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Applications of machine learning methods to identifying and predicting building retrofit opportunities

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ABSTRACT

Building energy conservation measures (ECMs) can significantly lower greenhouse gas (GHG) emissions from urban areas; however, uncertainties regarding not only ECM eligibility, but also associated costs and energy savings have slowed adoption of ECMs. To encourage ECM implementation, local governments have implemented a range of policies designed to increase the available information on building energy use. Energy audit mandates, such as New York City (NYC)'s Local Law 87 (LL87), require energy consultants to analyze installed building systems and provide building stakeholders with cost effective ECM recommendations on a multi-year cycle. However, complete audits are costly and time consuming. To accelerate ECM implementation, policymakers are exploring ways to utilize available data to target ECMs across a city's entire building stock. In this study, energy audit data for over 1100 buildings in NYC, submitted in compliance with LL87, are analyzed to identify opportunities for ECMs across building system categories (e.g. distribution system, domestic hot water, etc.). A machine learning classifier, specifically a user-facing falling rule list (FRL) classifier based on binary features derived from LL87 data, is developed here to predict ECM eligibility given a specific set of building characteristics. Overall, the trained FRL classifier performs well (ROC AUC 0.72–0.86) for predicting cooling system, distribution system, domestic hot water, fuel switching, lighting, and motors ECM opportunities, which represent a majority of the auditor-recommended ECMs in the sample. Additionally, linear decision lists developed by the model allow building stakeholders to easily conduct streamlined audits of building systems and identify possible ECM opportunities by limiting input to the most relevant factors and prioritizing likely retrofit candidates. The implications of this work are significant in accelerating the adoption of building ECMs and catalyzing energy use and GHG emissions reductions from buildings.

1. Introduction

The United Nations Framework Convention on Climate Change (UNFCCC) estimates that developed countries must reduce greenhouse gas (GHG) emissions by 80% from 1990 levels by 2050 to prevent the most devastating impacts of climate change [33,36]. To achieve this goal, mitigation efforts must focus on existing commercial and residential buildings, both of which provide ample opportunities for energy efficiency improvements [37]. The U.S. Energy Information Adminstration [35] estimates that residential and commercial buildings are responsible for 40% of total U.S. energy use and produce an equivalent percentage of GHG emissions. In dense urban areas like New York City, existing buildings can account for 75% of emissions [33]. Reducing building energy usage would not only significantly lower GHG emissions, but also stimulate economic growth, encourage clean technology innovation, and help to mitigate numerous environmental and public health impacts [6,15].

Numerous U.S. cities, including New York, San Francisco, and Washington, have committed to drastically cutting building energy consumption as part of strategies developed to improve urban sustainability and resilience [27]. For example, New York City has pledged to reduce GHG emissions by 80% from 2005 levels by 2050 in-line with the UNFCCC target [33]. Implementation of building energy conservation measures (ECMs) in existing buildings

Abbreviations: BMS, building management system; DHW, domestic hot water; ECM, energy conservation measure; EER, energy efficiency report; EMS, energy management system; FRL, falling rule list; GGBP, New York City's Greener Greater Buildings Plan; HWH, hot water heater; LL84, New York City's Local Law 84; LL87, New York City's Local Law 87; MOS, New York City's Mayor's Office of Sustainability; NYC, New York City; ROC AUC, receiver operating characteristic – area under the curve; TRV, thermostatic radiator valve; VFD, variable frequency drive.

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could significantly lower emissions; however, adoption of ECMs has been slow due to uncertainties regarding implementation costs and energy savings [12].

The difference between existing and potential energy use (after implementation of cost-effective ECMs) has been termed the "energy efficiency gap" [7]. Sorrell et al. [29] classified the barriers to implementing ECMs into the following categories: imperfect information, hidden costs, risk, access to capital, split incentives, and bounded rationality. City energy efficiency policies designed to overcome these barriers include energy management obligations, financial incentives, energy labeling schemes, minimum standards, audit subsidies and requirements, and energy disclosure laws [7,15,17].

Energy disclosure laws are a promising public policy tool in which data analytics can be applied to accelerate the adoption of energy efficient building strategies, design practices, and technologies in residential and commercial buildings. Municipal energy disclosure laws generally mandate annual building energy benchmarking, and such policies have also been implemented as part of a more robust energy reduction plans that include audits and mandates [12,33]. Benchmarking laws, such as New York City's Local Law 84 (LL84), require that building owners report utility energy data and basic building characteristics. Buildings are then compared based on their energy use intensity, defined as yearly energy usage in kWh or kBTU normalized by total gross floor space (in meters squared or square feet) [34]. To complement benchmarking data, audit laws, like New York City's Local Law 87 (LL87), require an energy consultant to conduct a more detailed analysis of building energy systems and make ECM recommendations [12,31].

Disclosed building energy data can reveal important information for owners, investors, residents, policymakers, and researchers [25]. These data reduce uncertainty in building energy usage patterns and expected savings from ECMs, and overcome information asymmetries. Governments can use these data not only to set standards for energy efficiency based on the performance of the existing building stock, but also to target policies and incentives towards clusters of high-consumption buildings [14]. In the private sector, building owners, investors, and tenants can benefit by using disclosure data to inform investment decisions in ECMs and energy efficient buildings. These energy disclosure laws can also facilitate the movement towards effective performance-based energy codes and standards, as opposed to those based on generic ECM recommendations and guidelines.

Energy audits performed in compliance with LL87, in particular, provide building stakeholders with clear ECM recommendations, along with expected cost and energy savings. For New York City's LL87, compliance is rolling, with 10% of LL84 covered buildings requiring an audit each year, equivalent to once over a ten-year cycle. However, a full energy audit is costly and time consuming. To increase the impact of energy audits conducted on a subset of buildings and accelerate the insights gained from the graduated timeline, municipal governments are exploring ways to apply collected data to encourage implementation of cost-effective ECMs across the entire building stock. As described in the *One City: Built to Last* plan, NYC is developing a Retrofit Accelerator program to encourage ECM implementation in privately owned buildings. The program will use data-driven analysis to focus energy improvement outreach and technical assistance efforts to buildings with high potential for energy savings [33].

