressing both the potential benefits and inherent uncertainties of extended lifetimes, this study offers actionable insights for refining economic evaluation methodologies. The findings underscore the importance of robust data frameworks, enhanced projection techniques, and balanced program designs that account for both short-term and long-term objectives. These approaches enable energy

efficiency programs to make more informed decisions, optimize resource allocation, and achieve broader social, economic, and environmental goals.

5.1 Introduction

Energy conservation measures (ECMs) are foundational to energy efficiency programs, offering substantial potential for reducing energy consumption and associated costs over their operational lifetimes. However, the economic evaluation of energy efficiency programs is often constrained by the measure lifetimes used in these assessments. For instance, the methodologies employed within the Weatherization Assistance Program (WAP) limit economic analyses to a maximum measure lifetime of 30 years. While WAP does not explicitly restrict default measure lifetimes to 30 years, its economic analyses rely on fuel price indices and discount factors documented in various editions of the National Institute of Standards and Technology (NIST) Handbook 135 and its annual supplements[2] [249], [250]. These projections are typically available for 30 years. Despite this limitation, many ECMs – such as durable building envelope components – can remain effective for over 50 years or for the entire lifespan of the buildings in which they are installed [251].

Using WAP measure lifetime as a case study, this study builds upon the insights from Chapter 4, which explored methodologies for estimating measure lifetimes to evaluate the economic implications of extending ECM lifetimes beyond the 30-year threshold. Specifically, it investigates how such extensions influence key economic metrics, focusing on the savings-to-investment ratio (SIR), a critical determinant for ECM prioritization and funding within WAP. Through scenario-based demonstrations, this analysis assesses the economic viability of longer-lifetime ECMs under various assumptions about energy prices, discount rates, and maintenance costs.

[2] The NIST Handbook and its annual supplement are published to facilitate the implementation of the Federal Energy Management Program (FEMP) Life Cycle Cost (LCC) rules. Handbook 135 explains the LCC method, describing the assumptions and procedures to follow in performing evaluations. The annual supplements (NIST-85-3273-X) to Handbook 135 provide the current discount rate, discount factors, and energy escalation factors used for conducting an LCC analysis in accordance with FEMP rules.

This study also explores the implications of extending ECM lifetimes, considering the trade-offs between increased uncertainty in long-term economic projections and the potential for enhanced cumulative energy savings. By addressing these aspects, the findings aim to guide program administrators, policymakers, and other stakeholders in evaluating the feasibility and impact of incorporating extended ECM lifetimes, thereby supporting more effective and equitable energy efficiency initiatives.

5.1.1 History of Default Measure Lifetime Values Used Within WAP

The Department of Energy (DOE) has historically adhered to default measure lifetime values established during the development of the Weatherization Assistant software. These default lifetimes serve as a baseline for assessing the cost-effectiveness of ECMs within the Weatherization Assistance Program (WAP). Over the years, DOE has updated these lifetimes to reflect advancements in ECM technologies and evolving industry standards. Notably, revisions were made through Weatherization Program Notice (WPN) 23-06 [252] and WPN 19-4 [253], which introduced new lifetime values based on contemporary research and technological progress.

The Weatherization Assistant software is critical for supporting state and local weatherization agencies implementing WAP. It encompasses two distinct energy audit tools: the National Energy Audit Tool (NEAT) for site-built single-family homes and the Manufactured Home Energy Audit (MHEA) for mobile or manufactured homes [254]. These tools provide a systematic approach to measure selection and cost-effectiveness analysis, ensuring that WAP-funded projects achieve maximum energy savings and value for participating households.

The evolution of the Weatherization Assistant software dates back to 1988 and reflects decades of development and refinement (Figure 5.1). Initially designed with a limited library of ECMs and associated default lifetimes, the software has been continuously updated to include new measures, accommodate technological advances, and reflect an improved understanding of measure performance over time. For example, early versions of NEAT and MHEA user manuals [280], [281], [282] documented measure lifetime values based on the best available data at the time. Research publications, such as Dalhoff [258], further contributed to establishing default values.

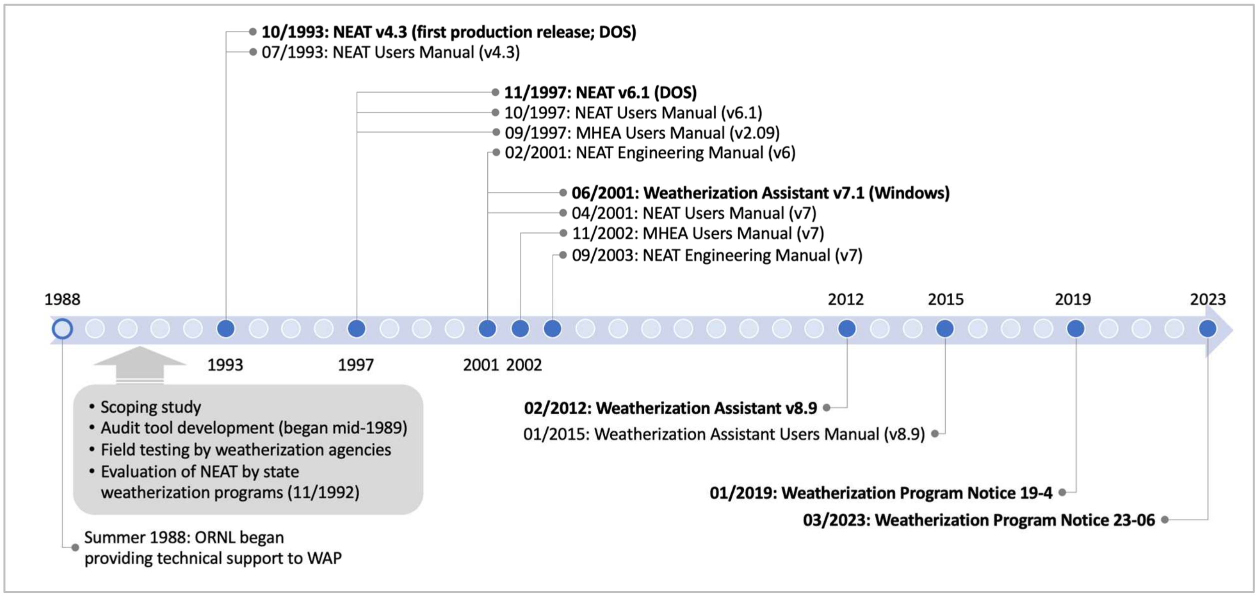

Figure 5.1. Evolution of the Weatherization Assistant software.

Subsequent updates to the software have expanded its capabilities, with the latest version – Weatherization Assistant v8.9 – featuring an extensive library of ECMs and their corresponding default lifetimes. Empirical data, field experience, and advancements in energy efficiency technologies inform these lifetimes. Figure 5.1 provides a visual overview of the software's development history, highlighting key milestones in its evolution. The ongoing refinement of default lifetimes underscores the DOE’s commitment to ensuring that WAP remains effective and responsive to emerging technologies and household needs.

The historical default measure lifetime values used in WAP since 1996, as found in various user manuals and WPNs, can be found in [252], [253], [280], [281], and [282].

5.1.2 Addressing Measures With Long Lifetime Values

Each measure and package of measures implemented under WAP must generate energy cost savings over the measure's lifetime that when discounted to present value, equal or exceed the measure's cost. This evaluation relies on projections of future energy prices using U.S. average or regional fuel price indices, which are computed annually by the National Institute of Standards and Technology (NIST) based on the most recent energy price forecasts from the U.S. Energy Information Administration (EIA). These projections are currently provided for 30 years, aligning with the maximum allowable ECM lifetime defined in Weatherization Program Notice (WPN) 23-06.

Despite this constraint, certain ECMs are known to have service lives extending well beyond 30 years. For measures with such extended lifetimes, assessing economic viability requires an approach that accounts for their benefits beyond the standard projection period. Without proper adjustment, these measures' long-term energy savings and cost-effectiveness risk being undervalued.

The Energy Independence and Security Act (EISA) of 2007 [259] extended the maximum service period for Federal Energy Management Program (FEMP) life-cycle costing (LCC) analyses from 25 to 40 years. To accommodate this change, the NIST Building Life Cycle Cost (BLCC) [260] program incorporated unofficial projections of energy prices for years beyond 30. Initially, these projections were simple extrapolations of the 30th-year growth rates [261]. However, starting in 2022, these projections transitioned to using the simple average growth rate of the last five years of available forecasts [262]. This shift aims to provide a more balanced estimate for out-year energy prices, though caution is advised when interpreting savings beyond the 30-year horizon.

Given the inherent uncertainties associated with long-term projections, sensitivity analyses play a key role in testing various out-year assumptions. These analyses help evaluate how different assumptions about future energy prices impact the economic viability of ECMs with extended lifetimes. Subsequent sections provide detailed sensitivity analyses to address these challenges.

5.2 Methodology

The analysis conducted in this chapter builds upon established principles of economic evaluation for energy conservation measures (ECMs)). The methodology integrates fuel price projections, discount rate application, sensitivity analysis, and extrapolation techniques to evaluate the impact of extending measure lifetimes beyond 30 years on their economic viability. Key steps in the methodological framework are outlined below:

5.2.1 Data Collection

Fuel price indices (FPIs) and escalation rates were obtained from the 2022 and 2023 Annual Supplements to NIST Handbook 135 [262], [263]. These data sets provided year-by-year projections for natural gas and electricity prices for 30 years. For years beyond 30, extrapolated FPIs were calculated based on the average escalation rates observed in years 26–30, as per guidelines from Kneifel and Lavappa [262]. Discount rates were sourced from the same NIST publications to ensure consistency with current WAP evaluation practices.

5.2.2 Economic, Sensitivity and Threshold Analysis

The savings-to-investment ratio (SIR) was used as the primary metric for assessing the economic viability of ECMs. The methodology incorporated constant terms (e.g., present value indices) and time-varying terms (e.g., cumulative discounted savings) derived from fuel price projections and discount rates for extended lifetimes.

