Review Article

Author(s):
Deb, Chirag; Schlueter, Arno

Publication date:
2021-07

Permanent link:
https://doi.org/10.3929/ethz-b-000478001

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Originally published in:
Review of data-driven energy modelling techniques for building retrofit

C. Deb*, A. Schlueter

Chair of Architecture and Building Systems, Institute of Technology in Architecture, ETH Zurich, Zurich, Switzerland

ARTICLE INFO

Keywords:
Building retrofit
Data-driven modelling
Energy models
Greenhouse-gas (GHG) emissions mitigation
Building simulation
In-situ measurements
Machine learning

ABSTRACT

In order to meet the ambitious emission-reduction targets of the Paris Agreement, energy efficient transition of the building sector requires building retrofit methodologies as a critical part of a greenhouse-gas (GHG) emissions mitigation plan, since in 2050 a high proportion of the current global building stock will still be in use. This paper reviews current retrofit methodologies with a focus on the contrast between data-driven approaches that utilize measured building data, acquired through either 1) on-site sensor deployment or 2) from pre-aggregated national repositories of building data. Differentiating between 1) bottom-up approaches that can be divided into white-, grey- and black-box modelling, and 2) top-down approaches that utilize analytical methods of clustering and regression, this paper presents the state-of-the-art in current building retrofit methodologies; outlines their strengths and weaknesses; briefly highlights the challenges in their implementation and concludes by identifying a hybrid approach - of lean in-situ measurements supplemented by modelling for verification - as a potential strategy to develop and implement more robust retrofit methodologies for the building stock.

1. Context & rationale

According to United Nation’s Sustainable Development Goals (SDGs) for 2030, improving the energy performance of buildings will have a significant impact on future global energy and emissions [1]. This is supported by the assessment that the building sector is the largest energy-consuming sector in the world, accounting for 35% of the final energy consumption, followed by industry and transport sectors [2]. Aggregated worldwide, in 2018 the building sector consumed 127 exajoules (EJ) or the equivalent of 3050 Mega-tons of oil equivalent (Mtoe) covering a floor area of 150 billion square meters (m²). What this highlights is that although the total floor area of buildings is only a fraction of the total 64 trillion m² of habitable land on earth, the contribution of the building sector to global warming is substantial. Additionally, the final energy consumption in buildings has grown steadily from 119 EJ in 2010 to 127 EJ in 2018, driven by improved access to energy in developing countries, greater ownership and an increased use of energy-consuming devices [3]. In order to meet the ambitious emission-reduction targets of the Paris Agreement, transitioning the building sector to more effective building retrofit methodologies will be a critical part of a greenhouse-gas (GHG) emissions mitigation, since in 2050 a high proportion of the current global building stock will still be in use.

The importance of retrofitting existing buildings is well recognized. The International Energy Agency (IEA) has been providing future energy projections on medium- and long-term basis since 1993. These projections are based on simulations using the World Energy Model (WEM) that generates a detailed sector-by-sector and region-by-region projection under different scenarios [4]. A special scenario, known as the ‘Efficient World Scenario (EWS)’ was released by the IEA in 2018 [5]. The projections using the WEM highlight the immense potential for a decline in global energy demand in buildings between now and 2040 [6]. This improvement is mainly attributed to energy efficiency, which is forecasted at an ambitious target of 40% as compared to current levels. It also considers the growth in total global building floor area by 60% and the global population by 20% respectively. The key measures in the EWS include more efficient heating equipment (e.g. increased deployment of heat pumps), improving the insulation of the building envelope to reduce the heating and the cooling demand. Specifically, highly efficient building envelopes enable the use of higher-efficiency equipment and energy sources, such as low-temperature waste heat, heat pumps and renewable energy [3]. Another example, known as the ‘Low Energy Demand’ scenario, proposed by Grubler et al. aims to curtail global warming to 1.5 °C by 2050 [7]. This scenario considers changes in the quantity and the type of energy services that further drive structural change in the intermediate and upstream supply sectors. It also requires doubling the current building retrofit rate along with higher use of service-efficiency thermal end-use technologies. A scenario focusing on
the energy projections in China, known as the ‘techno-economic potential’ scenario considers 70% of the current building stock to be retrofitted by 2050 [8]. Analyses at the regional level also shows that rigorous measures are required to improve the performance of the existing building stock. For example, future energy projections in the residential sector of Los Angeles County shows that the majority of the demand could be offset through the aggressive application of energy efficient technologies [9]. Most electricity efficiency savings in this scenario come from targeting of space-heating and cooling (around 48%).

Such large-scale projections stress the global importance of retrofitting, the retrofitting process, however is localised wherein every building is situated in a specific context and requires a detailed assessment. This detailed assessment requires information about the building to, with the help of simulated models, determine the most suitable retrofit measures. The development of such models strongly depends upon available data and information about the building.