This study attempts to increase the impact of building energy audit data collected in compliance with municipal disclosure laws by utilizing the first year of building, systems, and ECM recommendation data from New York City's Energy Auditing and Retro Commissioning Law, LL87, to develop a user-facing model of energy retrofit eligibility and predicted impact. A falling rule list classifier [39] is applied to predict building-specific eligibility across ECM categories (e.g. distribution system, domestic hot water, etc.), as defined by the American Society of Heating, Refrigeration, and Air-Conditioning Engineers (ASHRAE), for different building typologies. The classifier, based on binary features derived from audit records, will allow stakeholders to estimate a building's ECM eligibility based on a simple survey of building systems, thus providing an early screening tool that can either enhance or potentially replace the need for a full energy audit.

The remainder of the paper is organized as follows: Section 2 provides a review of relevant background literature. This is followed by a description of the data and methods. Results are provided in Section 4. Section 5 discusses the results and policy implications of this study. Section 6 concludes.

2. Literature review

Building energy audits can reveal important information about building energy usage patterns and expected savings from ECMs [12,20]. McKinsey & Company [21] predicted, that by 2020, the commercial and residential building sector in the United States could reduce baseline energy usage by 29% through cost effective energy investments. Lam and Chan [18] determined that, for a sample of commercial buildings in sub-tropical Hong Kong, HVAC was responsible for 40–60% of total electricity consumption, while lighting accounted for 20–30% of consumption. It was also found that operational changes (e.g. thermostat adjustment) could provide no-cost energy improvements in buildings.

While energy audits can be a valuable tool accelerating the adoption of ECMs, high ECM implementation costs and incomplete or incorrect energy efficiency reports can greatly reduce the impact of energy audits [28]. Fleiter et al. [7] analyzed barriers to adoption of ECMs by small and medium sized enterprises in Germany and determined that high initial investment costs impeded adoption of cost-effective ECMS. Additionally, results showed that high-quality, more detailed energy audits resulted in more frequent ECM implementation. Shapiro [28] conducted a detailed case study of 30 commercial and residential energy audits to determine common issues. These problems included missed ECMs, limited ECM scope, limited or missing cost assessment, inadequate building analysis, and overestimated savings. Additionally, results showed that audits conducted as part of government of utility company energy programs were less likely to have similar problems and issues. Shapiro also suggested a number of ways to improve the impact of energy audits: standardized templates, enhanced auditor training, clear standards, quality control, funding programs, and validation of proposed savings. Palmer et al. [23] surveyed 479 residential energy auditors in the United States and concluded that auditors were only partially filling the information gap. Specifically, auditors rarely validated projected energy savings, customers were uninformed about energy audits, and high initial investments and low energy costs discouraged adoption. Furthermore, The Building Energy Exchange [6] concluded that, in preparing LL87 audit reports, energy auditors may have provided conservative estimates of overall energy savings potential, omitting experimental or expensive ECMs which could greatly reduce energy use. Flourentzou and Roulet [8] developed a software tool and analysis methodology to improve audit accuracy and quality, and evaluate retrofit scenarios.

A number of studies have applied energy audit and benchmarking data to understand factors influencing energy use in buildings, ECM implementation decisions, and ECM eligibility. Gamtessa [9] analyzed records from the Canadian government's EnerGuide for Houses program, which provided financial incentives for ECM implementations in residences. Results from an econometric analysis showed that energy savings, financial incentives, and implementation costs were important factors behind retrofit decisions given other residence and demographic properties. In a study of the drivers of energy performance in commercial buildings, Kontokosta [14] integrated LL84 benchmarking data, land use and tax assessment data, and CoStar Group data to understand the primary factors affecting energy use in office buildings. The study identified several limitations of current benchmarking methods and found building occupant rates and type to have important implications for energy efficiency. Similarly, Hsu [12] developed a multilevel regression model from energy benchmarking and audit data in order to predict energy use in buildings in New York. Results showed that there was significant variation in building energy usage intensity (EUI) regardless of input building properties, indicating that operational efficiency improvements may be more cost effective than technical or system upgrades.

Villoria-Siegert et al. [38] applied commonly available data sets to infer residential building properties and energy system characteristics without the use of detailed on-site audits. Monthly utility and local temperature data were applied along with real estate records to estimate wall and window insulation values, leakage, and heating system efficiency. These values were then applied to prioritize building ECMs by targeting the least efficient residences first. Results showed that the studied community in the United States could achieve an overall reduction in HVAC energy use of 32% at a cost of $0.10 per mmBTU.

Using a dataset similar to the one used here, the Building Energy Exchange [6] analyzed ECM recommendations and building characteristics from the multifamily portion of the 2013 LL87 data. Buildings were grouped into ECM market segments by building height, period of construction, and fuel source. These segments were used to predict ECM implementations and savings in all multifamily buildings covered by LL84. The authors concluded that full implementation of ECMs could reduce total multifamily building energy use by 10% and greenhouse gas emissions by 11%. The analysis also showed that ECMs were cost effective, with 77% of ECMs having less than 10 years payback, 50% less than 5 years, and 26% less than three years. Additionally, results showed that over 50% of total greenhouse gas reductions came from post-war (i.e. built after 1946) buildings, which represented less than 38% of the area and 40% of total ECM costs. Furthermore, ECMs classified as distribution system, domestic hot water, or heating system improvements accounted for half of the energy savings potential.

Most often, energy consultants estimate potential ECM energy and cost savings according to ASHRAE specifications [2]. Tools for estimating savings include building energy simulations, subject matter expertise, equipment specifications, and ASHRAE defined inverse modeling techniques [2,24,30]. Neto and Fiorelli [22] determined that an artificial neural network provided similar energy use predictions to a physically based model simulation. However, the authors state that consultants can more easily evaluate different retrofit scenarios using the model simulation. To better understand savings and impact, a number of academic studies have focused on studying specific ECM implementations [26] as well as estimating total savings from performance based ECMs across a selected building stock [19,24]. Mata et al. [19] estimated, using building envelope, space, systems, and occupancy data from a 1400 building sample, a 53% reduction in energy demand can be achieved across Sweden's building stock by implementing twelve generic ECMs. However, the study was focused on generic performance based ECMs (e.g. reduction in 50% of power for lighting) and not prescriptive ECMs specific to the building stock (e.g. upgrade to LED), where savings would be determined by specific building properties (e.g. number of lighting fixtures, installed lighting types, etc.). Ballarini et al. [3] used reference building typologies defined from Intelligent Energy Europe's Typology Approach for Building Stock Energy Assessment (TABULA) project, to assess energy savings potential of the existing residential building stock. Reference typologies were based on location, construction period, and housing type. Results show that, defining reference buildings types helps define energy savings potential for a region's residential building stock, even while considering generic envelope and heating system ECMs.

