The Efforts Towards Development of an Energy Efficiency Upgrade Platform

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Abstract
This contribution presents the efforts towards the development of an energy assessment platform to assist building engineers, energy managers, policy makers, etc., evaluate the best revenue options from energy conservation investments in commercial buildings. Portfolio assessments commonly fall into three phases: benchmarking, detailed investigation, and assessment of findings across portfolio. The methodology involves, clustering buildings within a portfolio based on their energy performance, selecting the poorest performers for further analysis, and performing detailed investigations for the selected group. This study covers the development of a platform for convenient collection of the minimum building data required to support energy efficiency upgrade and investment decision makings.

Key Innovations
The analysis in the presented platform is assisted by Artificial Intelligence (AI). Novel load shape analysis, and energy disaggregation methods constitute the backbone of the development of the enhanced recommendation engine in the platform.

Practical Implications
The presented platform enables the users to a) benchmark their buildings' energy consumption, b) audit their building energy features, and c) explore different energy retrofit options.

Introduction
During the Covid-19 global pandemic, a period of time when people are asked to socially distance and work from home, a significant drop in buildings' energy consumption was expected. However, empty office buildings have not reduced their energy consumption as expected (Evans, 2020). Carbon Intelligence published the result of studying the energy consumption in the last week of March in 300 office, hotel, and retail buildings (Duggan, 2020). The report demonstrates a drop of only 16 percent in the energy consumption. One cause could be the resources that commercial buildings constantly require, even when they are vacant. Many buildings are designed to rely on a constant flow of resources — air, water and electrons (John, 2020). For commercial real estate, around one third of the building energy consumption relates to the heating, ventilation, and air conditioning (HVAC) systems, one third to plug loads, and 15 to 20% to lighting (non-emergency) (Hatch Data, 2020). The rest relates to systems like elevators and emergency lighting. In case of the latter, the rationale for ongoing use of energy is sensible because these features must remain active even in unoccupied structures. The same can be said for the likes of data centres, storing critical information, or some HVAC system use to avoid corrosion or the build-up of harmful chemicals. That said, HVAC systems should not have the same power draw as in occupied periods. Another power draw is the devices left behind, such as computers and appliances. The wasted energy not only costs money but also carbon. Self-evidently, huge long term environmental and financial gains could be achieved by improving energy management in commercial buildings (Duggan, 2020). Building managers should be able to cut energy use by at least half during unoccupied periods, assuming better training and ongoing monitoring of the building energy and operational data. Savings should be in the region of 50 per cent in order not to unnecessarily contribute to climate change and waste money (Duggan, 2020).

The energy efficiency upgrade platform presented in this paper is an intelligent option to manage operational energy performance in buildings, enabling benchmarking and controlling energy usage. Evaluation of the energy consumption patterns, and identification of potential energy cost savings is achieved through an analysis of the buildings' metered data. Energy conservation measures, including behavioural and operational recommendations are suggested by precise assessment of the load shape patterns and disaggregated energy consumption in buildings.

Load shape analysis

One data driven approach to explore energy consumption as a function of time is the concept of load shape. A load shape is a curve, illustrating the change in a building's energy load over time. Some relevant parameters used to interpret load shapes include near-base load [kW], near-peak load [kW], high-load duration (hours), rise time, fall time, base load percent, peak-to-base load ratio (Luo et al., 2017). Different clustering methods have been developed to generate these curves across datasets to, for instance, represent the consumption pattern in a specific building type, or to represent the typical load profile for a single building's daily consumption. Load shape analysis has been also used to calculate the components of a building's energy profile and benchmark the measured energy consumption of buildings accordingly. Each building can be benchmarked against the whole population or its peer buildings. This can be used to identify opportunities for improvement and investigate potential wastage quickly and effectively.

Building energy disaggregation

Building energy disaggregation is an attempt to break down an aggregate energy use signal into its constituent end uses. For example, a whole building energy use profile broken down into HVAC, lighting, small power and miscellaneous uses. For an aggregate signal to be disaggregated into end-uses it must be compared with some information about the building in question, be that building type and age or the conditions in which the building is operating.