1.1. Existing retrofit analysis procedures

The global norm in energy retrofitting of buildings begins by conducting an energy audit that involves a systematic inspection of the building. The ISO 50002 defines energy audit as ‘a systematic analysis of energy use and energy consumption of audited objects, in order to identify, quantify and report on the opportunities for improved energy performance’ [10]. In similar terms, the European standard EN 16247 and the ASHRAE standard 211–2018 provide guidelines and outline a series of steps required to conduct an energy audit. The most detailed auditing level requires a thermal simulation model of the building. This model could further be used for retrofit analysis. Similarly, the ASHRAE Standard 100–2015 – Energy Efficiency in Existing Buildings provides over hundred typical energy efficiency measures that can be applied to improve the energy performance of buildings. Many countries adopt these standards as the basis to produce their own. Although the importance of an accurate simulation model in these standards is evident, these standards do not yet include any guidelines on doing so. In addition, there are no recommendations on methods for improving a simulation model by calibrating it with measured data.

Many countries also maintain a benchmark of their building performances. These often culminates in national building certification standards. These certificate or levels are granted in terms of a building’s energy use per unit area. Although these provide a benchmark for energy use, the efficiency of the heating and cooling system, envelope characteristics, etc., the data analysis and modelling methodologies are still restricted to the research domain and seldom find their way into building standards. In similar terms, a generic guideline on high-level technology considerations based on economy, climate and construction type is provided by the IEA [2] (Table 1). This shows the large gap in customized analyses methods that cater to individual buildings.

A review on retrofit methodologies by Ma et al., in 2012 summarizes that the generic retrofit process can be divided into five phases [11]. The first phase is the pre-retrofit survey where the scope and project targets are set in consultation with the building owner. The second phase comprises of energy audit and performance assessment. This phase identifies the energy saving potential and areas of energy wastage. The third phase identifies the retrofit options using appropriate energy models, economic analysis tools and risk assessment methods. The fourth phase is implementation and commissioning. Followed by the fifth phase, which is the validation and verification of energy savings. A review on toolkits for retrofit analysis by Lee et al., in 2015 surveyed and compiled 18 toolkits available at that time [12]. It was observed that there is a fine line between having too much detail for modelling that resulted in a long time for analysis or too little detail which sacrificed fidelity of the retrofit models.

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<th>High-level technology considerations based on economy, climate and construction type as per the IEA [2].</th>
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Notes: BIPV = building-integrated photovoltaic; SHGC = solar heat gain coefficient.

1.2. Novelty of this review

Since the previously mentioned reviews, there has been a substantial development in modelling techniques due to advancements in data acquisition methods. For example, hybrid models based on the thermal balance of buildings in combination with data-driven calibration have been widely developed. In terms of data acquisition, sensing technologies have been profoundly penetrating the building industry. The use of sensor data has witnessed an expansion from monitoring and controls to aid the development and calibration and energy models to be used in the retrofit process. This review aims to collate the latest developments in data-enhanced and data-driven modelling methodologies for building retrofitting while throwing light on the potentials and challenges in the modelling methods. The review focuses on the contrast between data-driven approaches that utilize measured building data, acquired through either 1) on-site sensor deployment or 2) from pre-aggregated national repositories of building data. Differentiating between 1) bottom-up approaches that can be divided into white-, grey- and black-box modelling, and 2) top-down approaches that utilize analytical methods of clustering and regression, this review analyzes the state-of-the-art in current building retrofit methodologies; outlines their strengths and weaknesses; and concludes by identifying a hybrid approach - of lean in-situ measurements supplemented by modelling for verification - as a potential strategy to develop and implement more robust retrofit methodologies for the building stock.

A comprehensive literature survey is made using search engines such as the Web of Science (www.webofknowledge.com), Scopus (https://www.scopus.com), Google Scholar (http://scholar.google.com/) and Google (www.google.com). The keywords used for the first round of search include combinations of the following phrases: ‘building retrofit’, ‘building simulation’, ‘building modelling’, ‘data-driven modelling’,
2. Data-driven retrofit methodologies

The different retrofitting methodologies can be broadly classified into top-down and bottom-up analyses or approaches (Fig. 1).

Current research methods show the high potential of top-down approaches for retrofitting buildings. However, these are yet to be thoroughly implemented in practice. Top-down approaches utilize large datasets maintained by public authorities, such as the national or regional departments of building and infrastructure. For example, the Building Performance Database (BPD) in the US consists of building data from the state and local governments, utilities, energy efficiency programs, building owners and private companies, and makes it available to the public [13]. Similarly, the voluntary disclosure of Building Energy Performance Data for Commercial Buildings in Singapore freely provides the energy use intensity (kWh/m² yr), building type, gross floor area for most of the commercial buildings in Singapore [14]. Datasets on energy performance certificates are also used in the top-down approaches and provide more building variables for analysis, although these are seldom freely available. Examples of such datasets are the GEA (Gebäudeenergieausweis der Kantone) in Switzerland and the CENED (Certificazione Energetica degli Edifici) in Italy. These contain data on building characteristics such as conditioned floor area, energy consumption, energy systems for space conditioning and envelope characteristics. These datasets are generated by records of energy certification reports of buildings. These reports are submitted by certified energy consulting firms. Another such dataset is the smart meter-based energy consumption dataset which is possessed by utility companies that supply energy. Analysis of these datasets also provide a noteworthy understanding of large building stocks. For example, by analysing smart meter datasets, researchers are able to identify poorly performing buildings and calculate the demand reduction potential through retrofitting [15]. Research also shows that smart meter datasets can be used to categorize building-type and energy system-type [16]. However, this approach does not yet give a detailed retrofitting solution at an individual building level.