3. Data and methods

3.1. Data collection

With the goal of reducing building GHG emissions, New York City (NYC) enacted the *Greener, Greater Buildings Plan* (GGBP) in 2009. A major objective of this plan was to provide information to building decision makers (e.g. building owners, managers, superintendents, board members, buyers, sellers, and residents) to encourage investment in energy conservation measures. The GGBP included two data disclosure ordinances: (1) Local Law 84: Benchmarking (LL84) and (2) Local Law 87: Auditing and Retro Commissioning (LL87), which cover buildings with a gross floor area greater than 50,000 ft^2 (4,645.2 m^2) or lots with a combined building gross floor area of greater than 100,000 ft^2 (9,290.3 m^2) [34]. LL84 requires buildings to document and disclose yearly energy use and building characteristics (e.g. floor area, use type, heating system), using the U.S. Environmental Protection Agency's (EPA) Portfolio Manager website. Building stakeholders can also use Portfolio Manager to calculate weather normalized and source energy usage, useful for comparing energy use across buildings and time periods. To complement benchmarking data, LL87 requires an energy consultant to conduct a more detailed analysis of building energy systems and make ECM recommendations [12]. The "audit" portion of LL87 requires covered buildings to undergo the equivalent of an American Society of Heating, Refrigeration, and Air-Conditioning Engineers (ASHRAE) Level-2 Audit once every ten years [2,12,13]. Compliance is rolling with approximately 10% of lots reporting each year, beginning at the end of 2013. Analyses in this study are based on the first year of reported LL87 data from building audits conducted in 2013, most often based on energy use data from 2012. Certified energy consultants conduct audits by surveying the building systems and space uses which can influence building energy use, benchmarking energy usage by end-use, and making recommendations for ECMs [32].

In addition to reporting audit results and recommendations to building stakeholders, energy consultants must enter collected data into the NYC Mayor's Office of Sustainability's (MOS) standardized Energy Audit Data Collection Tool. Consultants then submit the completed tool to the New York City Department of Buildings as part of an Energy Efficiency Report (EER) [32]. MOS then compiles data from the submissions for analysis.

Each audit record in the compiled dataset contains all information entered in the Energy Audit Data Collection Tool as part of an EER: (a) Submittal Information, (b) Team Information, (c) Building Information, (d) Equipment Inventory, (e) ECMs, and (f) End Use Breakdown. The Submittal and Team Information sections of the EER include the building's tax lot information and energy consultant details, respectively. The Building Information section contains information on the building owner, size, space types, metering configuration, and building systems and EPA Portfolio manager energy use data. The Equipment Inventory section provides information on building systems and characteristics related to energy use, including heating, cooling and domestic hot water systems, ventilation, lighting, and building envelope details. The ECM portion contains a detailed list of conservation measures recommended by energy consultants, assigned with generic systems and usage based Categories and Measure Names, to provide unity between audit reports. For each ECM, the consultant also estimated energy savings, cost savings, and implementation cost based on energy simulations, inverse modeling, subject matter expertise, and equipment specifications. Lastly, the End Use Breakdown section contains information on current energy use, and proposed energy use (if ECMs are incorporated) split by fuel use and end use (space heating, space cooling, lighting, etc.).

3.2. Data selection and preparation

Each record in the compiled LL87 audit dataset consisted of a row of entries, where features represented the fields from the Energy Audit Data Collection Tool. For proper analysis, data needed to be extracted, cleaned, and transformed. The focus of this analysis was on features defined as either continuous, primarily Build Year, or categorical, such as Facility Type and ECM Category. Less focus was placed on open text fields, such as "ECM Description" and "Building System Spaces Served", due to variations in auditor entries. From the categorical and numerical features in the LL87 data, the features described in Table 1 were applied for the final model due to their applicability and completeness.

Because energy consultants entered numeric and categorical data manually, features were cleaned to identify and correct improper and missing entries. Non-numeric records that could not be directly converted to numbers were stripped of spaces, commas, and appropriate units (e.g. kBTU for Energy Savings). The remaining non-numeric records, which consisted of symbols, comments, and indications that the data was unavailable, were identified as missing data for the purpose of analysis.

Categorical data was also cleaned and manipulated for input in models. For certain categorical inputs, specifically Heating System Type and Exterior Wall Type, there were significant differences between how individual auditors entered data. For example, in the Heating System Type field, where the Fuel Source was district steam, some auditors entered the Heating System Type as Steam Boiler while others listed it as Other. To unify these data, a new Heating System Type, District Steam, was added for all systems where Fuel Source was defined as "District Steam". For Exterior Wall Type, many auditors with Mass walls listed wall type as Other and described the wall as masonry, concrete, or brick in the comments field. For all exterior walls that had one of these words in the comments, the wall type was changed to Mass. Additionally, the year of construction of the building was recoded to categorical bins of Before 1901, 1901–1920, 1921–1946, 1947–1970, 1971–1990, and After 1990. The Build Period divide in 1947 represents the observed separation of "Pre-War" and "Post-War" buildings. The year of construction field was recoded to account for observed non-linearity in the effects of build year on energy use and efficiency [14,16].

The Energy Audit Data Collection Tool permitted energy consultants to enter information for multiple energy systems. To account for this in model input data, the presence of each system type, fuel source, etc., in any of the categorical features of system entries was noted for each building. For example, if a consultant entered information for two separate heating systems that service different areas of the building, both system types and fuel sources would be recorded as "present" in that building.