Residential building energy disaggregation

Residential energy load profiles are defined by many clear changes in power state. Each appliance has a distinct effect on the aggregate signal (Kelly, 2016). Methods successfully applied to residential buildings include:

- Conditional Demand Analysis. Based on occupant surveys linking energy with variables such as floor area, number of appliances, etc. (Parti and Parti, 1980). This method was inherently inaccurate as it relied on reliability of survey information and monthly data, where all loads shared the same temporal profile.
- Non-Intrusive Load Monitoring. Appliances with capacitance or inductance consume real and reactive power. No two appliances will have exactly the same mix of real and reactive consumption. The state changes of appliances can then be matched with real and reactive power state clusters of equal magnitude and opposite sign (Hart, Kern and Schweppe, 1989).
- Analysing higher voltage frequencies in the range of 5-140 kHz to look for the unique voltage signal of individual appliances and their transient state (Froehlich et al., 2011).
- Power state transitions: A library of known power state transitions can be used to match changes in power usage with present devices being turned on or off (Kelly, 2016).

Commercial building energy disaggregation

The assumptions underpinning most residential disaggregation algorithms are not reliable in a commercial context (Batra et al., 2014):

1. One-at-a-time assumption. In a residential context it can be reasonable assumed that switch events or power state transitions in the data are attributable to a single appliance. This is not the case in commercial buildings where many loads can be coming on- and offline at the same time.
2. Steady-state loads. Many residential appliances draw constant loads. In a commercial context there are commonly devices with variable loads, such as fans or pumps with variable speed drives.
3. Temporal dependencies. Individual residential building profiles can vary greatly from one another therefore to increase accuracy each home’s energy profile must be “learnt” to detect recurring daily or weekly patterns. In contrast, commercial building types commonly have similar profiles to each other e.g. offices typically operate between 0800 and 1800. This reduces the need for pattern learning on an individual commercial building basis.
4. Feed correlations. Some residential loads are typically correlated, e.g., computer with computer monitor or televisions with streaming boxes. This correlation can aid in disaggregation. However, in a commercial setting, it is impossible to determine if simultaneous switching events are due to correlated loads or simply more than one appliance type coming on- or offline at the same time.

Examples of successfully applied disaggregation techniques to commercial buildings include:

- End-use Disaggregation Algorithm. A simple linear regression of seasonal energy use with outdoor drybulb temperature is used to determine the weather dependent load of the building, assumed to be HVAC heating or cooling. The remaining load is prorated based on a typical load (Akbari et al., 1988).
- Non-Intrusive Occupant Load Monitoring. Correlation of occupant entry events with power consumption is possible by accessing the wifi AP to identify occupants by MAC address or UUID. There are some issues with feed correlations for medium or large commercial buildings and consumer privacy concerns (Rafsanjani et al., 2018).
- Disaggregation of individual HVAC units on a single floor of an office building. Real and reactive power, compressor indexes and phase currents were used to identify which combination of HVAC terminal units were operating at a given time for an aggregated HVAC sub-meter. Various machine learning algorithms were tested with k-Nearest Neighbours giving the most satisfactory results (Rahman et al., 2018). The need for 1-minute interval data and compressor indexes makes this method impractical at scale.
- Fourier series disaggregation of HVAC from lighting and plug loads. This technique is based around developing a Fourier series model for lighting and plug loads from data that is known to be weather independent load (in between heating and cooling seasons). The lighting and plug loads were subtracted from the total energy to find the HVAC consumption (Ji et al., 2015).