The bottom-up approach on the other hand, targets individual buildings with a view to analyse the retrofit strategies in detail. Since it is done at an individual building level, these are intended for private building owners often leading to single retrofit measures and piecemeal interventions that inhibit comprehensive energy retrofitting [17, 18]. A significant challenge in this approach is to scale up the process since every building is individual and in a specific context. Many modelling methods have been used over the years. The recent surge in sensor technology and data-driven, machine learning methods have complemented building modelling techniques. The next sub-sections look into
these approaches in detail while discussing relevant examples from the literature.

2.1. Top-down approach

The main benefits of the top-down approach are its ability to utilize available datasets on building certification and energy consumption, provide benchmarks based on collated data and to provide guidelines for regional energy retrofit policies [19–21]. There have been significant efforts to develop statistical and machine learning models to predict post-retrofit conditions for large building datasets where data on post-retrofit conditions are also available [22,23]. The retrofit methodologies using these datasets develop either regression or rule-based models that relate the pre-retrofit data and retrofit measures to post-retrofit building conditions. This helps in limiting input to the most relevant factors and prioritizing likely retrofit candidates [24]. These relations can also be exploited by autoencoders that compress the inputs to arrive at an index of measuring retrofit capabilities [25]. Artificial neural networks are also used to model the post-retrofit inputs from large datasets of energy certificates to the energy performance index or energy use index which is measured as kWh/m².a [26].

In cases where the post-retrofit data and implemented retrofit measures are not available, studies focus on benchmarking buildings based on their current energy performance. This aids in identifying candidate buildings for retrofitting by comparing these to the benchmark. A widespread method to benchmark buildings considers only two factors: the building type and the normalized energy consumption with respect to the building floor area. There have been various perspectives on looking at this index. As an example, researchers have used the Lorenz curve to identify the distribution of inequality of energy consumption in buildings [27]. The advent of machine learning has enabled the inclusion and analysis of other factors in benchmarking as well. The most important technique that is used for this purpose is clustering. Researchers have made use of as many as 20 factors to cluster buildings into similar groups [28–30]. This results in more homogenous clusters of buildings. Clustering has been combined with decision trees for dynamic energy benchmarking [31]. This enables the benchmarking to use hourly energy consumption values as against the annual values. It is also possible to combine certification datasets with Geographical Information Systems (GIS) to support regional retrofit policies [32]. The geolocations help in defining the best policies for the most critical regional areas. In contrast, the bottom-up approaches provide a comprehensive analysis of individual buildings.

2.2. Bottom-up approaches

The bottom-up approaches entail analysis on the level of an individual building. It relies on data related to physical, environmental and energy characteristics of a building. The data is used to generate thermal models which are then used for retrofit analysis. These thermal models can either be developed through white-box, grey-box or black-box simulations. Contemporary goal of such simulations is to determine the best retrofit strategy in terms of cost-optimality and environmental considerations. The following sub-sections discuss these modelling techniques in detail.

2.2.1. White-box models

White-box models are the type of prediction models in which the internal mechanism can be clearly explained. In building applications, white-box models are widespread in the form of simulation software. The use of computers in simulating the thermal behavior of buildings dates back to the 1960s [33]. Since then, there has been a vast development in simulation software such as EnergyPlus, eQUEST, DOE-2, ESP-r, BLAST, TRNSYS, etc. These simulation engines are primarily based on thermal heat balance equations which, in its most simple form, could be written as in equation (1):

\[ Q_{\text{heating or cooling}} = Q_{\text{sol}} + Q_{\text{vent}} + Q_{\text{tran}} + Q_{\text{int}} \]  

where,

- \( Q_{\text{heating or cooling}} \) is the energy required for space-heating or cooling,
- \( Q_{\text{sol}} \) is the transmission heat loss or gains through opaque building elements like walls,
- \( Q_{\text{vent}} \) is the ventilation and infiltration heat loss or gain,
- \( Q_{\text{tran}} \) is the heat gained through internal elements like occupants and appliances, and
- \( Q_{\text{int}} \) is the heat gained through direct or diffused solar radiation.

In simulation software, each of these terms is extensively elaborated. For example, the heating or cooling energy required is combined with system efficiency and other system variables. A detailed software environment like EnergyPlus calculates the energy required to maintain each building zone at a specified temperature for each hour of the day [34]. A major benefit of using these engines is that these in principal can be used to test the retrofit potential of any building system or technology. It is therefore independent of the technological developments in building systems. For example, EnergyPlus has been recently used to compare Phase Change Material (PCM) applications for building retrofit [35].