All categorical features were then encoded as "One-Hot" binary features for each category, excluding undefined and other, if applicable. For "One-Hot" encoding, each categorical feature is split into a separate feature for each category, where each feature indicates the presence of that specific category. For example, the feature Heating System Fuel Source was encoded as separate features for each fuel, (for instance, Heating System Fuel Source IS Natural Gas, Heating System Fuel Source IS #6 Oil, etc.). The selected features, described in (Table 1) resulted in 136 "One-Hot" binary features for input in the FRL classifier.

The focus of this study is on predicting building-specific eligibility for various categories of ECMs, as grouped in accordance with the Energy Audit Data Collection Tool, rather than specific ECMs. ECM recommendations were converted in a similar manner to systems data. For each property (identified by the Borough-Block-Lot number or "BBL"), the number of recommendations in each category and the sum of energy savings, cost savings, and implementation cost are calculated. Finally, for each BBL, the presence of an ECM recommendation in each category is determined for each building in the dataset.

After data was transformed as previously discussed, records were removed based on the following rules: (1) the BBL was duplicated in the LL87 dataset; and (2) the auditor recommended no ECMs. It should be noted that due to the guidelines for entering data in the Energy Audit Data Collection Tool, it is possible for multiple buildings on the same lot to report individual audits and records. In this case, duplicate BBLs could represent different buildings; however, this could not be determined with sufficient certainty for this study. Audits without ECM recommendations were considered incomplete thus were removed for this analysis. Of the 1131 initial records (accounting for 1089 BBLs), 1064 records had unique BBLs, and a further 956 had at least one ECM recommendation. Of these buildings, 647 were classified as Multifamily, 159 as Office, 42 were not defined, and the remaining 108 were other categories of buildings, including Retail, Hotel, and Warehouse.

3.3. Energy conservation measures

When submitting an EER, an auditor can recommend ECMs in 15 system and usage based categories (Table 2). Auditors recommended a total of 6813 ECMs in the 15 EER specified categories across the entire dataset, and 6204 ECMs in the analysis sample of 956 BBLs. ECMs were then grouped by category for each BBL, resulting in 3829 integrated ECM records. Additionally, out of the remaining ECMs, 874 had incomplete descriptions of Implementation costs, cost savings, and energy savings. Missing values were primarily associated with the energy savings field; only 5 ECMs were missing cost data, but included energy savings. A further 63 ECMs had zero energy or cost savings. Incomplete and zero savings ECMs were included in the primary ECM recommendation analysis, but excluded from the cost and energy estimates.

A number of predefined ECMs were available for selection in each ECM category and the most often recommended ones are listed under "Example Measures" in Table 2. The most commonly recommended ECM category was lighting, recommended in 95% of buildings, followed by domestic hot water, recommended in 51% of buildings. Submetering and on site generation were both only recommended in 5% of buildings, possibly due to complex installations, uncertainty in savings, and in the case of on-site generation, high implementation costs.

The subset of ECM recommendations where auditors included implementation cost and annual cost and energy savings were evaluated to understand cost and energy savings potential (Table 2). Median simple payback period (i.e. the implementation cost divided by the annual cost savings) was lowest for distribution system improvements (2.07 Years). The most common distribution system ECM recommendation was the straightforward insulation of heat distribution pipes. Conversely, improvements to the building envelope, such as sealing leaks and improving roof insulation, were the least cost effective ECMs, with a median simple payback of 13.42 years. Additionally, ECM categories were compared based on the median ratio of their implementation cost in U.S. dollars to annual energy savings ($/kWh). Distribution system ECM recommendations also showed the lowest ratio, $0.10/kWh ($0.03/kBTU) of the categories, indicating a first cost of just ten cents per kWh saved. However, fuel switching (generally fuel oil to nat-

Table 1
Building Properties and Systems for input in model, as defined in the Energy Audit Data Collection Tool, based on ASHRAE [2]. Properties are grouped by system where applicable.

Feature	Example Values	Notes
Build Year	1920, 1946, 1970, 1990	Year of primary construction
Facility Type	Multifamily, Office, Retail, Hotel	Primary end use type
Exterior Walls:		
Type	Mass, Steel-Framed, Wood-Framed	Defined by ASHRAE [1]
Windows:		
# of Panes	Single, Double	
Framing Material	Aluminum, Wood, Fiberglass	
Roof:		
Type	Insulation Entirely Above Deck, Metal Building	Defined by ASHRAE [1]
Heating System:		
Type	Steam Boiler, Hot Water Boiler	
Fuel Source	Natural Gas, #6 Oil, District Steam	
Controls	None, Central BMS/EMS	
Burners:		
Type	On/Off, Full Modulation – Set to Modulating	Heating system fuel burners
Central Distribution:		
Type	Forced Air, 1-Pipe Steam, 2-Pipe Steam	Heating distribution system
Heating Terminals:		
Type	Radiator, Duct	
Controls	None, Direct Digital Control	
Cooling System:		
Type	Window A/C, Chiller – Absorption	
Fuel Source	Electric, Natural Gas	
Air/Water Cooled?	Air Cooled, Water Cooled	
Controls	Direct Digital Control, Central BMS/EMS	
Domestic Hot Water:		
Type	Tankless Coil, Separate Hot Water Boiler with Storage Tank	
Fuel Source	Natural Gas, #6 Oil	
From Space Heating Boiler?	Yes – Year Round, Yes – Heating Season Only, No	
Controls	Aquastat Based, Timer Based, Demand Based	
Lighting:		
Lamp Type	LED, Incandescent, Compact Fluorescent	
Ballast Type	Magnetic, Electronic	
Interior/Exterior Controls	None, Timer, Photo/Daylight Sensor	

Table 2
Summary of Energy Conservation Measure (ECM) Categories (Category Name), Most Often Recommended Measures (Example Measures), Number of total recommended ECMs and ECMs with cost and savings information in parentheses (Count), Median Implementation Cost divided by annual cost savings (Simple Payback), and Median Implementation Cost per Unit Annual Energy Saved in U.S. Dollars per kWh (Cost/Energy). 1 $/kWh equals 0.29 $/kBTU. ECMs were grouped by Category for each BBL to get Count, Payback Years, and Cost/Energy. For Simple Payback and Cost/Energy, lower is more cost effective.