Sensitivity analyses were performed to evaluate the robustness of SIR calculations under varying scenarios of extended measure lifetimes using derived fuel price escalation rates and discount rates. The analyses tested how the extrapolation method for FPIs – such as using 5-year average escalation rates – impacted the SIR for measure lifetimes of up to 100 years. Separate analyses were conducted for natural gas and electricity to reflect each fuel type's unique escalation trends and uncertainties.

Threshold analyses assessed the conditions under which extending measure lifetimes would yield economic benefits. These analyses determined the minimum year-30 SIR values required for ECMs to benefit from extended lifetimes. This was achieved by calculating the incremental percent increase in SIR as a function of additional measure years, using equations detailed in Appendix B.

5.2.3 Visualization and Interpretation

Figures and tables were generated to illustrate the trends and findings from the analysis. For instance, FPIs for years 31–100 were plotted to highlight the differences between 2022 and 2023 datasets, while SIR percent increases were presented as a function of extended measure lifetimes. These visualizations facilitated the comparison of results across different scenarios and provided actionable insights into the economic trade-offs of longer-lived ECMs.

The findings were contextualized within the WAP framework, highlighting the implications for program design, measure prioritization, and long-term energy savings. The results also informed recommendations for addressing uncertainties in fuel price projections and adapting WAP guidelines to accommodate measures with extended lifetimes.

5.3 Results and Analysis

5.3.1 Sensitivity Analysis of the Impact of Measure Lifetimes Exceeding 30 Years on the SIR

The approach utilized in BLCC programs to support FEMP service periods of up to 40 years provides a valuable framework for extending the economic analyses of ECMs within WAP beyond the current 30-year threshold. However, this extension introduces significant uncertainties, mainly due to the reliance on extrapolated fuel escalation rates for years beyond 30. These rates are based on the average escalation trends from the final five years of projections (years 26–30) rather than being derived directly from modeled energy price projections by the U.S. Energy Information Administration (EIA). Consequently, the degree of uncertainty increases substantially for these distant years.

To address this issue, a sensitivity analysis was conducted to evaluate the economic implications of extending ECM lifetimes beyond 30 years. Following the recommendations of Kneifel and Lavappa [262], the analysis assessed whether the potential benefits of increased measure lifetimes – measured through higher savings-to-investment ratios (SIRs) – justify the additional uncertainty. A series of equations was developed to project fuel price indices for future years and calculate changes in SIRs for ECMs with extended lifetimes. Detailed derivations of these equations are presented in Appendix B.

The fuel price index (FPI) for x years beyond 30 years is calculated using:

$$FPI_{30+x} = FPI_{30} * (1 + \bar{e}_{26\text{-}30})^x, \tag{1}$$

where

FPI_{30+x} is the fuel price index for x years beyond 30 years,

FPI_{30} does NIST publish the fuel price index for year 30 and

$\bar{e}_{26\text{-}30}$ is the average of the escalation rates for years 26 through 30

The escalation rate e_n for any year n is determined as:

$$e_n = \frac{FPI_n}{FPI_{n-1}} - 1. \tag{2}$$

The SIR of a measure initially calculated for a 30-year lifetime is adjusted for an extended lifetime of $30 + x$ year using

determined based on a 30-year lifetime. Accounting for a measure lifetime of $30 + x$ years, the percent increase in SIR of the measure can be expressed as

$$\%\text{Increase in SIR} = \frac{PV_{30}}{UPV_{30}} \times \sum_{i=1}^{x} \left(\frac{1+\bar{e}_{26\text{-}30}}{1+d}\right)^i, \tag{3}$$

where

PV_{30} is the present value index for year 30, calculated as $\frac{FPI_{30}}{(1+d)^{30}}$;

UPV_{30} is the uniform present value for year 30, calculated as $\sum_{i=1}^{30} \frac{FPI_i}{(1+d)^i}$; and

d is the real discount rate.

This sensitivity analysis was applied to both natural gas and electricity, using the economic parameters from the 2023 and 2022 Annual Supplements to NIST Handbook 135 [262], [263]. These parameters provided the baseline data for examining how variations in fuel price indices and discount rates affect the economic viability of ECMs with extended lifetimes. The results of this analysis are discussed in the following subsections.

Example 1: Using 2023 NIST FPIs

Figure 5.2 presents the fuel price indices (FPIs) for natural gas and electricity as published in the 2023 NIST energy price indices and discount factors for life-cycle cost analysis [263]. For years 1–30, the FPIs are based on official NIST projections, while years 31–100 represent extrapolated values derived from the average escalation rates observed in years 26–30. Specifically, the escalation rate for natural gas was 0.33%, indicating a gradual increase in prices, while the escalation rate for electricity was –0.45%, indicating a decline in prices. The extrapolated FPIs show significant deviations from the year 1–30 trends, resulting in exceptionally high natural gas prices and exceptionally low electricity prices over extended periods. These projections underscore the uncertainties associated with long-term energy price forecasting, significantly beyond the range of official projections.

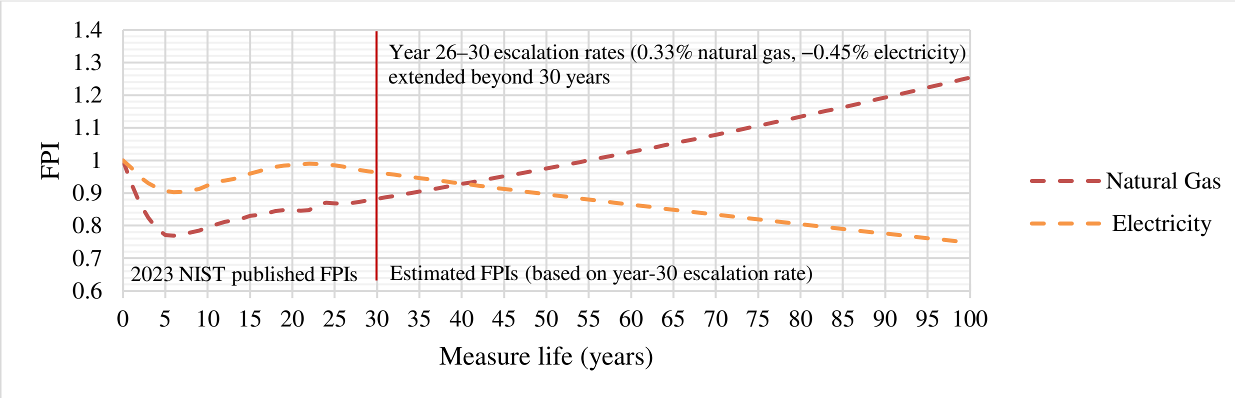

Figure 5.2. Estimated FPIs beyond 30 years based on 2023 NIST FPIs.

Table 5.1 summarizes the economic parameters derived from year-30 FPIs for natural gas and electricity, which are essential for calculating the percent increase in SIR. For natural gas, with a 3% real discount rate, the constant term based on the year-30 present value index, PV_{30}, is 0.0223, while the time-varying term, derived from the 0.33% escalation rate, is 0.974. These terms are summed over x years beyond the 30-year threshold. For electricity, the constant term is slightly lower at 0.0213, and the time-varying term, based on the –0.45% escalation rate, is 0.967, reflecting the projected decline in electricity prices. These differences highlight the varying impacts of fuel types on long-term SIR calculations.

Table 5.1. Summary of economic parameters relevant for sensitivity analysis based on 2023 NIST FPIs

Parameter	**Term**	**Natural gas**	**Electricity**
Real discount rate	d	3%	3%
Fuel price index for year 30	FPI_{30}	0.882	0.963
Present value index for year 30	PV_{30}	0.363	0.397
Uniform present value for year 30	UPV_{30}	16.268	18.605
Constant term	$\boldsymbol{PV_{30}/UPV_{30}}$	**0.0223**	**0.0213**
Year 26–30 average escalation rate	$\bar{e}_{26\text{-}30}$	0.33%	–0.45%
Time-varying term (to be summed over *x* years)	$\boldsymbol{(1+\bar{e}_{26\text{-}30})/(1+d)}$	**0.974**	**0.967**

Figure 5.3 illustrates the percent increase in SIR as a function of increasing measure lifetimes, calculated using Equation (3) and year-30 SIRs. Extending the measure life from 30 to 40 years for natural gas results in a 20% increase in SIR. Beyond 40 years, the percent increase in SIR grows at a diminishing rate:

- 35% for a 50-year lifetime,
- 47% for a 60-year lifetime,
- 56% for a 70-year lifetime,
- 64% for an 80-year lifetime,
- 69% for a 90-year lifetime, and
- 74% for a 100-year lifetime.

The results demonstrate that longer lifetimes significantly enhance the SIR, but the incremental benefits decrease as the lifetime extends. This reflects the compounding effect of discounted future savings, which diminishes over time. For electricity, the percent increases in SIR are lower than those for natural gas, consistent with the negative escalation rate and declining FPIs in the extrapolated period.

This analysis highlights the importance of considering both the fuel type and the length of the measure lifetime in economic evaluations. Given the high uncertainty in long-term projections, it also underscores the need for sensitivity analyses to test the robustness of these results under varying escalation and discount rate assumptions.