Energy efficiency recommendations

There are various instances of studies on common Energy Conservation Measures (ECM) for commercial buildings (for examples, see, Hendron, 2013; Liu, 2011; Jamieson, 2014: Franconi and Bendewald, 2014; Lee et al., 2015). Advanced Energy Retrofit Guides (AERGs) by the U.S. Department of Energy used energy simulation models to provide energy efficiency measures for commercial reference buildings together with cost estimates in different U.S. climate zones (Liu et al., 2011). Moreover, the Database for Energy Efficient Resources (DEER) is an open access database of common energy-efficient technologies and measures together with estimated energy-savings potential and cost (California Public Utilities Commission, 2013). Considering the known impact of the user behaviour on building energy performance, behavioural recommendations guide low/no-cost actions that can considerably improve the energy performance of the commercial buildings (Paone and Bacher, 2018, Tam et al., 2018).

Workflow

Figure 1 illustrates the workflow of the proposed energy efficiency upgrade platform and its three layers, including data acquisition, Artificial Intelligence (AI) engine, and investment engine, with their components. The subsequent sections describe in detail the flow of platform and how each layer is set up.

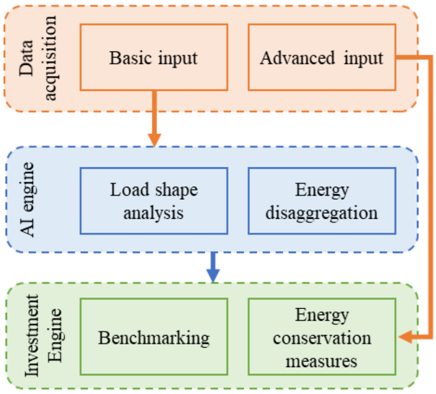

Figure 1: workflow

Data acquisition

A Graphical User Interface (GUI) is designed for a convenient and easy collection of building information. The idea is to enable an inexperienced user to provide the very basic building data using the interface. Some unspecified building input parameters can be estimated based on typical characteristics of a building, such as type, age, location. There are two sets of input data required for the analysis presented in this paper. First group is a set of basic and mandatory input data, which includes high resolution (hourly or better) energy consumption data, building location, usage type, year of construction or year of major renovation (see, basic input, Figure 1). The second group involves a set of more advanced but optional input data which will further guide the evaluations (advanced input, Figure 1). Each input:

- is connected to the relevant component of the calculation and results engines, e.g., disaggregation, benchmarking, recommendation, etc.
- is associated with a category, e.g., envelope, HVAC, lighting, etc.
- is associated with a use case, i.e., basic and advanced.
- is associated with condition(s), i.e., certain questions are relevant only for a certain condition, e.g., specific climate zone or building usage type.

Moreover, each advanced user input is associated with the following information in addition:

- Subcategory, for instance for the category envelope, there are two subcategories, enclosure, and aperture
- Input ID, which is used to define the connection between different input
- Input type, i.e., integer, real, selection
- Input range, e.g., bigger than zero for real, single or multiple choice for selection
- Condition(s), which defines if a specific user input is requird based on the response to a previous question. For instance, the user is asked about the roof area only if they specify that the roof is not insulated. In this case the system needs the roof area to estimate the cost associated with the roof insulation.

Artificial intelligence engine

Load shape analysis

The platform benefits from a data-driven approach to carry out load shape analysis. The results will be used to identify the biggest components of a building's load profile, so-called efficiency factors, and benchmark the measured energy consumption of the buildings. The efficiency factors are proposed to benchmark buildings by comparing the values among peer buildings with the same usage types and from the same climate zone. These include peak load per unit area, base load per unit area, daily mean load, and base load-to daily mean load ratio. Results of previous studies show that load shape of the buildings can be irregular and inconsistent as a result of change in the building base load over time (Taheri et.al., 2019). The load shape analysis here starts by capturing any change in the load shape patterns as a result of change in the building operation. In order to do this the data is first grouped into periods of similar operations by applying a Gaussian Mixture Model (GMM) to the daily base load and obtaining up to four periods. Any periods with an insufficient number of points are removed and these points assigned to the next most similar period. Then the efficiency factors for each of the up to four periods are calculated as:

- Peak load per unit area, equals the median of daily peak load per unit area.
- Base load per unit area, equals the median of the base load per unit area.
- Daily mean load, equals the median of the mean daily total energy consumption per unit area.