Category Name	Example Measures	Count (Buildings)	Simple Payback (Years)	Cost/Energy ($/kWh)
Conveying Systems	Upgrade Motors, Add Elevator Regenerative Drives	59(35)	11.2	2.01
Cooling System	Replace Packaged Units, Add or Upgrade Cooling Tower	158(105)	7.32	1.06
Distribution System	Insulate Pipes, Upgrade Pumps	393(352)	2.07	0.10
Domestic Hot Water	Separate DHW From Heating, Install Low-Flow Aerators	489(397)	3.78	0.20
Envelope	Sealing – Door, Increase Insulation – Roof	335(273)	13.42	0.82
Fuel Switching	#6 Oil or #4 Oil to Natural Gas, #2 Oil to Natural Gas	176(102)	3.78	3.75
HVAC Controls and Sensors	Install or Upgrade EMS/BMS, Install TRVs	343(260)	2.13	0.14
Heating System	Upgrade Burner, Replace Boiler	356(234)	5.45	0.24
Lighting	Upgrade to LED, Install Occupancy/Vacancy Sensors	910(717)	3.46	0.68
Motors	Upgrade Motors, Install VFDs	236(183)	5.83	1.06
On Site Generation	Install Solar/Photovoltaic, Install Cogeneration Plant	45(38)	7.21	1.36
Other	Install VFDs, Electric HWH Installation	67(35)	2.39	0.17
Process and Plug Loads	Replace Washing Machines, Install Solar/Photovoltaic	66(49)	5.91	0.85
Submetering	Install Submetering	44(13)	2.25	0.41
Ventilation	Install Demand Control Ventilation, Upgrade Fan/Air Handlers	152(99)	3.92	0.31

ural gas) showed the highest median cost/energy ratio, $3.75/kWh ($1.10/kBTU), because these improvements, while having significant cost and greenhouse gas emissions benefits, generally do not directly reduce energy consumption.

3.4. *Falling rule list*

Falling rule lists are classification models comprised of a series of *if-then* conditional decision statements, subject to the following constraints: (a) the order of decision statements or “rules” must be followed for classification and (b) the estimated positive probability decreases monotonically down the list [39]. Subsequently, the falling rule list follows the decision making process, whereby the most "at-risk" or "likely" candidates are classified first. Wang and Rudin developed the falling rule list classifier to be interpretable and prioritize high probability candidates, initially with applications to risk assessment and patient triage in the medical field. However, the design goals of the model are important for applied data science in various fields. Fitted falling rule lists can be printed and distributed, making them a data-driven alternative to manually generated assessment tools. For example, in reference to ECM recommendations, a falling rule list may state, based on the training data, buildings with single-pane windows have a 60% likelihood of an energy auditor recommending an envelope retrofit. Otherwise, the remaining Pre-War (Build Year before 1947) buildings are 40% likely, and buildings that meet neither condition are 20% likely.

Wang and Rudin's falling rule list methodology provides an interpretable model without sacrificing accuracy or computation time. First, a frequent item set mining algorithm, specifically FPGrowth [5], is applied to identify subgroups with a specified maximum number of clauses and minimum support. Afterwards, a Bayesian modeling approach determines a subset and permutation of the clauses to define the rules in the decision list, while enforcing monotonicity.

The model requires a number of user-selected parameters that affect final decision lists. For frequent item set mining, users specify the maximum number of clauses for each decision list rule, and the minimum sample on buildings meeting these criteria. In establishing the prior decision list, the prior length mean is the hyperparameter, λ, defining a Poisson distribution from which to draw an initial rule set length. Additionally, the hyperparameters α and β define a Gamma distribution which influences the model's rule set preferences. These parameters allow the user to configure the model to best satisfy the desired use case. Furthermore, the user may specify the number of simulated annealing steps and the temperature value For fitting the model and creating the decision list [39].

The falling rule list has been shown to have comparable receiver operating characteristic – area under the curve (ROC AUC) scores when compared to a number of prominent classification models (e.g. support vector machines, random forests, and logistic regression) applied to University of California – Irvine published public data sets [11,39]. The ROC AUC score is equivalent to the likelihood that a classifier will rank a randomly chosen "positive" instance higher than a randomly chosen "negative" one, and is often used for machine learning model comparison [10].

In this study, falling rule list classifiers were generated with Wang and Rudin's published falling_rule_list Python package for each category of ECM. To reduce the effects of variance during evaluation and simulate how the model performs on new data, the FRL model was trained on a randomly selected 80% sample of records in the binary encoded LL87 data, and tested on the remaining 20%. In order to maximize the applicability and interpretability of the results, the maximum number of clauses was set to 2 and the minimum support set to 5% of the data for input into the FPGrowth rule mining algorithm. Default values recommended by Wang and Rudin [39] were used for the remaining parameters so that no preferences were given for decision list structure, while optimizing computation time. These values were 8 for prior length mean, 1 for gamma α, 0.1 for gamma β, 5000 for simulated annealing steps, and 1 for temperature. To limit variance, FRL classifiers for ECM Categories were limited to features relevant to the specific building system. Primarily, lighting features were excluded from other energy systems models, and the lighting ECM model was limited to lighting and building characteristics (Exterior Wall, Windows, Build Period, and Facility Type). Additionally, the envelope model was restricted to building characteristics and a separate model specification included all inputs.

The performance of each model was evaluated through its receiver operating characteristic—area under the curve (ROC AUC) score [4]. The ROC AUC is calculated as the integral of the curve of the true positive rate against the false positive rate through the range of classification threshold settings. This score is equal to the probability that the classifier will rank a randomly selected positive instance higher than a randomly selected negative instance.

Table 3
Test data ROC AUC scores for each ECM Category.

