Benchmarking Building Energy Consumption Using Efficiency Factors

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Abstract

In planning the design and renovation of buildings, benchmarking helps contextualise the evolution of simulated or measured performance of a building through comparison with similar buildings. The present contribution proposes an extension of this concept based on efficiency factors calculated from timeseries of energy, weather, and occupancy (represented by usage). The variation in energy performance of buildings comes from weather and human usage, both of which are boundary conditions that cannot be controlled. This paper explores prediction of what the building does to modulate the effect of weather for providing a comfortable environment according to usage patterns and preferences.

Introduction

Comparing the performance of a tool, system, or organization with its peers or against some standard values is common practice in engineering design to have a consistent baseline for decision-making and quantifying changes in performance. In planning the design and renovation of buildings, this benchmarking helps contextualise the evolution of simulated or measured performance of a building through comparison with similar buildings (DOE 2018). This is a useful approach for evaluating buildings since it is not always clear how much energy a building *should* consume given its usage and location, i.e., it is difficult to create objective and universal performance standards. In practice, buildings are evaluated using one of two approaches: comparison with a standard or nominal building, e.g., ASHRAE 90.1 (ASHRAE 2013), or with a performance-based target like maximum energy used for space conditioning per unit area, e.g., the Swiss Minergie® label (Minergie 1994). Both approaches are targeted towards (re)designing a building, which presupposes accurate knowledge of the current site or building and specialist intervention. The total annual energy consumption of a building may also be compared to a database, such as the commercial buildings reference database (CBECS), which contains data from buildings in different regions and usage types (Michaels 2012). This type of database can be used to compare a building against its peers but provides no insights into how a building's rank can be improved. In this paper we propose a data-based approach to benchmarking the measured energy consumption of buildings that can be used to identify the biggest components of a building's energy (load) profile. A

globally consistent data-based benchmarking system, like the one proposed in this paper, has several advantages over comparisons with nominal buildings, context-insensitive performance targets, or comparison of annual energy figures only. It does this by allowing the estimation of the efficiency with which a building delivers a comfortable indoor environment given its climatic context and usage. This can be used to identify opportunities for improvement and investigate potential wastage quickly and effectively. The efficiency factors proposed in this paper are calculated from measured data and can be easily updated with new measurements to provide continuous feedback for improvements. The efficiency factor of each building can be compared to the whole population or only its peer buildings. Thus, a globally consistent benchmarking system, constructed from empirical efficiency factors, is a fast and simple tool for identifying inefficiencies in buildings.

Though efficiency factors have existed in one form or another for decades, they have been superseded by Building Performance Simulation (BPS), a numerical approximation of the thermo-physical processes in and around a building. To achieve acceptable accuracy, BPS requires accurate and detailed inputs about both the building and its boundary/operating conditions, and exhaustive computation over fine discretisation in space and time. Rapid predictions with acceptable accuracy are, thus, one of the main concerns in building performance analysis (Luo et al. 2017). However, the use-case studied in this paper, of inferring usable insights from high-level data gathered with low specialist involvement, does not provide sufficiently detailed information about the building to properly specify a numerical simulation. Lack of information could be addressed by simplifying the simulation using one of two methods: standardised reference building models, and regression models trained on simulated or monitored data. The role of standardised building models is limited to examining the impact of changing physical assets like lighting using nominal weather and usage inputs. They cannot identify areas of concern that are likely to yield the most savings in the actual building. Regression models work directly with data from the target building and, thus, may yield more pertinent information. The most popular regression models are linear models, especially those based on monthly or yearly heating and cooling degree days (HDD and CDD) (Fels 1986). The degree day works as a proxy for energy consumed for space conditioning because the