Then an annual weighted average across all four periods gives the final value for each efficiency factor. Moreover, the annual energy consumption per floor area is also calculated for each building. In the initial version of the platform any building is benchmarked against the standard building of the same usage type and climate zone (OpenEI, 2009). As another result of the load shape analysis, percentage of out-of-hour energy consumption is also calculated. This is generated based on comparing the occupancy patterns (business hours) and energy consumption patterns in the building. For this purpose, the wastage calculated as the actual energy consumption at each unoccupied time step minus the base load at the time. The preconditioning time, assumed to be two hours prior to the occupied time, is excluded from the calculations.

Energy disaggregation

A novel application of a disaggregation algorithm for commercial whole building energy data is used to disaggregate the consumption data into categories of weather dependent, scheduled, and base loads.

Through the load shape analysis presented in the previous section, when a building is "on", i.e., occupied, or "off", i.e., unoccupied, is determined. In essence, it is similar to the on/off definition based on load shape parameters defined in Mathieu et. al. (2011). The key difference is the base load is defined based on representative load shapes of each day as well as a percentile of the original signal itself. As this is not the main focus of this paper it will not be explored in any more detail here.

The LBNL model assumes an energy response of a building to temperature to be constant at any given temperature. A building will use no heating or cooling energy in temperate conditions (dead-band) and more energy above or below these temperatures once heating or cooling are needed. In some cases, the building's capacity to heat or cool will be maxed-out, at which point the building's energy consumption remains constant with additional changes in temperature (Figure 2).

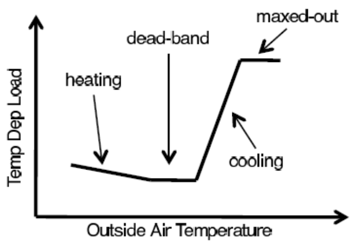

Figure 2: Temperature dependent load as defined by the LBNL model (Mathieu et al., 2011).

Occupied load $\hat{L}_o$ is a function of temperature T and time t at time-of-week interval i. The regression coefficient α varies with i. The temperature parameter β varies with each temperature interval j (Equation 1).

$$\hat{L}_o\big(t_i, T(t_i)\big) = \alpha_i + \sum_{j=1}^{6} \beta_j T_{c,j}(t_i) \qquad (1)$$

For unoccupied hours it is assumed the heating and cooling systems are off. In other words, the relationship between temperature and energy consumption is linear. This requires only a single value for β, β_u (Equation 2).

$$\hat{L}_u\big(t_i, T(t_i)\big) = \alpha_i + \beta_u T(t_i) \qquad (2)$$

The LBNL model was developed to predict building energy consumption. This could aid in identifying opportunities for energy conservation measures and act as a verification tool to quantify energy savings from such measures. It is not an energy disaggregation tool in itself. In an occupied period, at any given time-of-week interval i at temperature T_j weather dependent energy consumption E_{Wd} can be calculated by subtracting the weather independent load E_{Wi} from the total load E_{Tj} (Figure 3). E_{Wi} is equal to the minimum value of $\hat{L}_o$ (at a minimum β_j) for each value of i (see, Equation 1). By solving the equation, values of E_{Wd} can be found for any value of T at each interval i.

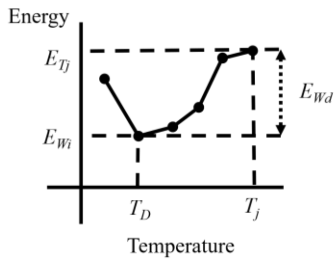

Figure 3: Calculating occupied weather dependent load at any given time of week interval.

Unoccupied times are 100% base load (see below). The weather independent load at time-of-week i can be further decomposed into scheduled loads, i.e., loads that occur during operating or "on" hours, and base loads, i.e., the minimum load of the building below which energy consumption rarely falls. Across a given day the base load is calculated, and the remaining weather independent load is scheduled load (Figure 4).