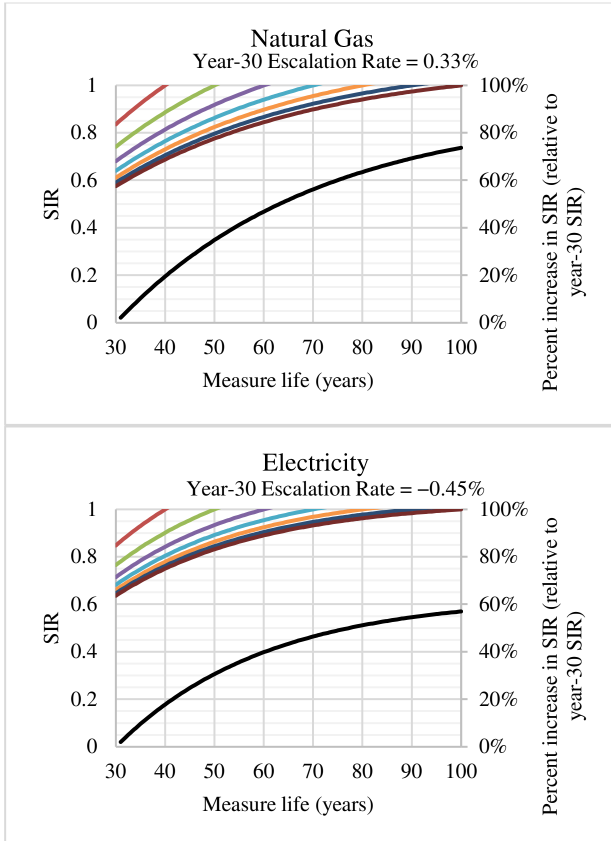

Figure 5.3. Analysis for extending measure life beyond 30 years based on 2023 NIST FPIs.

The bold black line represents the percent increase in SIR (right *y*-axis). Colored lines represent the minimum year-30 SIRs necessary to achieve 1.0 SIR (left *y*-axis) if measure life is increased beyond 30 years in 10-year increments up to 100 years: red represents an increase from 30 to 40 years, green represents an increase from 30 to 50 years, purple represents an increase from 30 to 60 years, and so on.

The minimum year-30 SIR required to achieve 1.0 SIR by the end of the measure life is 0.84 if the measure life is increased to 40 years, 0.74 if the measure life is increased to 50 years, and so on. Measures with year-30 SIRs below 0.575 do not benefit even if the measure life is increased to 100 years.

Likewise, for electricity, growth in the percent increase in SIR diminishes as measure life is increased beyond 30 years. The percent increase in SIR is 18% if measure life is increased from 30 to 40 years, 31% if measure life is increased from 30 to 50 years, 40% if measure life is increased from 30 to 60 years, and so on up to a maximum of only 57% if measure life is further increased up to 100 years. The minimum year-30 SIR to achieve 1.0 SIR by the end of the measure life is 0.85 if the measure life is increased to 40 years, 0.765 if the measure life is increased to 50 years, and so on. Measures with year-30 SIRs below 0.64 do not benefit even if the measure life is increased to 100 years.

Example 2: Using 2022 NIST FPIs

Figure 5.4 presents the fuel price indices (FPIs) for natural gas and electricity published in the 2022 NIST energy price indices and discount factors for life-cycle cost analysis. Unlike the 2023 FPIs, which showed more extreme projections due to higher average escalation rates for years 26–30, the 2022 FPIs reflect more moderate trends. Specifically, the average escalation rates for years 26–30 are 0.13% for natural gas and –0.22% for electricity. These more conservative rates result in extrapolated FPIs for years 31–100 less extreme than those derived from 2023 data, leading to more stable long-term cost-effectiveness evaluations.

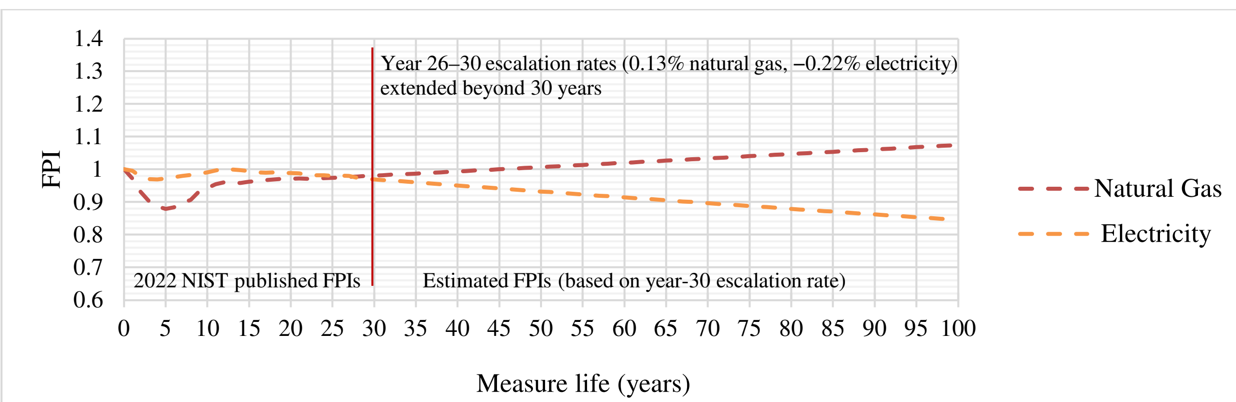

Figure 5.4. Estimated FPIs beyond 30 years based on 2022 NIST FPIs.

Table 5.2 lists the constant and time-varying terms used to calculate the percent increase in SIR for natural gas and electricity based on the 2022 FPIs. For natural gas, the constant term derived from the present value index, PV_{30}, is 0.0218, while the time-varying term, based on the 0.13% escalation rate, is 0.972. For electricity, the constant term is slightly lower at 0.0207, while the time-varying term, reflecting the –0.22% escalation rate, is 0.969. These terms demonstrate the relative stability of long-term price projections in the 2022 dataset.

Table 5.2. Summary of economic parameters relevant for sensitivity analysis based on 2022 NIST FPIs

Parameter	Term	Natural gas	Electricity
Real discount rate	d	3%	3%
Fuel price index for year 30	FPI_{30}	0.981	0.969
Present value for year 30	PV_{30}	0.404	0.399
Uniform present value for year 30	UPV_{30}	18.510	19.292
Constant term	$\boldsymbol{PV_{30}/UPV_{30}}$	**0.0218**	**0.0207**
Year 26–30 average escalation rate	$\bar{e}_{26\text{-}30}$	0.13%	–0.22%
Time-varying term (to be summed over *x* years)	$\boldsymbol{(1 + \bar{e}_{26\text{-}30})/(1 + d)}$	**0.972**	**0.969**

As shown in Figure 5.5, the percent increase in SIR when extending measure lifetimes grows at a diminishing rate, consistent with the compounding effect of discounted future savings. For natural gas, extending the measure lifetime from 30 to 40 years increases the SIR by 18.7%, while extending it to 50 years results in a 32.4% increase. Beyond 50 years, the incremental growth in SIR slows significantly, reaching a maximum increase of 65.6% at 100 years. Similarly, for electricity, extending the measure lifetime from 30 to 40 years increases the SIR by 17.5%, while extending it to 50 years yields a 30.9% increase, with a maximum increase of 57.5% at 100 years.

The analysis also reveals minimum year-30 SIR thresholds for measures to benefit from lifetime extensions. For natural gas savings, measures must have year-30 SIRs of at least 0.84 to benefit from a 40-year lifetime and 0.75 for a 50-year lifetime. Measures with year-30 SIRs below 0.6 do not see any benefit, even with lifetimes extended to 100 years. For electricity savings, measures require year-30 SIRs of at least 0.85 to benefit from a 40-year lifetime and 0.77 for a 50-year lifetime, with a minimum threshold of 0.635 for 100-year lifetimes.

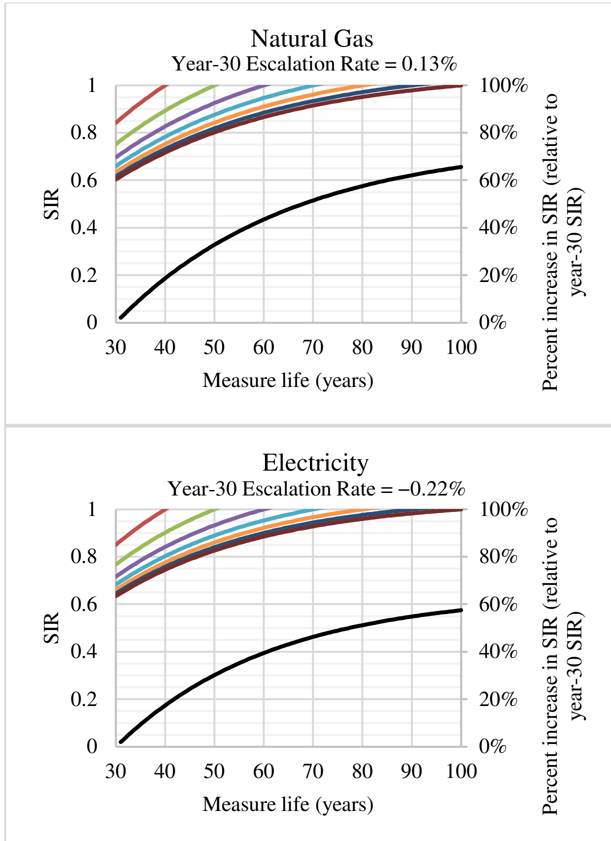

Figure 5.5. Analysis for extending measure life beyond 30 years based on 2022 NIST FPIs.

The bold black line represents the percent increase in SIR (right *y*-axis). Colored lines represent the minimum year-30 SIRs necessary to achieve 1.0 SIR (left *y*-axis) if measure life is increased beyond 30 years in 10-year increments up to 100 years: red represents an increase from 30 to 40 years, green represents an increase from 30 to 50 years, purple represents an increase from 30 to 60 years, and so on.

5.3.2 Uncertainty Analysis for Extended Lifetime Projections

Extending measure lifetimes beyond the standard 30-year period introduces significant uncertainties in economic evaluations of ECMs. These uncertainties arise primarily from the extrapolation of FPIs and the application of discount rates over extended periods, both of which are subject to substantial variability.

Sources of Uncertainty

Fuel price indices for years beyond the 30-year horizon are derived through extrapolation methods, which rely on average escalation rates observed in years 26–30. However, these methods assume that recent trends will persist, ignoring potential market disruptions, technological advances, or policy changes. For example, unforeseen shifts in global energy markets or adopting renewable energy technologies could drastically alter long-term fuel price trajectories.