System	ROC AUC
Conveying Systems	0.6559
Cooling System	0.8055
Distribution System	0.7590
Domestic Hot Water	0.7170
Envelope	0.5566
Fuel Switching	0.8553
HVAC Controls and Sensors	0.6779
Heating System	0.6155
Lighting	0.7969
Motors	0.7851
On Site Generation	0.5951
Other	0.4661
Process and Plug Loads	0.5568
Submetering	0.5791
Ventilation	0.6564

4. Results

4.1. Prediction of ECM eligibility

For each of the 15 ECM categories, a FRL classifier was fit based on the training sample of the data (764 buildings), and evaluated against a test data set (192 buildings). Across ECM categories, receiving operator characteristic—area under the curve (ROC AUC) scores ranged from 0.47 (other) to 0.86 (fuel switching) (Table 3). Overall, the trained FRL classifier performs well (ROC AUC 0.72–0.86) for predicting cooling system, distribution system, domestic hot water, fuel switching, lighting, and motors ECMs, which together represent 62% of recommended ECMs in the analyzed sample.

Poor model performance in certain categories is often the result of relevant features being excluded from the EER, omitted ECM recommendations by auditors (due to high implementation cost, auditor unfamiliarity with ECM, etc.), or both. For example, in the case of conveying systems, the LL87 Energy Audit Data Collection Tool does not have fields for elevator system information, which were the main focus of conveying system ECM recommendations. The other ECM category was modeled in this exercise, and as expected, the model was unable to identify opportunities for unclassified ECMs (ROC AUC = 0.47) given the range of possible specific ECMs grouped in the other category.

4.2. Falling rule list decision tables

While the FRL model's classification performance is useful, the model's largest contribution is the set of linear decision lists it creates. A sample of the tables, specifically those for conveying, distribution, domestic hot water, and heating systems as well as motors, are included here (Tables 4–7), while the remainder are included in the appendix (Tables A1–A11). These decision lists, which prioritize the most likely eligible BBLs, not only reveal the building properties most correlated with ECM eligibility and interactions between multiple properties, but separate buildings into distinct eligibility groups.

Table 4
Conveying System ECM Eligibility Decision List.

	Conditions		Probability	Support
IF	(Facility Type IS Office) AND (Heating Terminal Controls ARE None)	THEN	43.75%	32
ELSE		THEN	5.33%	732

Table 5
Distribution System ECM Eligibility Decision List.

	Conditions		Probability	Support
IF	(End Use Terminal Controls ARE Central Building/Energy Management System) AND (Domestic Hot Water System IS Tankless Coil)	THEN	92.31%	65
ELSE IF	(Burners Equipment Type IS On/Off) AND (Terminal Type IS Radiator)	THEN	68.42%	57
ELSE IF	(End Use Terminal Controls ARE None) AND (Domestic Hot Water System Controls ARE Aquastat Based)	THEN	56.54%	191
ELSE		THEN	23.73%	451

Table 6
Heating System ECM Eligibility Decision List.

	Conditions		Probability	Support
IF	(Burners Equipment Type IS On Off) AND (Domestic Hot Water System IS Tankless Coil)	THEN	97.92%	48
ELSE IF	(Facility Type IS Office)	THEN	50.0%	134
ELSE IF	(Heating System IS Hot Water Boiler)	THEN	52.46%	61
ELSE		THEN	24.95%	521

Table 7
Motors ECM Eligibility Decision List.

	Conditions		Probability	Support
IF	(Burners Equipment Type IS On Off) AND (Domestic Hot Water from Space Heating Boiler IS Yes—Year Round)	THEN	81.03%	58
ELSE IF	(Cooling System IS Water Cooled)	THEN	52.68%	112
ELSE IF	(Domestic Hot Water System Fuel Source IS District Steam) AND (Heating System IS District Steam)	THEN	45.83%	24
ELSE IF	(Cooling System IS Air Cooled)	THEN	26.79%	209
ELSE		THEN	4.43%	361

For each ECM category, a building owner, or other stakeholder, can conduct a simplified audit by checking each statement in the decision list in succession, comparing building characteristics to the if/else statements until the stakeholder finds a match. For each statement, the Conditions specify the building properties associated with the statement. For example, if the Conditions are "(DHW System Fuel Source IS Dual Fuel) AND (End Use Terminal Controls ARE None)" a building must meet both criteria, otherwise the building is checked against the succeeding condition. If a building does not meet conditions specified in any statement, it defaults to the group defined by the final "else" statement. The Support describes the number of buildings matching that statement, excluding buildings matching earlier statements. The sum of support is equal to be number of buildings in the training data, 764. The Probability reveals the proportion of buildings matching the conditions that received an ECM recommendation in the specified category, which a building stakeholder can use to understand ECM eligibility.

For example, consider a hypothetical building owner interested in distribution system ECMs. Based on the first statement in Table 5, the owner surveys his building and finds that the building has no end use terminal controls, and the domestic hot water system is a tankless coil. Not meeting the conditions of this statement, the owner then checks the building against the second statement. Finding that the burners are "On/Off" type and the heating terminals are radiators, the owner then concludes the building is 68.42% likely to be eligible for a distribution system ECM. With this information, the owner can then review the expected savings (Table 2) and decide whether to pursue the ECM.

FRL decision lists varied significantly among ECM categories, in both conditions and decision structure. Decision lists had up to five statements, including the final "else" statement. For individual statements, Support ranged from 32 (4.2%) to 517 (68%), excluding the final default statements. The FRL classifiers were also able to distinguish highly eligible and highly ineligible buildings, with a maximum and minimum probability of 98% and 2.5% respectively across statements in ECM categories. The most divided ECM category was motors, where ECM eligibility for the initial group was 81% and eligibility for the default group was 4.4% (Table 7). The decision list for heating system ECMs (Table 6) reveals that, even though ROC AUC score is only 0.62, buildings with "(Burners Equipment Type IS On Off) AND (Domestic Hot Water System IS Tankless Coil)" are 98% likely to be eligible for a heating system ECM, based on 48 buildings in the LL87 data. For systems where important information was missing from the EER, the FRL classifier uses other general building characteristics to define the decision and thus can be useful in accounting for incomplete audits. For example, the decision list of conveying systems (e.g. Elevators) specifies "(Facility Type IS Office) AND (Heating Terminal Controls ARE None)" as the primary conditional statement (Table 4).