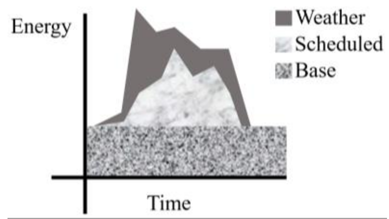

Figure 4: Disaggregation of a daily load profile into weather dependent and weather independent load. Weather independent load is further disaggregated into scheduled and base loads.

In a review of available building energy datasets the authors were unable to find any that had submetering of end uses. Whole building energy consumption can be disaggregated but the results cannot be validated. Some sub-metered data from buildings from other projects were reviewed but similarly the heating and cooling loads cannot be separated from the ancillary loads (fans and pumps). A simulated dataset was the only dataset found that can be easily validated. Heating and cooling can be separated entirely from ancillary energy consumers like fans or pumps. The Department of Energy's reference buildings dataset simulated for TMY3 gives 936 climate locations with 16 buildings simulated for each (NREL, 2020). The energy is divided into the same end uses for each simulation. A qualitative analysis of the data was undertaken to tag the simulated meters with labels for weather, scheduled and base loads. Some buildings in more extreme climates have space conditioning (heating and cooling) loads 24hrs of the day. This effectively makes space conditioning both a weather and a scheduled load. In this case the load is treated as a scheduled load because it behaves as such. These were scoped out of use for testing as, once the signal has been aggregated, there would be no way to determine which scheduled loads are weather dependent and which are normal scheduled loads.

Investment engine

The platform aims at supporting the users to scope energy consumption reduction and cost saving opportunities. The results of load shape analysis and disaggregation provide the basis for benchmarking and recommendation of the ECMs (Figure 1). Two levels of recommendations are considered, i.e., basic and advanced ECMs. The basic recommendations database is generated based on the review of literature and commonly suggested ECMs for specific building usage types, including those listed in the introduction section. These recommendations are divided in four categories, consisting of building upgrade, surveys, operation and maintenance, and behavioural recommendations. The advanced ECM database is generated based on the Database for Energy Efficient Resources (DEER) (California Public Utilities Commission, 2013). DEER includes the commonly installed energy-efficient technologies and measures. The measures are presented together with an estimated cost and energy-savings potential. They are costed based on the prices in the state of California. Location adjustment factors can be used to modify the material and labour cost for other locations in the US. More details are added to the available ECMs, and each measure in the platform is associated with:

- Measure name
- Category and subcategory of the measure, which is matching with the categories defined in the input database
- Measure description
- Existing pre-measure condition, for instance, for the measure "reflective window film", two pre-measure conditions are specified, *a)* windows installed before 2008, *b)* clear, single-pane glass
- Installation type, for instance, retrofit add-on, early retirement/replacement
- Initial investment cost per floor area [$\$.m^{-2}$]
- Annual energy savings per floor area [$kWh.m^{-2}$]
- Annual cost savings per floor area [$\$.m^{-2}$]
- Annual carbon savings per floor area [$kgCO2.m^{-2}$]
- Payback period [years].

The advanced recommendations are refined based on the users' advanced input (see Figure 1).

Results

At the current stage of this work, the above-mentioned systems and subsystems have already been or are still being developed. Fifty buildings from an online library of data from non-residential buildings have been selected for the purpose of demonstration. The library is published by the Building Data Genome 2 Dataset (Miller et al., 2020). From the available buildings in this library, office buildings in the U.S. with available hourly electricity data were selected. The associated metadata provides the basic required input, i.e., building location, size, usage type, area, and two full years (2016 and 2017) of measured energy consumption.

Benchmarking

Figure 5 presents the benchmarking results and the scores associated with different efficiency factors for each building (building 01 to 50). The scores are sorted as very good (20 scores), good (15 scores), poor (10 scores), and very poor (5 scores). This means that, considering these five benchmark categories, the maximum and minimum total score of a building is 100 and 25, respectively.