Discount rates used to calculate present value indices are typically held constant over the analysis period. However, real-world discount rates may fluctuate due to changes in inflation, economic growth, or monetary policy [264]. Such variability can significantly affect the present value of long-term savings, particularly for lifetimes extending to 50 or 100 years.

Some ECMs' effectiveness may degrade over time, reducing their energy-saving potential. While this degradation is accounted for in some evaluations, uncertainties in degradation rates for newer or less-studied ECMs add complexity to long-term assessments. Also, changes in energy policies, subsidies, or program guidelines could influence the economic viability of long-lived ECMs. For example, introducing carbon pricing or renewable energy mandates may alter cost-benefit dynamics.

The compounded effects of these uncertainties can lead to either overestimation or underestimation of ECM cost-effectiveness. Overestimation may result in selecting measures that fail to deliver expected savings, while underestimation could exclude measures with significant long-term benefits. This has critical implications for program administrators tasked with optimizing resource allocation under WAP.

Quantifying and Mitigating Uncertainty

One approach to quantifying uncertainty is through scenario analysis, where multiple projections of FPIs and discount rates are tested to evaluate their impact on savings-to-investment ratios (SIRs). For instance, optimistic, baseline, and pessimistic scenarios can be developed to reflect varying assumptions about future energy prices and economic conditions [265].

Monte Carlo methods provide a probabilistic framework for uncertainty analysis [266]. This approach generates a range of possible outcomes by sampling from distributions of fuel price escalation rates, discount rates, and other variables, offering insights into the likelihood of achieving specific SIR thresholds. Also, sensitivity analysis, as discussed earlier in this chapter, evaluates how variations in key parameters affect SIR calculations. This approach is beneficial for identifying parameters that exert the most significant influence on results, allowing for targeted risk mitigation strategies.

A way to mitigate uncertainty is to incorporate dynamic discount rates that adjust to changing economic conditions. This can provide more realistic estimates of long-term present value indices. Also, frequent updates to extrapolation methods for FPIs, incorporating the latest market data and trends, can improve the reliability of long-term projections. For measures with lifetimes extending well beyond 30 years, incorporating residual value in economic assessments can partially offset uncertainties in long-term projections.

5.3.3 Policy and Broader Implications for Energy Equity and Sustainability

Analyzing measures with extended lifetimes has profound implications for energy efficiency programs seeking to optimize economic, social, and environmental outcomes. Incorporating longer measure lifetimes into program frameworks requires revisiting established methodologies and policies to ensure that the full value of durable measures is accurately accounted for in cost-effectiveness evaluations. This shift can improve resource allocation, enhance energy equity, and contribute to long-term sustainability goals.

A key policy implication is adapting cost-effectiveness criteria for longer-lived energy conservation measures (ECMs). Traditional approaches are often limited to short-term future projectable periods (for example, a 30-year horizon) and fail to capture the cumulative savings and benefits of measures that remain effective for long-term periods (for example, 50 years or longer). Adjustments such as incorporating residual value into cost-benefit analyses or dynamic discount rates reflecting economic variability over extended periods are necessary for more accurate evaluations. Additionally, aligning program guidelines with broader energy policies, such as federal or regional sustainability targets, ensures consistency in assessing the long-term benefits of ECMs.

Economic projections also play a critical role in assessing measures with extended lifetimes. Current methods for extrapolating fuel price indices and escalation rates beyond modeled periods introduce decision-making uncertainties. Enhancing the accuracy and reliability of these projections through collaboration with research institutions and energy forecasting agencies can provide a more robust foundation for evaluating long-term cost-effectiveness. This is particularly important for durable measures whose benefits depend on stable and realistic economic assumptions over decades.

Beyond economic considerations, integrating long-lived ECMs into energy efficiency programs carries significant implications for energy equity. Durable measures provide sustained energy cost savings, improved indoor comfort, and healthier living environments, which are particularly impactful for underserved or low-income communities. However, higher upfront costs and extended payback periods may limit these measures' accessibility. Addressing this disparity requires targeted program designs, such as grants or financing mechanisms, to ensure equitable access to the long-term benefits of durable ECMs.

From a sustainability perspective, measures with extended lifetimes contribute to reducing overall energy consumption and greenhouse gas emissions, aligning with global decarbonization goals. These measures also support community resilience by mitigating exposure to energy price volatility and reducing dependence on fossil fuels. Energy efficiency programs can achieve a more significant and sustained environmental impact by prioritizing investments in durable, high-impact measures.

To maximize the potential of long-lived ECMs, energy efficiency programs must adopt a holistic approach considering their economic and technical feasibility and broader societal and environmental benefits. This includes refining evaluation methodologies, addressing barriers to access, and fostering collaborations between stakeholders to create equitable and sustainable programs. Such efforts will ensure that the benefits of energy efficiency are distributed fairly while advancing long-term goals of environmental stewardship and social equity.

5.4 Chapter Summary

This study has explored the economic implications of extending ECM lifetimes beyond the conventional 30-year threshold often employed in energy efficiency programs. By examining methodologies for projecting fuel price indices (FPIs), applying discount rates, and conducting sensitivity analyses, the chapter provides a comprehensive framework for evaluating the long-term viability of ECMs. Key findings highlight the potential benefits and challenges of extending measure lifetimes, emphasizing the need for refined economic evaluation criteria and robust analytical approaches.

The historical context of default measure lifetime values reveals a reliance on short-term projections, which, while practical, may undervalue durable measures that deliver energy savings over several decades. Using extrapolated FPIs to extend projections beyond 30 years demonstrates the importance of balancing potential economic benefits against the inherent uncertainties of long-term forecasting. Sensitivity analyses confirm that while extending lifetimes significantly increases savings-to-investment ratios (SIRs), the marginal benefits diminish as lifetimes extend further, underscoring the compounding effects of discounting future savings.

This analysis also highlights the nuanced trade-offs between short-lived and long-lived ECMs. While short-lived measures offer immediate, accessible savings, long-lived ECMs provide sustained benefits that align with broader energy equity and sustainability goals. Addressing fuel prices and discount rates and measuring degradation uncertainties is critical to ensuring that economic evaluations remain reliable and actionable over extended periods.

Moreover, the study highlights the broader implications of integrating long-lived ECMs into energy efficiency programs. Beyond economic metrics, such measures contribute to social equity by reducing energy burdens for underserved communities and advance sustainability by mitigating greenhouse gas emissions and enhancing resilience. By adopting policies and methodologies that account for the entire lifecycle benefits of ECMs, energy efficiency programs can more effectively achieve their objectives of reducing energy consumption, promoting equity, and supporting global decarbonization efforts.

CHAPTER 6
CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions for Each Chapter

This section provides a detailed summary of the outcomes of the research objectives pursued in this study toward developing a multicriteria framework for energy audit software and evaluation methodologies for energy conservation measures in low-income energy efficiency programs. The outcomes of each research objective are highlighted below:

6.1.1 Developing a Multicriteria Framework For Residential Energy Audits that Addresses the Specific Needs and Complexities of Low-Income Households

Chapter 2 successfully addressed the above objective by presenting a comprehensive framework tailored to the unique needs of low-income households in residential energy audits. The framework integrates over 50 carefully curated factors organized under 14 critical criteria, encompassing energy and non-energy considerations. It emphasizes essential aspects such as accuracy, scalability, sustainability, cost, and user-friendliness while addressing health, safety, and the socio-economic impacts of energy efficiency.

The proposed framework aligns technical functionalities with practical requirements, enabling energy auditors, software developers, and program managers to evaluate, improve, or select the most suitable energy audit software for low-income households. This systematic approach addresses the complexities of diverse building types and user behaviors and highlights the non-energy benefits often overlooked, such as health, safety, and indoor air quality improvements.

The framework lays the groundwork for more equitable and effective energy efficiency interventions by bridging gaps in existing methodologies and offering a structured, holistic assessment model. It will ultimately contribute to reduced energy costs, improved living standards for vulnerable populations, and progress toward global net-zero emission targets.

6.1.2 Demonstrating how the Framework Works with Existing Energy Audit Software: A Comparative Analysis Of Three Software

This chapter demonstrated the applicability of the proposed multi-criteria framework by evaluating three energy audit software tools – REM/RATE, Weatherization Assistant (WA), and TREAT – against criteria particularly relevant to low-income households. The comparative analysis revealed that while each software has distinct strengths and limitations, the framework effectively highlighted their suitability for specific contexts and identified areas for improvement.

REM/RATE exhibited substantial compliance with established energy standards and the inclusion of renewable energy modeling capabilities, making it a good choice for sustainability-focused audits. However, its limited health and safety features and scalability options restrict its applicability for broader, low-income household programs. WA excelled in health and safety considerations and scalability, emphasizing its suitability for large-scale applications, but its lack of renewable energy and sustainability features presents a significant limitation. TREAT provided a balanced user experience and notable scalability features, yet it underperformed in compliance with energy standards and renewable energy integration, limiting its effectiveness for holistic energy audits.

The framework proved robust in capturing quantitative and qualitative performance metrics, enabling a comprehensive assessment of each tool. The framework facilitated a nuanced understanding of each tool's capabilities and limitations by organizing the evaluation into software-focused, user-focused, and household-focused criteria. Additionally, it underscored the need for software enhancements, including improved health and safety features, sustainability modules, and better integration with renewable energy technologies.

This evaluation validated the framework's effectiveness and provided actionable insights for developers, policymakers, and energy program administrators. By adopting a structured approach to assessing energy audit software, stakeholders can make informed decisions that align with the specific needs of low-income households, ultimately advancing energy efficiency and improving living conditions for vulnerable populations.

6.1.3 Establishing a systematic and Repeatable Methodology for Assessing the Lifetime of Energy Conservation Measures

This chapter establishes a systematic and repeatable methodology for assessing the lifetimes of Energy Conservation Measures (ECMs), ensuring applicability across diverse measure types with a focus on low-income households. The study critically reviewed and compared methodologies – ranging from survival analysis and manufacturer data to field surveys, accelerated life testing, data-driven modeling, and expert judgment – highlighting their strengths, limitations, and applications. It also incorporates a detailed exploration of economic analyses for measures with extended lifetimes, addressing the unique challenges and opportunities associated with ECMs expected to last beyond conventional study periods.