Despite these benefits, a reasonable EnergyPlus model requires thousands of inputs. As these inputs are often cumbersome to obtain, they are replaced by standard assumptions. In addition, these models are very sensitive to a single parameter input, for example, infiltration, which might often be difficult to obtain. The validation and calibration of these models is only possible when the building has been constructed. These factors lead to a gap between simulated and actual energy consumption, which is a major setback for white-box modelling [36]. In addition, energy calculations are time-intensive and can take up to days even for a building with simple geometry.

In order to reduce the uncertainties of white-box models, sensor data from buildings is widely used for calibrating them. Research on calibrating white-box models using full-scale measurements shows a reduction in the performance gap, although discrepancies still exist [37]. Along with calibration using real data on HVAC systems and schedules, researchers have also proposed an optimization-based framework to calibrate whole building energy models [38]. White-box models could also be coupled with microclimatic data and computational fluid dynamics (CFD) simulations for analyzing the buildings thermal performance [39]. The calibrated models have been found useful in comparing the performances of various retrofit scenarios. For example, Cetin et al. used a calibrated EnergyPlus model to evaluate an on/off HVAC controller and found that the controller improves the energy use by 19% [40].

2.2.2. Grey-box models (resistance-capacitance analogue models)

A grey-box model combines a partial theoretical structure with measured data to complete the model. In thermal modelling of buildings, these pertain to electrical analogue models, known as the Resistance-Capacitance or RC models that are computationally efficient and simpler. The intention of such models is to closely represent the thermal behavior of a building. The ISO 13790 standard introduced a monthly method and a simplified RC-based hourly method that can be used to calculate the heating and cooling needs for buildings [41]. This standard is now replaced by the ISO 52016-1 which includes a more detailed RC network. The basis of the RC model is to construct and define nodes that are interconnected with thermal conductance (reciprocal of resistance) and capacitances. In simple terms, the resistances are the building elements that account for heat transmission, whereas, the capacitances are building elements and air volumes (indoor spaces) that account for heat retention. Theoretically, a sufficiently detailed model could be used for retrofit analysis as the R and C elements provide room for testing the retrofit measures. An example of such a theoretical RC model is provided in Fig. 2.

The heat balance at any thermal node ‘n’ is modelled as a first order
differential equation as shown in equation (2).

\[ \frac{dT_n}{dt} = \sum_{i \in I_n} T_i - T_n + Q_n \]

Equation 2

where 'Ri' is the thermal resistance between elements 'i' and 'n', 'Cn' is the thermal capacitance of the node, 'Tn' is the node temperature and 'Qn' is the heat flux through the node. The set 'In' includes all the nodes connected to the node 'n'.

Although these models are based on quasi-steady states, there has been development on dynamic RC models based on time series input data. In these cases, numerical methods like the finite difference method are introduced for solving the differential equations involving temperature variations in a thermal mass. The solutions to these equations are the temperature values (either surface or indoor temperature) based on the thermal properties of the building elements. The model coefficients are determined using inverse modelling or parameter estimation methods. The most popular of these methods has been the state-space models that not only focus on the input-output relations but also on the internal state of the system. There are various packages such as the 'System identification' toolbox in MATLAB and statsmodels.tsa.statetestspace in Python that are used in solving input-output relations using state-space methods. In cases where the internal, external and surface temperatures are known, these equations can also be used to obtain information on the thermal properties of the building elements. The characteristics of the thermal properties are reflected in the estimated R and C values. A subtask of the IEA EBC Annex 58 (2011–2016) explored all the data analysis methods applicable to dynamic datasets for thermal modelling [42].

One of the first successful applications of the RC model used a transfer function with parameters that are constrained to satisfy a simple physical representation for energy flows in a building [43]. These parameters are identified by a method wherein initial values and bounds on physical parameters are estimated from a rough building description and better estimates are obtained using a global direct search algorithm. This is followed by the identification of optimal parameters using a nonlinear regression algorithm. Software packages like LORD are often used to develop these models and estimate the parameters [44]. The successful development and application of RC models in the past decade are commendable. Studies show that low-order models provide good estimates of heat transfer coefficients and internal temperatures if heating, electricity use and CO2 concentration are measured during the winter period [45]. The flexibility of the RC models allows the formulation of a hierarchy of models with higher complexity [46]. The input data usually available for parameter identification is time series data of the indoor temperature, the outdoor temperature and the heating or cooling input. It is also noted that sudden changes in the outdoor temperature perturbs the identified parameter set [47]. Much research has
been done to develop simple RC models that can accurately model the thermal balance in a building [48,49]. Recently, there have also been advances in developing a simulation toolkit to integrate the RC model, calibration, and optimization of the retrofit options [50,51]. One of the first published works on using RC models for retrofit analysis attempts to translate the model parameters as ‘retrofit functions’ that are associated with energy conservation measures [52]. However, this study focused on integrating thermal models with electricity grid flexibility analysis than on an individual building retrofit. Studies that attempt retrofit using RC models, often report the difference between the theoretical and estimated R and C values. This has a significant impact on using these models for retrofit analysis as the estimated parameter properties should ideally match with the properties of the retrofit measures. In addition, the parameter estimation methods require extensive mathematical processing. We see that even for a simple thermal balance, there are many elements and variables involved in a RC model. Each node in a RC model has a set of transient equations which need to be solved to identify the R and C values. A standard and accurate method to estimate the parameter of the RC model is yet to be developed. Although this method heavily relies on inverse modelling techniques, the model parameters can still be linked to physical phenomena and effects in buildings. However, this link between estimated parameters and physical values of resistance and conductance is difficult to establish.