5. Discussion and policy implications

5.1. ECM distribution and recommendations

The distribution of recommended ECMs reveals interesting information about methods and opportunities for improving energy efficiency in urban buildings. By far, the most common recommendation was for lighting system improvement, mainly upgrading bulbs to LEDs and installing occupancy sensors (Table 2). Lighting ECMs are not only low cost and can be easily installed, but can also be implemented gradually, reducing the initial implementation cost. Additionally, among the EERs which did not include lighting ECM recommendations, it is believed that some of these buildings are eligible, but the auditor did not consider lighting ECMs. In contrast, submetering and on site generation ECMs, were only recommended in only 5% of buildings, possibly due to complex installation requirements and uncertainty in future savings, which supports the assertion that energy auditors omitted experimental or expensive ECMs [6].

ECM cost and energy savings data provide evidence to determine which ECM categories should be the focus of energy efficiency investments and policies. Cost effective ECMs, such as distribution system improvements, are most attractive to building stakeholders. These ECMs also have significant energy benefits, and should be a priority for information campaigns and energy efficiency policies. Audit data can also be used to prioritize ECMs with high annual energy savings, but low annual cost savings for financial incentives. For example, heating system ECMs are ranked 5th among ECM categories for median Cost/Energy, but 9th for Simple Payback (Table 2). Financial incentives and other policies could make these ECMs more attractive to building stakeholders.

The distribution of ECM recommendations in the LL87 dataset differs from recommendations for home auditors. Large buildings audited in compliance with LL87 were most often recommended lighting and distribution system improvements, while Palmer et al. [23] found the home energy auditors most often recommended insulation and envelope improvements, which are more easily implemented on wood-framed single family homes than large brick, concrete, and steel-framed buildings in dense urban environments. This finding demonstrates the importance of developing energy efficiency policies and recommendations based on data from a similar building stock.

5.2. Falling rule list classifier and decision lists

Fitted FRL classification models showed good performance for a subset of ECM categories, based on ROC AUC scores, while providing an interpretable and actionable result (Table 3). It is believed that poor model performance in certain categories resulted from missing relevant features or omitted ECMs from the EERs. In addition, the decision lists generated by the FRL classifier separate buildings into distinct groups with varying ECM eligibility. Decision lists separated buildings into groups with ECM eligibilities as high as 98% and as low as 2.5%.

The decision lists generated by the FRL model provide a useful tool for building stakeholders. By using the decision lists, a building owner, manager, or tenant can conduct a simplified audit of the building properties and estimate ECM eligibility and potential energy and cost savings. With this knowledge, stakeholders would be more likely to pursue specific system audits and ECM implementation, and would be able to more efficiently allocate resources to maximize energy efficiency improvements. The decision lists also prioritize most likely candidates first, and given the monotonically decreasing probability and if-then organization, the decision list can cater to multiple levels of interest and desired audit comprehensiveness. For example, if a building stakeholder is only interested in pursuing a more detailed motors audit if their building is at least 80% likely to be eligible for this ECM, they can discontinue the simplified audit after the initial statement.

Not only building stakeholders, but also policymakers and energy consultants can benefit from FRL decision lists. Policymakers can use decisions lists to target policies and financial incentives towards groups of buildings with high ECM eligibility, as well as common and cost effective ECMs. For example, if New York City offered financial incentives for distribution system audits restricted to buildings where "(End Use Terminal Controls ARE Central Building/Energy Management System) AND (Domestic Hot Water System IS Tankless Coil)", the City would receive a higher return on investment than if the incentive was available for all buildings. Overall, multiple targeted financial incentives would be more successful than a large generic incentive of the same scale. Energy consultants may use FRL decision lists to focus marketing towards highly eligible buildings, and include decision lists in promotional material to better inform potential customers. Furthermore, consultants can use the FRL decision lists as a tool for making future ECM recommendations. After conducting the systems audit, a consultant can use the decision list to support their ECM recommendations. Finally, consultants can identify ECMs they may have missed during an audit, based on recommendations in similar buildings, and investigate if the ECM is applicable.

5.3. Influence on auditing policy and process

As stated by the Building Energy Exchange [6], additional guidance for energy auditors could significantly improve the quality of audits. The development and application of decision lists and data-driven models presented here can significantly improve energy auditing policies and procedures by identifying common causes of uncertainty and improper reporting, encouraging and defining categorical data fields, and more efficiently allocating resources across possible ECMs. In turn, these changes would greatly improve future models and their applicability for encouraging energy efficiency investments. Energy consultants can provide domain expertise and feedback on ECM decision lists, suggesting features for EERs that may improve models and insight into the relationships between various building characteristics and ECM eligibility. Analysts and researchers can provide input to improve data quality without increasing the burden on energy consultants.

Expanded data and changes to auditing policy can further improve the quality of data driven ECM recommendation models. New York City is continuing to receive audit data for new buildings, and will continue to do so until 2023. New data can be used to improve the current model, or allow development of a model catered to more specific ECMs or building types. The FRL model can be rapidly updated with new data, allowing dynamic adjustments as new audit data is collected. Additionally, adoption of municipal energy audit mandates in other regions would allow development of a region-specific ECM recommendation model, catered towards the unique features of the region's building stock. To improve the quality of ECM recommendation models, a few changes to the reporting process should be made. Currently many of the fields in NYC's auditing tool were open text entry. Restricting numerical fields, such as Energy Savings, to numbers will make the cleaning process easier, and reduce the number of excluded records. Additionally, changing open text fields to categorical fields where possible will drastically increase the number of usable features in the final model. Furthermore, categories themselves should be defined based on ASHRAE standards, energy consultant input, and observed data in order to reduce the number of "Other" selections when submitting energy efficiency reports.

Audit analysis could also be improved by expanding audits requirements to tenant spaces and a wider range of buildings. With the current system, auditors only focus on systems controlled by the building owner – typically considered "base building" systems – which represent approximately 50–75% of total energy use in a multi-tenanted building [6]. Implementation of a "tenant space" audit program and classification model can be applied to develop a tenant self-audit tool to encourage further energy efficiency improvements. This tool could focus on tenant systems and recommend lighting improvements, vacancy sensors, efficient appliances, etc. Additionally, to provide a larger building sample, NYC is considering expanding the Greener, Greater Buildings Plan coverage to all buildings over 25,000 ft^2 (2322.6 m^2), increasing the sample size of covered buildings for analysis, and increasing ECM model performance [33].