The analysis adapts established frameworks for ECMs with lifetimes exceeding 30 years, such as the Federal Energy Management Program (FEMP) lifecycle costing rules. It integrates sensitivity analyses to account for uncertainties in fuel price projections. The results underscore the importance of extending study periods for long-lived ECMs while balancing these benefits with the inherent uncertainties of extrapolated economic parameters. The findings demonstrate that extending the analysis period increases cost-effectiveness (as measured by the Savings-to-Investment Ratio, or SIR), though this effect diminishes with longer durations.

The chapter also emphasizes integrating multiple lifetime estimation approaches, such as using statistical techniques like the Weibull distribution, to derive representative lifetime values that reflect real-world variability. Additionally, it underscores the critical role of environmental factors, maintenance practices, and user behavior in influencing measure persistence and savings persistence. These insights are pivotal for stakeholders prioritizing ECMs that deliver sustained benefits, particularly in programs designed for low-income households.

This chapter provides actionable tools for optimizing ECM selection and implementation by combining robust lifetime estimation methodologies with a comprehensive economic analysis framework. The outcomes support informed decision-making, ensuring that resources are directed toward measures with the most significant potential to maximize energy savings, reduce costs, and improve the quality of life for underserved populations.

6.2 Impact and Significance of this Thesis

The global push for energy efficiency and sustainability has underscored the critical importance of targeted interventions in the residential building sector, particularly for low-income households. This thesis contributes to advancing the field of residential energy audits by addressing the multifaceted challenges of energy conservation within this demographic. By developing a comprehensive framework and robust methodologies, this work provides practical tools and actionable insights to enhance energy efficiency, improve living conditions, and reduce energy costs for vulnerable populations. The broader significance of this thesis is detailed below:

6.2.1 Development of a Comprehensive Energy Audit Framework

This research introduces a novel, multi-criteria framework tailored to the unique needs of low-income households. This framework is the most extensive and comprehensive outline relevant to a broad spectrum of energy audit stakeholders, including developers, users, administrators, and beneficiaries. The framework goes beyond conventional energy audit practices by integrating energy and non-energy considerations, such as health, safety, and socio-economic impacts. Its holistic approach equips stakeholders with a structured, equitable methodology for developing, evaluating, and selecting energy audit software. By bridging gaps in existing practices, the framework lays the foundation for more effective and inclusive energy conservation programs, ultimately advancing energy equity.

6.2.2 Demonstration of Framework Applicability with Energy Audit Software

To demonstrate and prove the practicality of the framework, the thesis rigorously applies the proposed framework to existing energy audit software tools – REM/RATE, Weatherization Assistant, and TREAT. This comparative analysis highlights their relative strengths, limitations, and alignment with the specific requirements of low-income households. The findings provide actionable recommendations for software developers to enhance user-friendliness, scalability, and the integration of sustainability features. Furthermore, the framework's ability to identify gaps and opportunities underscores its potential for driving innovation in energy audit software, facilitating widespread adoption and impact.

6.2.3 Establishment of Methodology for Assessing Energy Conservation Measures (ECMs)

The research pioneers a systematic and repeatable methodology for evaluating the lifetimes of Energy Conservation Measures (ECMs). The methodology ensures accurate, context-specific lifetime estimates by employing diverse approaches – including survival analysis, manufacturer data, field testing, and data-driven modeling. This enables more precise lifecycle cost analyses and informed decision-making for program administrators. Additionally, the economic analysis of ECMs with lifetimes exceeding 30 years addresses a critical knowledge gap, providing a framework for evaluating long-term energy efficiency investments that guarantee a positive SIR.

6.2.4 Contributions to Energy Equity and Sustainability

This thesis makes significant strides in addressing energy poverty by tailoring solutions to the specific needs of low-income households. The proposed solutions empower communities to access energy-saving technologies and programs at scale by prioritizing scalability, cost-effectiveness, and implementation time. The work also advances sustainability efforts by promoting the adoption of durable ECMs and enhancing the resilience of residential energy systems. These contributions align with global decarbonization goals, aiding in reducing greenhouse gas emissions and mitigating climate change impacts.

6.2.5 Broader Implications for Policy and Practice

The findings and methodologies presented in this thesis have implications that extend beyond academia. Policymakers can leverage the insights to design targeted programs that address energy inequities, while software developers and energy auditors can refine tools and processes to maximize their effectiveness. Furthermore, the comprehensive approach to ECM lifetime assessment offers a replicable model for evaluating energy efficiency programs' economic and environmental benefits across diverse contexts.

6.3 Limitations of the Study

This thesis addresses significant challenges in residential energy auditing and energy conservation measure (ECM) evaluation; however, several limitations must be acknowledged, particularly regarding the scope, methodology, and data dependencies.

A key limitation lies in the complexity and subjectivity of the multi-criteria framework for evaluating energy audit software. The framework incorporates quantitative and qualitative criteria to provide a comprehensive assessment, but assigning weights to these criteria is inherently subjective. Stakeholders may prioritize criteria differently based on their goals and perspectives, leading to outcome variability. While unavoidable in multi-criteria decision-making, this subjectivity highlights a potential challenge in achieving consistency across applications and contexts.

Another significant limitation pertains to the reliability of ECM lifetime estimation, which depends on data availability and quality. The methodologies employed in this study rely on various sources, including manufacturer data, field testing, statistical models, and expert judgment. However, inconsistencies in these data sources or the lack of historical performance data for newer ECM technologies can compromise the accuracy of lifetime estimates. For example, field surveys may capture real-world usage patterns but often require extensive resources and execution time. In contrast, accelerated life testing may yield results quickly but does not always replicate real-world conditions. The reliance on data-driven methods also makes the analysis sensitive to errors or biases in the input data, which could affect the overall conclusions.

The scope of validation for the framework and ECM lifetime estimation methodologies also represents a limitation. The framework was applied to three specific energy audit software tools – REM/RATE, Weatherization Assistant, and TREAT. Although widely recognized, these tools do not encompass the full range of functionalities or scenarios relevant to energy audits in different contexts. Similarly, the ECM lifetime estimation methodologies were applied to a limited number of scenarios informed by available data. This limited scope may not reflect the diverse conditions encountered across various building types, climate zones, and operational practices. As such, the findings may not fully generalize to all energy audit applications or ECM categories.

Economic analyses of ECMs with lifetimes exceeding 30 years further highlight the limitations of long-term projections. Evaluating the cost-effectiveness of such ECMs relied on extrapolated fuel price projections, which inherently become less reliable as the analysis period extends. Although sensitivity analyses accounted for uncertainties, the variability of factors such as energy prices, inflation rates, and discount rates over long periods introduces additional complexity. This uncertainty limits the precision of the economic assessments and underscores the challenges of projecting cost-effectiveness for long-lived ECMs.

Finally, this study does not explicitly address behavioral and institutional factors influencing the adoption and implementation of energy audits and ECMs. While the research focuses on the technical and economic dimensions, factors such as user behavior, programmatic challenges, and institutional constraints can significantly affect the scalability and success of energy efficiency measures. Although beyond the scope of this research, these non-technical barriers remain critical to understanding the practical challenges of achieving widespread adoption.

6.4 Recommendation for Future Work

This thesis has contributed significantly to residential energy auditing by developing a multi-criteria framework, demonstrating its application with existing energy audit software, and establishing a systematic methodology for assessing ECM lifetimes. However, several areas for future research and development can build upon this study's findings to further advance energy efficiency and equity in low-income households.

6.4.1 Enhancing Framework Applicability and Objectivity

The subjectivity associated with assigning weights to the criteria within the multi-criteria framework presents an opportunity for future work. Research efforts could focus on developing standardized or algorithmic approaches for determining criteria weights, potentially incorporating participatory decision-making techniques or machine learning tools. Such advancements could reduce bias and enhance the framework's objectivity, replicability, and widespread adoption.

Additionally, the framework should be validated across a broader range of energy audit software tools and in diverse geographic and socio-economic contexts. Testing the framework in international and regional settings would provide insights into its adaptability and limitations, ensuring its robustness for varying household types, climates, and energy policies.

6.4.2 Expanding ECM Lifetime Data Sources and Models

While this study integrated multiple approaches to assess ECM lifetimes, data availability and quality limitations remain a barrier. Future research could explore the development of standardized data repositories that aggregate ECM performance data across various regions and conditions. This would enhance the reliability of lifetime estimates and reduce dependence on manufacturer data or expert judgment.

Moreover, there is potential to improve statistical and machine learning models to capture variability in ECM performance under real-world conditions. These models could incorporate dynamic environmental factors, usage patterns, and technological advancements, providing more nuanced lifetime estimates.

6.4.3 Addressing Uncertainty in Long-Term Economic Analysis

The economic evaluation of ECMs with lifetimes exceeding 30 years remains inherently uncertain due to extrapolated parameters such as energy prices and inflation rates. Future research should aim to refine long-term economic modeling techniques by incorporating probabilistic approaches or scenario-based analyses that can better capture uncertainties over extended periods. These advancements would improve the precision of cost-effectiveness assessments for long-lived ECMs.

6.4.4 Integrating Behavioral and Institutional Factors

The adoption of energy audit software and ECMs is influenced by technical and economic considerations and behavioral and institutional factors such as household energy-use habits, reluctance to adopt new measures, skepticism about long-term benefits, restrictive eligibility criteria, and limited outreach efforts. Future work could investigate how user behavior, programmatic constraints such as limited funding or insufficient auditor training, and institutional barriers affect the implementation and scalability of energy audits. Such research would provide valuable insights into how energy efficiency programs can be designed to maximize participation and impact in low-income households.