conditioning load correlates to the difference between a balance-point or base temperature and outdoor temperature (CIBSE 2006). This base temperature is defined as the outdoor temperature at which a building would require neither heating nor cooling. This is a form of weather normalization and is the most commonly used form of an efficiency factor for a building, predicting energy consumption data as a function of (temperature-based) degree days. This method is the foundation of many energy management tools and decision-making services, including the widely used ASHRAE climate zones (ASHRAE 2013). However, temperature is only one component of the climate and there are other weather or non-weather parameters, such as wind speed, humidity, and solar radiation, which also influence the building energy performance (Dong et al. 2005). Moreover, since degree days are calculated using a balance point, an incorrect assumption of this baseline could result in a misleading outcome about the climate-appropriateness of a building. This limits the scope and accuracy of linear models based on degree days, since consumption profiles dominated by boundary conditions other than temperature cannot be estimated well. These shortcomings suggest the inclusion of other inputs. The limitations of these conventional approaches have spurred the development of new techniques to aid the improvement of building energy performance, many of which are based on measured data. Like linear regression models, these new techniques are so-called black-box models, i.e., causal relationships are replicated entirely by mathematical relationships learnt from data that cannot be broken down to simple physics-based rules (Luo et al. 2017). We discuss two approaches: machine learning and load shapes. Modern machine learning techniques use nonlinear regression models trained on simulated or measured data to approximate building performance rapidly (e.g., Rastogi et al. 2017). Their inputs are simple and may be calculated from high-level building information (Rastogi 2016). As opposed to physics-based building performance simulation tools, these methods "learn" relationships between independent variables (e.g., weather conditions) and dependent variables (e.g., energy consumption) from data. They are, therefore, difficult to generalise. Another data-based approach that has been used to explore energy consumption as a function of time is the concept of "load shape". A load shape is a curve illustrating the load over time. Different methods have been developed to generate the respective curves and interpret the relevant parameters, including near-base load [kW], near-peak load [kW], high-load duration (hours), rise time, fall time, base load percent, peak-to-base load ratio, etc. (Luo et al. 2017). Like machine learning techniques, these too are based on data from a specific building and are, therefore, difficult to generalise.

This paper builds on existing approaches to efficiency factors by proposing two improvements: augmenting existing regression approaches based solely on temperature inputs (degree days) with other weather variables, e.g., outdoor solar radiation and relative humidity; and including estimates of the "base" and

"peak" load of a building. Base load is an estimate of the energy apparently used by essential services, and it is useful to compare their contribution with that of weather-driven envelope loads. Peak load is an estimate of the maximum demand, a combination of weather and non-weather demand, and which can either result in significant energy expenditure or system failures. In this work, we show how these concepts can be combined with weather-based regression models for improved insights using so-called "efficiency factors".

Data

The use of a standard test database confers several benefits, like reducing the required time and effort for data collection and processing and replicability (Tenopir et al. 2011, Taheri and Mahdavi 2018). Efforts have been made to develop a systematic ontology and standardized format as an essential requirement of universal data sharing (e.g., Mahdavi and Taheri 2017). For this study we used an online library of data from non-residential buildings, published by Miller and Meggers (2017). The library includes one year of hourly, whole-building electrical meter data for 507 non-residential buildings, together with building size and the weather file (Miller and Meggers 2017). By eliminating buildings with long gaps in the data, we used 385 buildings in this study. This was the only data check applied. The methodology used here should provide a tracking of consumption against expectation to flag where further investigation is needed. Therefore, for instance, buildings with considerably low total annual consumption rate have not been eliminated. The buildings are distributed across the USA (New York, Phoenix, Chicago, Los Angeles, Denver), Europe (London, Zurich), and Asia (Singapore). The buildings are educational, governmental, and commercial and the use types cover offices (134 buildings), primary/secondary classrooms (33 buildings), college laboratories (85 building), college classrooms (69 buildings), and dormitories (64 buildings). The weather data includes outdoor temperature and relative humidity but not solar radiation. The hourly solar radiation is calculated using the Zhang-Huang model given in Equation 1 (Zhang and Huang 2002).

$$\begin{cases} I = \frac{I_0 \cdot \sin(h)}{k} \{c_0 + c_1 \cdot CC + c_2 \cdot CC^2 \\ + c_3 (T_n - T_{n-3}) + c_4 \cdot \phi + c_5 \cdot V_w\} - \frac{d}{k} & I > 0 \\ I = 0 & I < 0 \end{cases} \quad (1)$$

where:

I = estimated hourly solar radiation [$\text{W} \cdot \text{m}^{-2}$]

I_0 = global solar constant, 1355 [$\text{W} \cdot \text{m}^{-2}$]

h = solar altitude angle, i.e., the angle between the horizontal and the line to the sun (NREL solar altitude)