2.2.3. Black-box models

Black-box models are systems that are viewed in terms of their inputs and outputs without any knowledge of their internal mechanism. Benefitting from their classification and prediction capabilities, numerous models have been developed in the building domain for fault detection, diagnosis and building system control [53–55]. Successful applications have seen the timely detection and prediction of faults in heating/cooling cycle, appliance and lighting energy use as well as changes in indoor environmental conditions [56–58]. Machine learning has also been immensely explored to optimize the operating conditions of heating and cooling systems of buildings and districts [59–61].

Machine learning models are based on measured or generated data. In cases where real data is unavailable, simulated or synthetic data is generated and used for modelling and retrofit analysis. Such applications are also known as surrogate models in which white-box simulation engines are used to generate the inputs and outputs to train machine learning models. Feed forward neural networks have been vastly successful for this purpose. A general machine learning model for retrofit analysis based on measured data can be presented as in Fig. 3. Such machine learning models greatly reduce the simulation time while maintaining the accuracy of results that are obtained from white-box models [62]. In cases where measured data is available, linear parametric models such as autoregressive with exogenous inputs (ARX) and seasonal autoregressive moving average with exogenous inputs (SARMAX) models have been used by many authors to simulate the thermal behavior of buildings [63]. These models are based on time series data and make predictions for certain time steps ahead. These models could also be used to calculate the overall heat loss coefficient (HLC) of buildings.

However, there are two challenges in using these models for retrofit analysis. First, there is no scope to look into the effects of individual retrofit measures as the model parameters cannot be physically interpreted [42]. And second, the building is considered as a non-time-varying system. The analysis of temporal aspects of the

![Diagram of Measured variables, Features, Input layer, Hidden layers, and Output layer.](image-url)

Fig. 3. The steps involved in developing a machine learning model for retrofitting buildings.
thermal behavior of buildings requires measured data of the building properties over a period of time. Although the data collection technologies in buildings have improved, purely black-box models that provide energy-efficient retrofit strategies based on measured data haven’t been reported yet. The essential mechanism to develop black-box models for retrofit analysis relies on training models with data on thermal and operational characteristics of a building. The trained models adapt to existing conditions which are then tested on a supervised or ‘known’ dataset. Generally, these test datasets are extracted out of the same sample space to which the training dataset belongs. Once the models are deemed accurate on training and testing datasets, these are used to predict outcomes based on new inputs. However, these new inputs are to be within the parameter space of the training and testing inputs. Otherwise, there is a risk of the model being inaccurate in making predictions. This is also a general limitation of machine learning models as these are wholly based on stipulated datasets [64]. In the retrofit analysis, this is a grave limitation since there is no availability of training data from post-retrofit conditions. Whereas, to make a successful retrofit decision, it is important to predict future conditions with various retrofit strategies. With this limitation, there has not been any study that solely uses machine learning models to predict future energy scenarios based on in-situ measurement data for a given building.

2.3. Cost-optimal retrofit models

Another aspect of retrofit analysis where machine learning has been utilized is in obtaining cost-optimal retrofit solutions. In building retrofits, cost-optimality refers to the retrofit strategy that leads to the lowest global cost taking into account retrofit-related investment costs and running costs until the end of the economic life cycle. The cost-optimal analysis is exercised when the objective function is to select a cost-effective retrofit strategy. In such cases, machine learning models are used to navigate through different retrofit combinations. The European Union’s Directive on the energy performance of buildings emphasizes the need to take cost-effectiveness into account. The Directive 2010/31/EU has introduced the life cycle cost analysis (LCCA) in the European legislation [65]. The global cost (GC) of a design alternative can be calculated with the following equation (equation (3)).

\[
GC(t) = C_i + \sum_{j=1}^{n} \left( \sum_{i=1}^{n} (C_{a(i)} \times RD_{d(i)} - V_f \times T) \right)\
\]

Equation 3

where: \( T \) is the calculation period; \( GC(t) \) is the global cost over the calculation period, referred to the starting year; \( C_i \) is the initial investment cost for the element \( j \); \( C_{a(i)} \) is the annual cost during year \( i \) for the element \( j \); \( V_f \), \( T \) is the residual value of the element \( j \); \( RD_{d(i)} \) is the discount factor for year \( i \) based on discount rate \( r \) to be calculated.