6.4.5 Innovation in Energy Audit Software Design

There is a need to encourage innovation in energy audit software to address identified gaps in current tools. Future efforts could focus on developing software with enhanced user interfaces, better health and safety features integration, and the ability to analyze renewable energy systems. Additionally, exploring how artificial intelligence (AI) and machine learning could streamline data acquisition, input, and analysis processes would improve software efficiency and accuracy.

6.4.6 Bridging the Gap Between Research and Practice

Demonstrating the practical application of findings in real-world settings is critical for scaling energy efficiency programs. Future studies could focus on pilot projects implementing the proposed framework and methodologies in low-income communities, assessing their effectiveness, and identifying areas for refinement. Strong collaboration between researchers, policymakers, and industry stakeholders will be essential to ensure the practical impact of these efforts.

6.4.7 Addressing Energy Equity Holistically

Finally, addressing energy equity requires a broader perspective beyond technical solutions. Future work should consider the socio-economic dimensions of energy efficiency programs, including how they intersect with housing quality, access to technology, and community engagement. This holistic approach will ensure that the benefits of energy conservation reach the most vulnerable populations and contribute to long-term energy security and sustainability.

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APPENDICES

APPENDIX A: SUPPLEMENTARY DATA FOR CHAPTER 4

UTILIZING MEASURE LIFETIME DATA SOURCES

Obtaining Reference Service Life from an Environmental Product Declaration Document

To find the RSL of a product from an EPD, one may use the following steps:

Step 1: Access https://www.environdec.com/library and locate the EPD library at the top right of the menu bar as shown in Figure A-1.

Step 2: To obtain the EPD document of a desired product or product type, type a keyword and/or select additional search criteria for Product Category (such as chemical products, construction products, infrastructure & building, etc.), PCR (which provides a finer breakdown of the options in the Product Category field), Geographical scope (to search by country, region, or continent), and/or Validity (to select a date or period when the EPD documents ought to be valid). The search results list the most recent EPD documents available in the library that match the specified search criteria, as shown in Figure A-1.

Step 3: Select a desired match to view the product information summary page, as shown in Figure A-2. Locate the EPD document provided on this page. The estimated service life of the product can be found in the EPD document, as shown in Figure A-3.

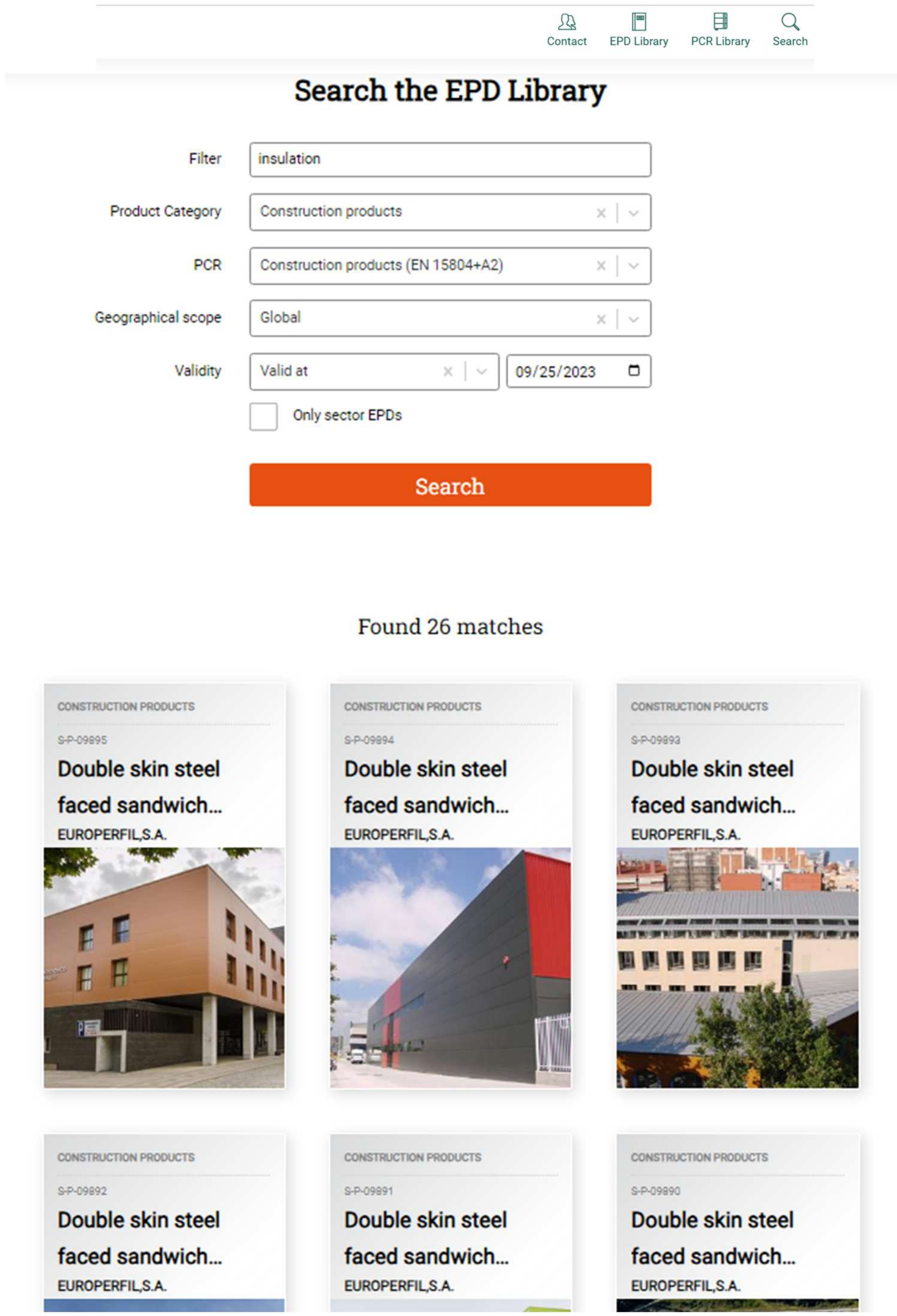


Figure A-1. Representative example with completed EPD search/selection fields showing results.

Double skin steel faced sandwich panels with PIR (polyisocyanurate) insulation core for facades.

Product information

This EPD covers the representative product of prefabricated double skin steel faced sandwich panels with polyisocianurate core and intended for discontinuous laying in external walls. Its aesthetic is enhanced by hidden fixings and its external facing available either in ribbed, micro-ribbed, lined or smooth finish.

The inner and outer skin is made of a core of steel, which is protected against corrosion with a metallic and organic coating. The thermal insulating core material is made of polyisocyanurate according to EN 13165 with sealing tapes.

All of them are produced by EUROPERFIL, S.A. at its production site, located in Cervera (Lleida -Spain).

From 22 different references, one representative product has been analysed with the goal of obtaining an average virtual product. Results of the Life Cycle Assessment (LCA) are presented for this average virtual product. The average product, has been calculated based on a set of references which are certified with CE according to EN 14509 & EN 13165.

Detailed information

Registration number:	S-P-09895
Status:	Valid
PCR:	2019:14
En15804 Compliant:	Yes
Registration date:	July 28, 2023
Valid until:	July 26, 2028
Geographical scopes:	Global, Europe, Spain
LCA practitioner:	MariaRosa.Riera@anthesisgroup.com

Company information

Company Name:	EUROPERFIL,S.A.
Country:	Spain
Contact:	moises.alvarez@europerfil.com
Website:	https://www.europerfil.com/

EPD documents

EPD document S-P-09895 en.pdf

Other documents

Included products in this EPD

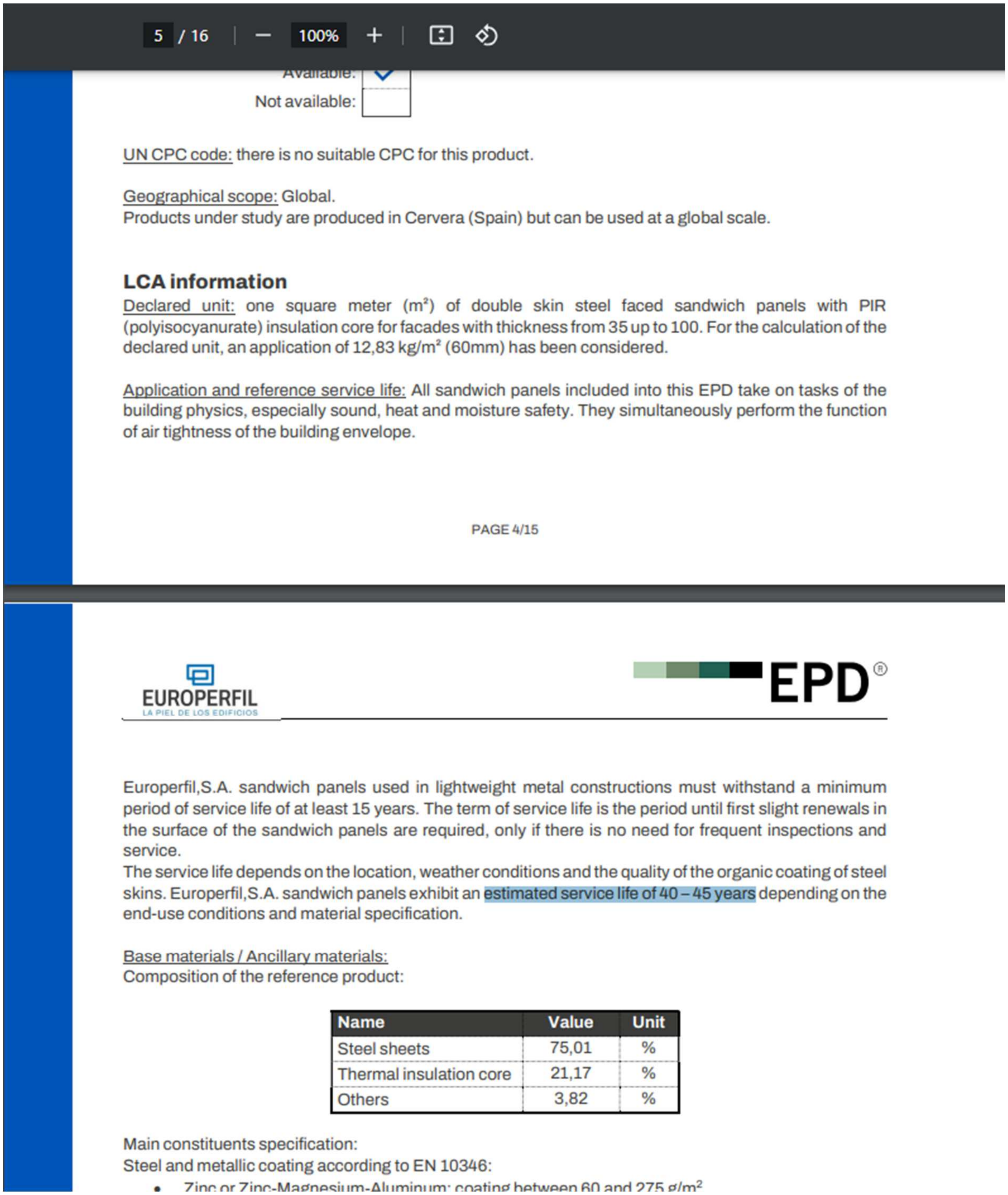
All references included are a double skin steel faced sandwich panels with polyisocyanurate core and specially designed for discontinuous laying in external walls.