Figure 6 presents distribution of the scores for each efficiency factor and gives an overview of the most critical efficiency factors in this portfolio of office buildings. A higher number of buildings with the score "very poor" for base load as compared to the standard office buildings can indicate that potentially a larger part of the total energy consumption in this portfolio is due to non-weather factors, such as occupants' behaviour and usage of equipment and appliances. Percentage of out-of-hour energy consumption is presented in Figure 7. This graph demonstrates the potential wastage (i.e., the excessive energy consumption out of the business hours) in each building and the potential for savings by reviewing and controlling equipment and systems schedules for better building performance.

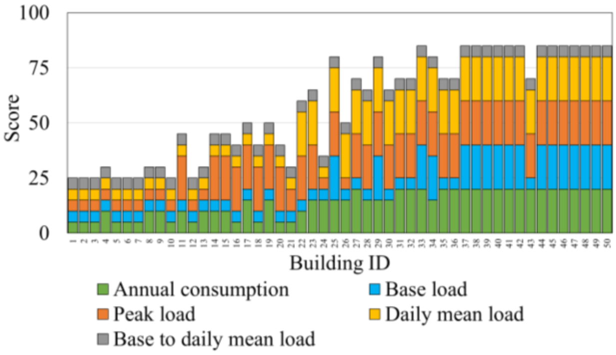

Figure 5: Benchmarking results and the scores (very good 20, good 15, poor 10, and very poor 5 scores) associated with efficiency factors for each building.

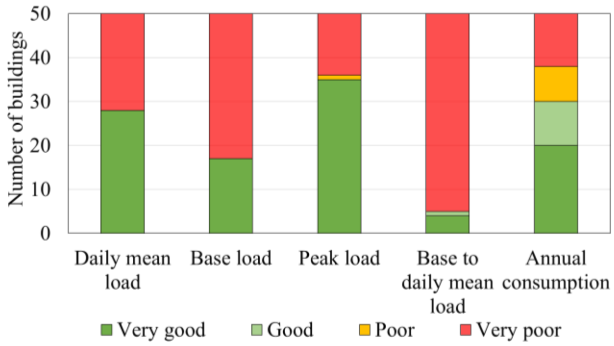

Figure 6: Distribution of the scores in each efficiency factor.

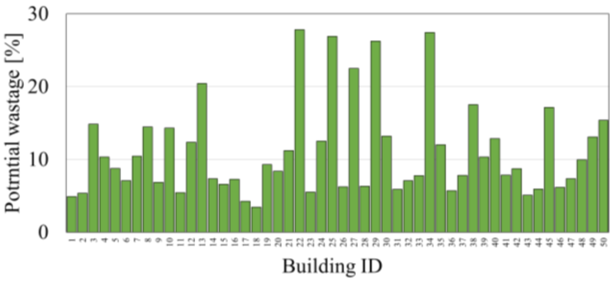

Figure 7: Percentage of the out-of-hour energy consumption as the potential wastage in each building.

Note that, the scores in Figure 5 demonstrate the performance of the buildings as compared to other buildings of the same usage type. The potential wastage in Figure 7 is calculated based on comparing each buildings load profile and its occupancy pattern. For instance, building 34 is ranked as very good compared to its peers. However, investigating its load profile demonstrates above 25% of potential wastage, which relates to the consumption exceeding the base load during unoccupied hours.

Disaggregation

Disaggregation fit performance was satisfactory. There was good agreement between hourly values of simulated and predicted data (Figure 8). Figure 9 shows the breakdown of each building's total energy consumption into three components, i.e., building base load, weather dependant, and scheduled loads.

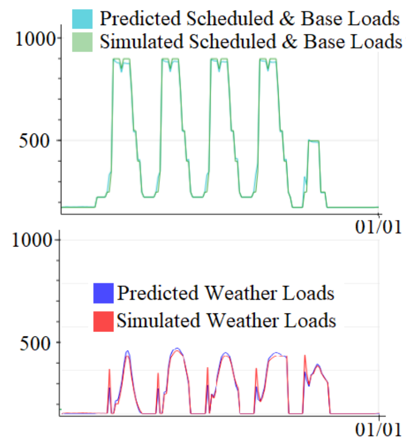

Figure 8: Comparing predicted and simulated energy consumptions for a Large Office.