Cost-optimal analysis is often based on a double-stage optimization method, considering total and marginal investment costs of retrofit measures as well as associated net present values of total and marginal cost savings [66]. At the same time, the cost-optimal solutions for abatement cannot be generalized as these are strongly influenced by initial conditions and climatic context [67]. In some research, a risk factor is also considered while evaluating the economic rate of return of the applied retrofit technologies. Since the future risk is unknown, Monte Carlo simulations are used to vary the risk and identify the best retrofit strategy [68]. Integrating Life Cycle Analysis (LCA) approaches in retrofitting analysis drastically changes the optimal solutions [69]. This multi-criterion assessment has recently gained significant momentum. In these multi-objective optimization models, the economic goals are the net present value and time of return, and the environmental goals are the energy saving and emission reduction. This is followed by intelligent optimization methods like combing particle swarm optimization and genetic algorithm to search the best retrofit investment strategy [70,71]. In cases where the optimization problem is computationally intensive, it can be simplified by using measured and verified energy savings of sample retrofits [72]. Ascione et al. developed a framework for cost-optimal analysis by multi-objective optimization (CASA) which provides a cost-optimal energy retrofit for any type of building [73]. A multi-objective genetic algorithm (MOGA) is used to select recommended packages of energy retrofit measures (ERMs) by minimizing primary energy consumption (PEC) and thermal discomfort hours (DH). A general cost-optimal curve and solutions to the retrofit strategies for a case study building by Ascione et al. are shown in Fig. 4. It is to be noted that the simulations regarding energy savings are based on a simulation program using a white-box model (EnergyPlus).

Cost-Optimal retrofit analysis has produced several interesting results. Case studies on high-rise apartment buildings in the Mediterranean climate show that the energy saving potential through cost-optimal analysis is as high as 70–80% [74]. Researchers also observe that as costs of retrofit measures are further reduced and energy prices likely to rise in future, the cost balance will change more in favor of whole building retrofit [75]. The optimization models can also allow breaking down the long-term building retrofit project into smaller projects spanning over multiple financial years [76].

2.4. Challenges in modelling

White-, grey- and black-box modelling approaches for retrofit analysis have specific advantages and disadvantages, which can be summarized as follows. White-box models are transparent and do not require real data. These have been found effective in comparative studies where various retrofit options are tested on a building. Although, there is a deviation between actual and simulated energy performance values, these get nullified when comparing scenarios and observing the changes. Another advantageous feature of white-box models is their ability to be coupled with other simulation programs, like CFD or urban microclimate software.

![Fig. 4. A. Cost-optimal curve. B. Retrofit solution based on the global cost for a case study office building in South Italy [73].](image-url)
The major disadvantage of white-box models is the extensive preparation required to perform a detailed thermal simulation. This requires information on the building geometry, properties of building components, type of HVAC systems, climate data, and knowledge of occupancy schedules, culminating to hundreds of inputs. Since it is impossible to provide sufficient information on each of the parameters, there is a gap between simulated and real energy performance. Although, this gap can be reduced by calibrating white-box models using measured data, their accuracy is found to be lower than that of grey-box and black-box models.

Grey-box models are simplified representations of buildings and are systematically calibrated using measured data. Unlike the calibration of white-box models, which is done by inputting measured data, grey-box models are calibrated using inverse modelling techniques which determine the model parameters. However, parameter estimation presents a major challenge, particularly in setting the boundary conditions of the parameters to be estimated. Studies that use grey-box models for retrofit analysis report the difference between the theoretical and estimated parameters. This has a significant impact on using these models for retrofit analysis as the estimated parameter properties should ideally match with the properties of the retrofit measures. A detailed grey-box model also has identifiability issues which hampers its parameter estimation.

Black-box models have higher accuracy as these are trained on data with no prior model structure like the white- and grey-box models. These do not require any previous knowledge of the thermal behavior of a building. Since the main objective of these models is the input-output mapping, these are independent of the number, frequency and length of measurements of the inputs and output. Since these are purely based on data, the quality of the measured data is significant. Therefore, they require extensive cleaning and pre-processing of the measured data. In their application to building retrofit analysis, black-box models are unacquainted with heat transfer principles. This limits the interpretability and potential for predicting the outcome of retrofit measures.

A major challenge for all types of modelling approaches is the uncertainty in predictions with retrofit measures. Developing a model with precise prediction capabilities for future retrofitted scenarios will always pose a challenge as validation of the modelling results can only be performed after a building has been retrofitted. A way to tackle this is to be trained on data sets and learn from representations of pre- and post-retrofit data. The lack of scalable measurement techniques hinders the creation of such data repositories. In relation to this, Table 2 summarizes the building variables used for developing white-, grey- and black-box models and the existing data collection methodologies and technologies associated with these. However, as a limitation to this review, the costs for the sensor setup, costs for the modelling software and processors, costs for the databases and costs of manpower are not included in the discussion as most of the studies reviewed herein seldom mention the cost aspect.

3. The way forward

This review underscores the lack of retrofit methodologies that are both easily viable, scalable and sufficiently accurate. In view of this, we introduce a framework based on current technological and modelling advances, proposing the integration of three essential components: 1) data collection technologies and methodologies, 2) interpretable machine learning and hybrid models and 3) cost-optimal retrofit analysis.