The representative product ofthis family has been obtained from the calculation of the average product weighted by production of all the references of double skin steel faced sandwich panels with polyisocyanurate core and made of XCarb® Recycled and Renewably Produced Steel, produced on the same continuous foaming line during the year of study in the center of EUROPERFIL S.A.

Within this EPD are included the next references:

OLIMPIA 1.100, GALATEA 1.100, ÁTICA 1.100, NILHO 1.100/1.000/900/600, NILHO PRO 1.000/900/600, ETNA

Figure A-2. Product information summary page from an EPD search result.



5 / 16 100%

Available:

Not available:

UN CPC code: there is no suitable CPC for this product.

Geographical scope: Global.
Products under study are produced in Cervera (Spain) but can be used at a global scale.

LCA information

Declared unit: one square meter (m²) of double skin steel faced sandwich panels with PIR (polyisocyanurate) insulation core for facades with thickness from 35 up to 100. For the calculation of the declared unit, an application of 12,83 kg/m² (60mm) has been considered.

Application and reference service life: All sandwich panels included into this EPD take on tasks of the building physics, especially sound, heat and moisture safety. They simultaneously perform the function of air tightness of the building envelope.

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EUROPERFIL
LA PIEL DE LOS EDIFICIOS

EPD®

Europerfil,S.A. sandwich panels used in lightweight metal constructions must withstand a minimum period of service life of at least 15 years. The term of service life is the period until first slight renewals in the surface of the sandwich panels are required, only if there is no need for frequent inspections and service.
The service life depends on the location, weather conditions and the quality of the organic coating of steel skins. Europerfil,S.A. sandwich panels exhibit an estimated service life of 40 – 45 years depending on the end-use conditions and material specification.

Base materials / Ancillary materials:
Composition of the reference product:

Name	Value	Unit
Steel sheets	75,01	%
Thermal insulation core	21,17	%
Others	3,82	%

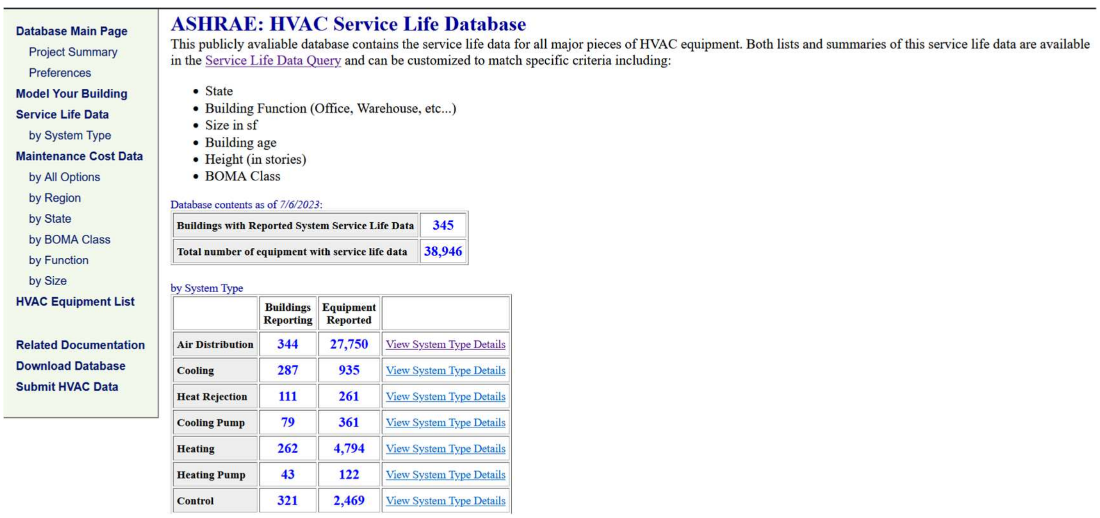
Main constituents specification:
Steel and metallic coating according to EN 10346:
- Zinc or Zinc-Magnesium-Aluminum: coating between 60 and 275 g/m²

Figure A-3. Screenshot of a typical EPD document showing the product's estimated service life (highlighted).[3]

Obtaining HVAC Service Life from the ASHRAE Database

ASHRAE maintains a public database that provides current information on the service lives and maintenance costs of all major pieces of HVAC equipment. Users may access the database by following the following steps:

Step 1: Access the HVAC Service Life Database at http://weblegacy.ashrae.org/publicdatabase/service_life.asp (Figure A-4).



Database Main Page
Project Summary
Preferences
Model Your Building
Service Life Data
by System Type
Maintenance Cost Data
by All Options
by Region
by State
by BOMA Class
by Function
by Size
HVAC Equipment List
Related Documentation
Download Database
Submit HVAC Data

ASHRAE: HVAC Service Life Database

This publicly avaliable database contains the service life data for all major pieces of HVAC equipment. Both lists and summaries of this service life data are available in the Service Life Data Query and can be customized to match specific criteria including:

- State
- Building Function (Office, Warehouse, etc...)
- Size in sf
- Building age
- Height (in stories)
- BOMA Class

Database contents as of 7/6/2023:

Buildings with Reported System Service Life Data	345
Total number of equipment with service life data	38,946

by System Type

	Buildings Reporting	Equipment Reported	
Air Distribution	344	27,750	View System Type Details
Cooling	287	935	View System Type Details
Heat Rejection	111	261	View System Type Details
Cooling Pump	79	361	View System Type Details
Heating	262	4,794	View System Type Details
Heating Pump	43	122	View System Type Details
Control	321	2,469	View System Type Details

Figure A-4. Screenshot of the ASHRAE HVAC Service Life Database.

Step 2: Use the Service Life Data Query (Figure A-5) to customize your search from the database by filtering equipment by system type (air distribution, cooling, heat rejection, cooling pump, heating, heating pump, control, miscellaneous), region, state, building

[3] For the product information summary page, visit https://www.environdec.com/library/epd9895. For the EPD document, visit https://api.environdec.com/api/v1/EPDLibrary/Files/cec394d0-0901-4ded-5767-08db8f4b80b8/Data.

function, size of building, height of building or number of stories, Building Owner and Managers Association (BOMA) classification, and location.

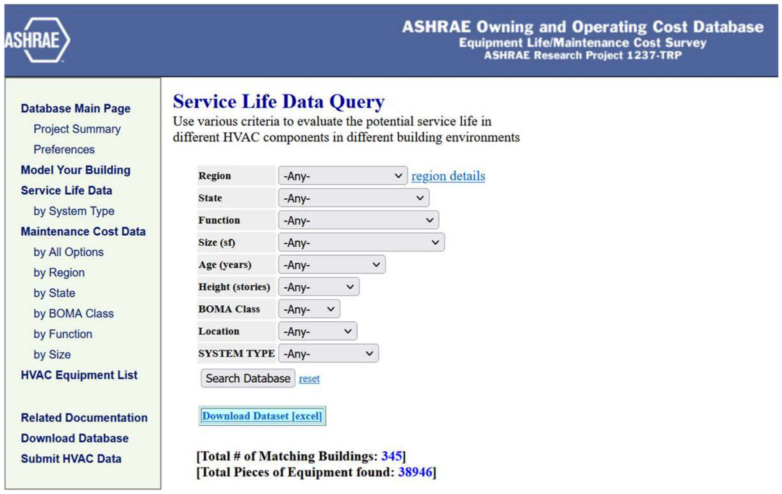


Figure A-5. Screenshot of Service Life Data Query.

The database allows users to search for equipment service life data by building type or function. This can be found by selecting Function to expand the field and then scrolling through the options to select the desired building type or function, as shown in Figure A-6. However, an obvious limitation of this database is that it is more focused on commercial buildings and has minimal residential building types. Figure A-7 shows a sample table of results for filtering the database by building function (multifamily residential) and system type (air distribution equipment).