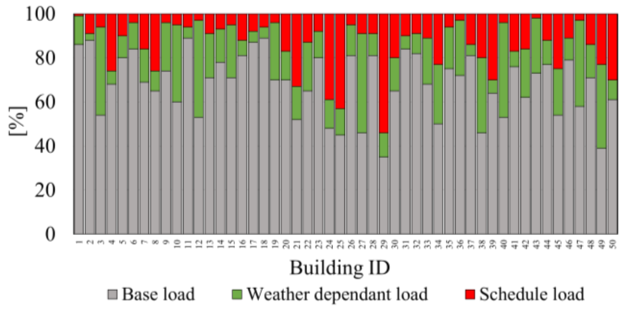

Figure 9: Breakdown of each building's total energy consumption into three components, i.e., building base load, weather dependant, and scheduled loads.

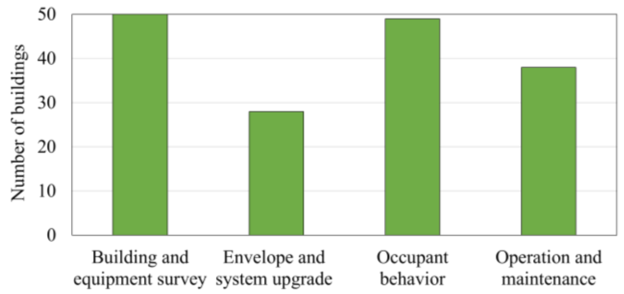

Figure 10: Number of buildings receiving recommendation from each category.

This helps determining the building's response to its environment and identifying the signature of systems and devices in the metered data. It also assists to identify the malfunctioning or faulty systems and provides a measure of energy consumed by specific activities. According to the results, a bigger portion of the energy consumption in this portfolio relates to the base load.

ECMs

Based on the building energy performance analysis and scores presented above, the initial list of energy conservation measures is presented to the user. Figure 10 presents the number of buildings which received recommendations from each of the four ECM categories. This result was guided by the results presented in Figure 5 to Figure 9. Considering none of the buildings received the full score, and all buildings showing at least 5% of potential wastage, it describes the fact that almost all buildings received building and equipment surveys and behaviour related recommendations (low/no-cost recommendations). Almost half of the portfolio received envelope and system upgrade which matches with Figure 5, where around half of the buildings received total score of 50 or less out of 100.

More user input regarding the building envelope and systems will then guide generation of the advanced ECMs. By this, the platform will present a more bespoke list of energy efficiency recommendations.

Table 1 presents an exemplary list of user input from the HVAC category. The user interface should guide the user through the process of providing the requested input data in a smart user-friendly way. For instance, in the example of

Table 1, question H3 is asked when the user selects the answer "AHU: Single Zone" or "AHU: Multi Zone" for question H2 (Table 1, column "Condition 2"). Table 2 presents an example from the costed recommendations database. The cost of each ECM is calculated using the DEER database, which presents the labour and material cost per measure norm unit, and further assumptions regarding the amount of measure's norm unit per square feet area of different building use types. These additional assumptions were made using the measure's DEER documentation or the Department of Energy's reference buildings, in that order of priority.

Conclusion

This work presented a project on the development of a portfolio-scale energy assessment decision-making service, with an example of its implementation. The output is a set of energy efficient alternatives for building operation as well as its elements and systems which improves the energy performance. The process starts with an initial portfolio screening, to identify worst performing buildings with the greatest energy saving potential for further detailed analysis. The data-based approach presented in this paper is used to evaluate different components of a buildings' energy profile and opens up the possibility of identifying the biggest retrofit opportunities with minimal specialist time over large building stocks. The platform suggests actions, including energy efficiency retrofits, related to building fabric, lighting, and HVAC efficiency, as well as behavioural changes.