3.1. Data collection technologies and methodologies

Empirical measurements of a building’s physical properties, systems and indoor environment are an essential component to advance to more effective retrofits. They can be used for three purposes. First, to assess the current performance of buildings and improve their operational efficiency and whether these adhere to the energy standards second, to utilize measurement data to build bespoke models for retrofit analysis, and third, for quality control of retrofit measures. Recently, there has been a rapid penetration of sensing technologies in the building domain. Monitoring systems for indoor environments have become affordable and there are chances that their penetration in the built-environment will increase. In the research domain, data collection using drones in indoor and outdoor environments have been successfully developed [86, 87]. The recent advances in the open-source hardware (OSH) realm has enabled quick dissemination of knowledge of hardware design that allows for a lean and robust measurement hardware [88,89]. This knowledge can be used to develop customized sensor modules depending on the requirements of the type of building and their location. For example, in an open-office environment, where occupants do not have enough control, multiple air temperature sensors might be needed to see whether all occupants experience similar thermal environments. Contrasting, in a residence, where occupants are much more in control, sensors that measure window opening instances provide relevant information about air exchange. OSH platforms are enablers of such customization, acknowledging the challenges in sensor network communication and demonstrating substantial progress to integrate these into existing physical systems [90,91]. The challenges of securing occupant data privacy are still a major hurdle in data gathering and sharing. To mitigate this challenge requires an early participation in the data gathering process by the stakeholders such as building owners and tenants as well as clear data protection/anonymity rules and guidelines [92]. There have also been early efforts in sharing datasets for research and development. Sharing data will enable researchers to build on the work of others, and allow for a comprehensive analysis with a potential for replicability. Existing and emerging data sharing platforms such as Nature Scientific Data, Elsevier Data-in-Brief, and Kaggle have recently been used to share complete and peer-reviewed datasets. These are great avenues to develop and test preliminary data-driven models before developing one’s own data collection methodology.

3.2. Interpretable ML and hybrid models

The ubiquitous availability of data in the building domain has propelled applied data science and black-box modelling. However, for retrofitting buildings, the black-box models will be widely accepted only if physical principles are integrated. The framework of interpretable machine learning is a promising enabler for this. Interpretable machine learning entails methods of interpreting black-box models like feature importance and accumulated local effects and explaining individual predictions with Shapley values and LIME [93]. This trend has just taken off with researchers attempting to explain black-box models for building energy performance [94]. First results indicate that models with higher prediction accuracies may result in less trustworthy predictions. This means that the predictions outside the training dataset may be inaccurate or less trustworthy when compared to the training sample. In addition, the concept of hybrid models that combine the benefits of white- and black-box models is a promising direction, although it is challenging to combine two fundamentally different modelling techniques. Therefore, the hybrid approach usually leads to surrogate models wherein the white- and the black-box models are utilized sequentially rather than coherently. There are also grey-box models that utilize measurement data to build RC models, which, however, still require a high level of expertise and manual calibration. Since these models are limited by the translation capacity of building elements into the RC model structure, these end up being very simple representations of the thermal model of a building. Therefore, in order to scale up such approaches, automating the process of developing and calibrating RC models presents a necessary yet challenging field of investigation.

3.3. Cost-optimal retrofit analysis

The concept of cost-optimal retrofit in general aims at achieving the...
Table 2
Building variables used for modelling approaches and their existing data collection methodologies and technologies [77–85].

<table>
<thead>
<tr>
<th>Building variables</th>
<th>Static (*); time series (+)</th>
<th>Existing data collection methodologies and technologies</th>
<th>White-box</th>
<th>Grey-box</th>
<th>Black-box</th>
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<td>Manual measurements using CAD drawings of the building</td>
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<td>Energy audit datasets from public institutions and bureaus</td>
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<td>3D models of buildings using drone-based aerial thermographic imagery</td>
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<td>Internal air volume</td>
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<td>Theoretical calculations based on building geometry</td>
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<td>Material properties: U-values, G-values of –</td>
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<td>Theoretical values from laboratory tests as supplied by manufacturers</td>
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<td>Walls</td>
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<td>Measured values using heat flux measurements</td>
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<td>Windows</td>
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<td>Heat flux sensors, drone-mounted thermography[77,78]</td>
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<td>Roofs</td>
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<td>Heat loss through –</td>
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<td>Walls</td>
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<td>Floors</td>
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<td>Surface temperature of external surfaces</td>
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<td>Surface temperature sensors</td>
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</tbody>
</table>

and internal surfaces (walls, windows and roofs)
- Thermal cameras – manual or drone-mounted[79]

Energy consumption

- Heating and cooling energy for indoor spaces and domestic hot water consumption
- Depending on the system –
  - Electricity based heating or cooling: Disaggregation of total electricity consumption or sub metering
  - Burner based: Fuel consumption; measurement of hot water supplied using ultrasonic flow meter with temperature sensors
  - AHUs in cooling systems – Flow meters with temperature sensors

- Electricity consumption
- Monthly electricity bills
- Data from smart meters and sub meters