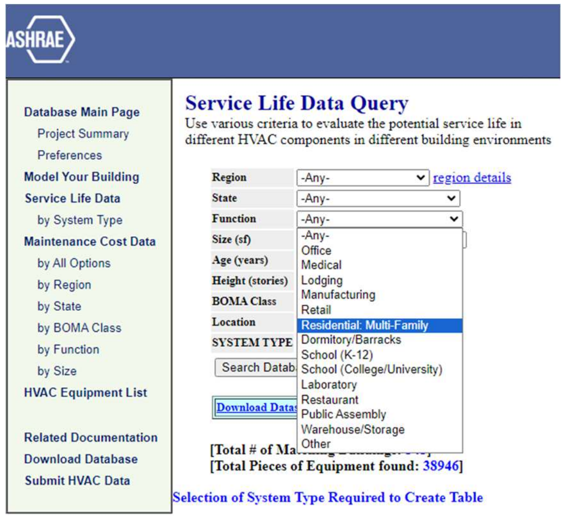
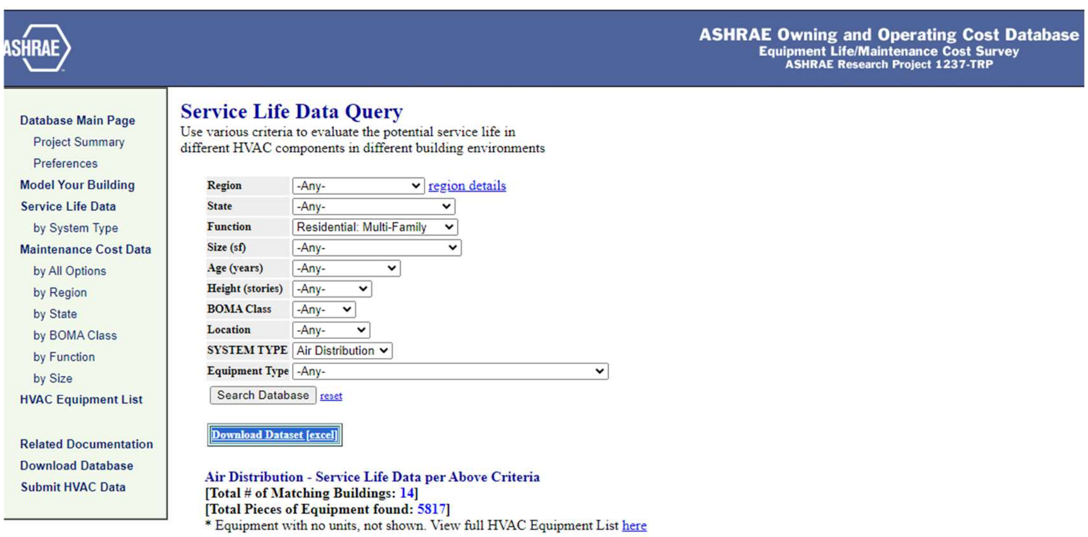


Figure A-6. ASHRAE HVAC Service Life Database showing building types.



	Total Units	Currently in Service							Replaced						
		No.of Units	Equipment Age (years)						No.of Units	Age at Removal (years)					
			Mean	Median	Std Dev	95% C.I.	Max	Min		Mean	Median	Std Dev	95% C.I.	Max	Min
Fan coil unit	1	1	42.0	42.0	n/a	n/a	42.0	42.0	0	n/a	n/a	n/a	n/a	n/a	n/a
Heat pump, air-to-air	1270	1270	14.0	14.0	0.0	0.0	14.0	14.0	0	n/a	n/a	n/a	n/a	n/a	n/a
Heat pump, water-to-air, geothermal application	4188	2345	9.6	6.0	4.3	2.3	17.0	6.0	1843	16.3	15.5	8.8	6.1	25.0	8.0
Heat pump, water-source	226	226	15.0	15.0	n/a	n/a	15.0	15.0	0	n/a	n/a	n/a	n/a	n/a	n/a
Residential furn. and pkg'ed condensing unit/heat pump	132	132	31.0	31.0	n/a	n/a	31.0	31.0	0	n/a	n/a	n/a	n/a	n/a	n/a

Figure A-7. Sample table of results for filtering the database by building function (multifamily residential) and system type (air distribution equipment).

APPENDIX B. DERIVATION OF FORMULA FOR ESCALATION RATES BEYOND 30 YEARS

Defining Economic Parameters

Escalation Rate, $e_n = \frac{Fuel\ Price_n}{Fuel\ Price_{n-1}} - 1$

Fuel Price Index, $FPI_n = \frac{Fuel\ Price_n}{Fuel\ Price_0} \Rightarrow\ FPI_0 = 1$

Present Value, $PV_n = \frac{FPI_n}{(1+d)^n}$, where $d =$ discount rate

Uniform Present Value, $UPV_n = \sum_{i=1}^{n} PV_i = \sum_{i=1}^{n} \frac{FPI_i}{(1+d)^i}$

Savings to Investment Ratio, $SIR = \frac{Annual\ Energy\ Cost\ Savings * UPV_{measure\ life}}{Measure\ Cost}$

Expressing FPI_{30+x} as a Function of $\bar{e}_{26\text{-}30}$ and x

$$FPI_n = \frac{Fuel\ Price_n}{Fuel\ Price_0} = \frac{Fuel\ Price_n}{Fuel\ Price_{n-1}} * \frac{Fuel\ Price_{n-1}}{Fuel\ Price_{n-2}} * \ldots * \frac{Fuel\ Price_1}{Fuel\ Price_0}$$

$$= (1+e_n) * (1+e_{n-1}) * \ldots * (1+e_1) = \prod_{i=1}^{n}(1+e_i)$$

Assuming $e_n = \frac{\sum_{i=26}^{30} e_i}{5}$ or $\bar{e}_{26\text{-}30}$ for year $n = 31$ and beyond,

$$FPI_{30+x} = \prod_{i=1}^{30+x}(1+e_i) = \prod_{i=1}^{30}(1+e_i)\ * [(1+e_{31}) * \ldots * (1+e_{30+\mathrm{x}})]$$

$$= FPI_{30} * (1+\bar{e}_{26\text{-}30})^x$$

Expressing Percent Increase in SIR as a Function of $\bar{e}_{26\text{-}30}$ and x

For measure life $= 30$ years, $SIR_{30} = \dfrac{Annual\ Energy\ Cost\ Savings}{Measure\ Cost} * UPV_{30}$

For measure life $= 30 + x$ years, SIR_{30+x}

$$= \frac{Annual\ Energy\ Cost\ Savings}{Measure\ Cost} * UPV_{30+x}$$

$$\Rightarrow\ \%\ Increase\ in\ SIR = \frac{SIR_{30+x} - SIR_{30}}{SIR_{30}} = \frac{UPV_{30+x} - UPV_{30}}{UPV_{30}}$$

$$= \frac{\sum_{i=1}^{30+x} \frac{FPI_i}{(1+d)^i} - \sum_{i=1}^{30} \frac{FPI_i}{(1+d)^i}}{UPV_{30}} = \frac{\sum_{i=31}^{30+x} \frac{FPI_i}{(1+d)^i}}{UPV_{30}}$$

$$= \frac{\sum_{i=31}^{30+x} \frac{FPI_{30} * (1+\bar{e}_{26\text{-}30})^{i-30}}{(1+d)^{30} * (1+d)^{i-30}}}{UPV_{30}} = \frac{\sum_{i=31}^{30+x} PV_{30} * \frac{(1+\bar{e}_{26\text{-}30})^{i-30}}{(1+d)^{i-30}}}{UPV_{30}}$$

$$= \frac{PV_{30}}{UPV_{30}} * \sum_{i=1}^{x} \left(\frac{1+\bar{e}_{26\text{-}30}}{1+d}\right)^i$$

AUTHOR'S LIST OF PUBLICATIONS

1. **Amoo, C**., Malhotra, M., Eckman, B. & New, J. (2025). A Comprehensive Review of Lifetime Estimation Methodologies for Energy Conservation Measures and Their Impact on Energy Savings Calculations. ASHRAE Transactions (*accepted for publication*)
2. Malhotra, M., Eckman, B., & **Amoo, C**. (2024). *Web-Based Weatherization Assistant Getting Started Guide* (No. ORNL/TM-2023/2833-R1). Oak Ridge National Laboratory (ORNL), Oak Ridge, TN (United States).
3. **Amoo, C. N. B**., New, J., & Eckman, B. W. A Multicriteria Framework for Assessing Energy Audit Software for Low-Income Households in the United States. *Available at SSRN 4714592*.
4. Bass, B., New, J., Clinton, N., Adams, M., Copeland, B., & **Amoo, C**. (2022). How close are urban scale building simulations to measured data? Examining bias derived from building metadata in urban building energy modeling. Applied Energy, 327, 120049.

Under Review or To Be Submitted

1. **Amoo, C**., Malhotra, M., Eckman, B. & New, J. (2025). Optimizing Energy Savings Calculations: A Comprehensive Review of Measure Lifetime Estimation for Energy Conservation Measures. *Renewable and Sustainable Energy Reviews* (*undergoing external peer review*)
2. **Amoo, C**., Eckman, B. & New, J. (2025). A multicriteria framework for assessing energy audit software for low-income households in the United States. *Energy Efficiency* (*undergone two rounds of peer reviews, awaiting acceptance notice*).
3. **Amoo, C**., New, J. & Eckman, B. (2025). Evaluating Energy Audit Software for Low-Income Households: A Comparative Analysis of Three Software Using a Multicriteria Framework. (*To be submitted*)
4. **Amoo, C**. Malhotra M, Eckman, B. (2025). Economic Analysis of Long-lived Energy Conservation Measures Exceeding 30 Years. (*To be submitted*).

VITA

Charles Amoo was born in Accra, Ghana. He pursued and earned a B.Sc. in Petroleum Engineering from the Kwame Nkrumah University of Science and Technology (KNUST), Kumasi, Ghana, and a M.S. in Energy from the University of Auckland, New Zealand. He is pursuing a Ph.D. in Energy Science and Engineering at the Bredesen Center, University of Tennessee, where he works on energy efficiency research on low-income households for the Weatherization Assistant Program. Throughout his educational pursuits, Charles Amoo was awarded several prestigious awards and scholarships, including the Society of Petroleum Engineers (SPE) Star Scholarship for the Africa Region in 2011, the New Zealand Development Scholarship (NZDS) in 2016, and the Graduate Advancement and Training Education (GATE) Fellowship in 2023.

Charles' research interests focus on improving the energy efficiency of residential buildings through energy audit software development frameworks, assessments, and economic analyses of energy conservation measures (ECMs), and building energy modeling. He works with the Building Technology Research and Integration Center at Oak Ridge National Laboratory to develop the Weatherization Assistant (WA) software suite to support energy audits for low-income households.