In the next phase, functionality of scoping different investment alternatives will be added to the platform. The financial metrics will be further expanded to include net present value, internal rate of return, simple payback, discounted payback period, etc. Moreover, a renewable module will be added to investigate the viability of renewable energy systems including PV, wind, and battery storage.

Acknowledgement

The team working on the project presented in this paper includes, in addition to the authors, F. Gielow, A. Medeiros, K. Nejad, M. Mafra, V. Maselli. The authors would like to also thank Maureen Eisbrenner and Simon West for their support.

Table 1 An exemplary list of user input relevant for guiding the HVAC-related ECMs.

ID	Category	Sub-category	Question	Options	Range	Condition1 – Fuel Type	Condition 2
H1	HVAC	Space Heating Cooling	Cooling source	No cooling | Terminal DX coil | Chiller, Central Plant | Condenser with cooling tower, Central plant | Condenser with ground heat exchanger, Central Plant | District chilled water, Central plant | Central DX coil	Selection, Single	Elect. | Elect. & Gas	
H2	HVAC	Space Heating Cooling	Distribution equipment	AHU: Single Zone | AHU: Multi Zone | Zone Equipment (e.g., fan coil, forced air, packaged terminal units)	Selection, Multiple	Elect. | Elect. & Gas	
H3	HVAC	Space Heating Cooling	Air Handling Units (AHU)	Packaged Rooftop Heat Pump | Dedicated Outdoor Air System (DOAS) | Ventilation Only	Selection, Multiple	Electricity	H2: AHU: Single Zone
				Packaged Rooftop Air Conditioner | Packaged Rooftop Heat Pump | Warm Air Furnace | Dedicated Outdoor Air System (DOAS) | Ventilation Only		Elect. | Elect. & Gas	H2: AHU: Single Zone
				Rooftop VAV with Electric Reheat | VAV with Electric Reheat | Dedicated Outdoor Air System (DOAS)		Elect.	H2: AHU: Multi Zone
				Packaged Rooftop VAV with Hot-Water Reheat | Rooftop VAV with Electric Reheat | VAV with Hot-Water Reheat | VAV with Electric Reheat | Dedicated Outdoor Air System (DOAS)		Elect. | Elect. & Gas	H2: AHU: Multi Zone
H4	HVAC	Space Heating Cooling	Zone equipment	Window Air Conditioners | Packaged Terminal Heat Pump | Water-Loop Heat Pump | Ground Source Heat Pump | Baseboard (secondary system)	Selection, Multiple	Elect.	H2: Zone Equipment (e.g., fan coil, forced air, packaged terminal units)
				Four Pipe Fan Coil Unit | Packaged Terminal Air Conditioner | Window Air Conditioners | Packaged Terminal Heat Pump | Water-Loop Heat Pump | Ground Source Heat Pump | Baseboard (secondary system)		Elect.& Gas	
H5	HVAC	Space Heating Cooling	Heating source	No heating | Central Furnace | Electric heat pump | District hot water, Central plant | District steam, Central plant | Convective electric baseboard | Convective hot water baseboard	Selection, Single	Elect.	
				No heating | Central Furnace | Electric heat pump | District hot water, Central plant | District steam, Central plant | Convective electric baseboard | Convective hot water baseboard | Boiler, Central plant		Elect.& Gas	

Table 2 An example from the costed ECMs database.

Category	Sub-category	Measure name	Description	Existing condition	Installation Type	Condition
HVAC	Space Heating Cooling	Unoccupied Fan Control on AC Only Unit	Set fan control on AC only units to "Auto" or intermittent during unoccupied periods to reduce overventilation. Energy savings are achieved through reducing unoccupied supply fan runtime unless zone conditions call for cooling/heating. Reduction in unoccupied supply fan runtime also prevents bringing potentially unfavourable outside air into the conditioned space through leaky economizer dampers, causing an increase in space heating or cooling.	Existing AC Only Unit HVAC equipment with the supply fan operating continuously 24/7 during unoccupied periods	Retrofit add-on	Usage Type: Commercial except hospital, nursing homes, and motels Climate zone: Any Fuel Type: Electricity | Electricity & Gas

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