- Fuel consumption
- Depending on the fuel and heating system –
  - Oil: Volumetric flow meter with data logger
  - Gas: Gas consumption meter with data logger

- Efficiency of the system
- Theoretical calculations

- Appliance use
- Disaggregation using electricity meter data[80]

Environment

- Outdoor
  - Air temperature
  - Humidity
  - Solar radiation
  - Wind speed
  - precipitation
- Local weather stations
- Real-time weather databases based on regions
- Installing outdoor weather monitoring equipment
3.4. A note on the influence of climate change

Due to the long life span of buildings, climate change has to be taken into account for defining suitable retrofit measures. This requires future weather data to model the thermo-hygic behavior of buildings in a changing climate. The most utilized source for future weather data stems from the Data Distribution Center (DDC) [100] of the Intergovernmental Panel on Climate Change (IPCC). The DDC provides global climate model (GCM) data based on future scenarios through their assessment reports. The data can be retrieved on a monthly frequency for Assessment Report 4 (AR4, 2007). Different frequencies are available for ARS which was released in 2013. A total of twenty-three climate models, eight scenarios and nine forecasted climatic variables are available. Beginning in 2014, the IPCC commissioned a new series of emission scenarios known as the ‘Representative Concentration Pathways (RCPs)’ [101]. In relation to building performance assessments, the future forecasts of weather data based on these scenarios are not suitable in their available form. This is because the temporal and spatial resolution of the forecasted climatic data is too high. For example, the climate models forecast on a monthly frequency with a range of spatial resolution between 100 and 300 km². Therefore, this dataset needs to be downscaled to hourly frequency for better performance assessment of buildings. This downscaling could be done by many methods, including the one proposed by Belcher et al. [102]. In their method, they use present-day, high-resolution weather files and morph these using projections from either a global or regional climate model using ‘shift’ and ‘stretch’ methods. It is also seen that the retrofit models considering the influence of climate change alter the optimal choice of retrofit strategies [103]. The future weather files should consider not only typical but also extreme conditions [104]. It is observed that in a heating-dominated region, the emission reduction capacity (ERC) is projected to increase in the presence of global warming, while, in a cooling-dominated region, the ERC is projected to decline [105]. A region-specific simulation for a residence in Argentina showed that for each 1 °C of increment in monthly mean outdoor temperature in summer (January), an increase of cooling energy demand of about 2.2 kWh/m² per month is predicted. Similarly, for each 1 °C of increment in monthly mean outdoor temperature in winter (July), a decrease of 3.0 kWh/m² per month is predicted [106]. Another region-specific analysis in Sudan compares design strategies from the year 2015 to those for 2070 and discovers that strategies must shift to more active cooling by the year 2070 when natural ventilation and active heating will no longer be beneficial design strategies during all seasons [107]. The uncertainty of retrofit analysis due to the influence of climate change is found to be similar to that of consumer price development and fuel emission factors [108]. Fonseca et al. developed a Hierarchical Bayesian Linear model (HBLM) that combines a physics-based and statistical model technique. The model also quantifies uncertainty and captures causal associations between multiple scales of data aggregation. These include the building, the building sector, the city and the climate zone. The HBLM was used to forecast the potential impact of climate change on building energy consumption across the United States for the 21st century [109]. The
results show that climate change could increase the Energy Use Intensity (EUI) of buildings for most cities and climate zones of the United States, with warm and humid climate zones experiencing the highest growth rates. In contrast, the EUI of buildings in cold climates could decrease.

4. Conclusions

Energy demand in buildings continues to rise, driven by improved access to energy in developing countries, greater ownership and use of energy-consuming devices, and rapid growth in global buildings floor area, at nearly 3% per year [5]. While we need to ensure that new buildings comply with the highest energy standards, we cannot overlook the enormous building stock that already exists. The need to improve the energy standards of existing buildings is of particular importance to developed countries where all buildings are equipped with often inefficient heating and cooling systems. Recognizing this, the European Union’s Horizon 2020 framework has funded a number of projects exemplifying retrofitting methodologies and systems [110–120]. All these projects are currently running and are expected to deliver the complete set of results and reports by 2020 or later.

The mathematical models of buildings used for retrofit analysis are the core for producing an accurate estimation of retrofitting strategies. This review has discussed the state-of-the-art of the existing modelling methodologies, along with their challenges. In the current state of modelling, the different techniques such as white-, grey- and black-box models are integrated rather sequentially than coherently. To the best of our knowledge, a more tenable integration that harnesses the individual strengths of these methods needs yet to be developed. We also identify that a combination of simple in-situ measurements, data-driven hybrid modelling methodologies and cost-optimal retrofit analysis has the potential to overcome many barriers in establishing an retrofit assessment process that leads to cost-optimal solutions. Establishing such procedures will not only enhance the retrofit rate but will contribute to an improved performance assessment and quality control of buildings as well. This improved accountability opens a pathway to reduce the performance and knowledge gap, thus aiding decision making for reducing the carbon emissions of the current and the future building stock.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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