The analysis provided here creates the potential to automate much of the initial audit process. This would not only lead to more precise and complete audit reports, but also allow for a quick, low-cost alternative for building owners and other stakeholders to assess energy efficiency opportunities. The decision list audit process could be used to rapidly assess the energy efficiency potential of a building, a portfolio of buildings, or an entire city, and provide a data-driven framework for enacting urban sustainability and environmental policies. For the building owner and portfolio manager, the machine learning applications presented here could significantly reduce both cost and time relating to energy efficiency investments, thus reducing the opportunity cost of capital for energy improvements and increasing return of investment.

6. Conclusion

Energy audits and whole building energy modeling are expensive and time consuming, requiring significant investments prohibitive to some stakeholders. Subsequently, data-driven empirical models based on existing benchmarking and audit data may provide effective low-cost options for building owners, investors, and local governments to determine ECM eligibility and potential savings. The FRL classification model developed in this study can increase the impact of energy audits, provide an alternative rapid assessment tool for energy efficiency potential, and encourage energy efficiency investments by reducing the cost and complexity of the energy retrofit process.

Based on ROC AUC scores, the FRL ECM eligibility models performed well for a subset of ECM categories, which together represent a majority of recommended ECMs, and provide interpretable and actionable results. Future collaboration with energy consultants and policymakers could improve the performance and impact of similar classification models by enhancing data quality and determining further relevant building features. Most importantly, the user-facing FRL decision lists generated by the model could be used by building stakeholders to easily conduct simplified audits of building systems and identify possible ECM opportunities. This work provides an important contribution that demonstrates the potential of machine learning applications to the growing ecosystem of building energy data.

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Appendix A

See Tables A1–A11.

Table A1
Cooling System ECM Eligibility Decision List.

	Conditions		Probability	Support
IF	(Central Distribution Type IS Forced Air)	THEN	59.18%	49
ELSE IF	(Cooling System IS Water Cooled)	THEN	52.75%	91
ELSE IF	(Facility Type IS Office)	THEN	40.0%	70
ELSE		THEN	5.6%	554

Table A2
Domestic Hot Water ECM Eligibility Decision List.

	Conditions		Probability	Support
IF	(Domestic Hot Water System Fuel Source IS Dual Fuel) AND (End Use Terminal Controls ARE None)	THEN	98.04%	51
ELSE IF	(Central Distribution Type IS 1-Pipe Steam) AND (Cooling System Fuel Source IS Electric)	THEN	81.03%	116
ELSE IF	(End Use Terminal Controls ARE None) AND (Domestic Hot Water System Controls ARE Aquastat Based)	THEN	67.42%	132
ELSE IF	(Domestic Hot Water System IS Separate Hot Water Boiler With Storage Tank)	THEN	54.43%	79
ELSE		THEN	28.5%	386

Table A3
Envelope ECM Eligibility Decision List.

	Conditions		Probability	Support
IF	(Windows ARE Single Pane) AND (Facility Type IS Multifamily)	THEN	62.5%	32
ELSE IF	(Build Period IS 1920–1946) AND (Facility Type IS Multifamily)	THEN	44.04%	193
ELSE IF	(Build Period IS 1946–1970) AND (Facility Type IS Multifamily)	THEN	39.26%	163
ELSE		THEN	25.53%	376

Table A4
Fuel Switching ECM Eligibility Decision List.

	Conditions		Probability	Support
IF	(Domestic Hot Water Fuel Source IS #6 Oil) AND (Domestic Hot Water from Space Heating Boiler IS Yes—Year Round)	THEN	61.32%	106
ELSE IF	(Heating System Fuel Source IS #4 Oil) AND (Terminal Type IS Radiator)	THEN	51.52%	66
ELSE IF	(Heating System Fuel Source IS #6 Oil) AND (Terminal Type IS Radiator)	THEN	47.06%	17
ELSE IF	(Heating System Fuel Source IS #2 Oil)	THEN	41.94%	62
ELSE		THEN	2.34%	513

Table A5
HVAC Controls and Sensors ECM Eligibility Decision List.

	Conditions		Probability	Support
IF	(Cooling System Controls ARE None) AND (Exterior Wall Type IS Steel- Framed)	THEN	78.38%	37
ELSE IF	(End Use Terminal Controls ARE None) AND (Heating System Controls ARE Direct Digital Control)	THEN	61.61%	112
ELSE IF	(Facility Type IS Office)	THEN	57.76%	116
ELSE		THEN	25.25%	499

Table A6
Lighting ECM Eligibility Decision List.

	Conditions		Probability	Support
IF	(Facility Type IS Multifamily)	THEN	97.29%	517
ELSE		THEN	90.69%	247

Table A7
On Site Generation ECM Eligibility Decision List.

	Conditions		Probability	Support
IF	(Heating System Controls ARE Direct Digital Control) AND (Burners Equipment Type IS Full Modulation—Set to Modulating)	THEN	13.58%	162
ELSE		THEN	2.49%	602

Table A8
Other ECM Eligibility Decision List.

	Conditions		Probability	Support
IF	(Heating System Fuel Source IS District Steam) AND (Interior Lighting Control Type IS None)	THEN	22.03%	59
ELSE		THEN	5.53%	705

Table A9
Process and Plug Loads ECM Eligibility Decision List.

	Conditions		Probability	Support
IF	(Domestic Hot Water Fuel Source IS #6 Oil) AND (Heating System Controls ARE Direct Digital Control)	THEN	20.0%	65
ELSE		THEN	5.15%	699

Table A10
Submetering ECM Eligibility Decision List.

	Conditions		Probability	Support
IF	(Domestic Hot Water System IS Separate Hot Water Boiler With Storage Tank) AND (Heating System IS Steam Boiler)	THEN	26.67%	45
ELSE		THEN	2.5%	719

Table A11
Ventilation ECM Eligibility Decision List.

	Conditions		Probability	Support
IF	(Build Period IS 1990–2015) AND (Cooling System IS Air Cooled)	THEN	41.18%	34
ELSE IF	(Facility Type IS Office)	THEN	33.85%	130
ELSE		THEN	10.5%	600

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