CC = cloud cover

ϕ = relative humidity [%]

T_n, T_{n-3} = dry-bulb temperature at hours n and $n-3$

V_w = Wind speed [m.s^{-1}]

$c_0, c_1, c_2, c_3, c_4, d, k$ = regression constants as:

$c_0 = 0.5598, c_1 = 0.4982, c_2 = -0.6762, c_3 = 0.02842,$

$c_4 = -0.00317, c_5 = 0.014, d = -17.853, k = 0.843.$

For the purpose of the calculations dry-bulb temperature, cloud cover, relative humidity, wind speed, and solar altitude angle are needed. All the above-mentioned independent variables are included in the weather files, except the solar altitude angle and cloud cover. The solar altitude angle is calculated using the NREL solar altitude formula (Reda and Andreas 2003). The cloud cover percentage is estimated based on sky condition data available in the weather files.

Method

Choice of regression model

We examined two types of regression models to model the measured time series of energy data: linear and nonlinear. A linear model is one where the inputs (features) can be transformed through simple operations like squaring to use in a linear equation. Nonlinear models are those where such transforms of the inputs are not possible. In this paper we tested three model types:

- **Linear regression (LR)** – models the relationship between a single (multiple) independent variable(s) and a dependent variable using a line. The inputs are not transformed in anyway. It is useful and fast for simple relationships and small amounts of data.
- **Polynomial Regression (PR)** – is a linear combination of variables that have undergone nonlinear transformations.
- **Gradient Boosted Trees Regression (GBR)** – models the relationship between independent and dependent variables by training a series of decision tree weak learners, which successively reduce the training error by learning from the residuals of the previous trees. These models train quickly and are good at modelling non-linear relationships.

The best regression model is one that best predicts the real data consistently. Simpler models are preferable to more complex models with similar performance. The error of prediction can be estimated using one of several error metrics, and in this study, we used the Mean Absolute Error (MAE):

$$MAE = \frac{\sum_{i=1}^n |\hat{y}_i - y_i|}{n} \quad (2)$$

where $\hat{y}_i$ is the value of dependent variable predicted by regression model, y_i is the observed dependant variable, and n the number of observations.

Weather normalization has been used for the comparison of energy consumption from different periods and locations with different weather conditions. Weather normalization is commonly based on regression analysis of energy consumption data and the degree days. This method is the foundation of many energy management tools and decision-making services. However, temperature is only one component of the climate that

influences building energy performance. To compare the conventional degree day method with our augmented approach and select the best regression model, we defined five scenarios (Table 1). The difference between the scenarios is in independent variables, data resolution, and the choice of the regression model. In addition, we tested the performance of degree-day-based versus multi-weather-variable regression with the regression model types at different temporal resolutions. The output in all models is always the metered electricity use. Since the fuel source for heating and cooling is not specified for all buildings in the database, uncertainty is introduced in the correlations between weather and metered electric consumption. For example, if gas is used for space heating, electricity usage becomes decoupled from winter temperatures. Differentiating weekdays from weekends was considered as a simple method to include the impact of occupancy pattern on energy consumption. This was applied by adding an independent variable representing the weekends to the models. Building type has previously been shown to be a strong predictor of energy use (e.g., Rastogi et al 2017) as it is a good proxy for occupant-driven usage and base load. Instead of using building type as a regression input, we divided the data by building type to show the performance of each combination of input, resolution, and model for that category of buildings. To choose the best regression model in a scenario with hourly data (i.e., scenarios 3, 4, and 5), k-fold cross validation was used. Each model is fit to a randomly selected training set of 90% of the total training data, and the remaining 10% is used as a holdout set for validation. This is applied to each building.

Table 1: Fit options, changing the independent variables, data resolution, and regression model type

Scenario	Independent variables	Data resolution	Regression model
1	Heating Degree Days (HDD) Cooling Degree Days (CDD)	Monthly	Linear
2	"	"	Polynomial
3	Temperature (T) [$^{\circ}\text{C}$] Solar Radiation (SR) [W.m^{-2}] Relative Humidity (RH) [%] Weekends	Hourly	Linear
4	"	"	Polynomial
5	"	"	GBR

Efficiency factors

The "base load" is defined as the energy used to meet the constant (background) power demand of a building, i.e., the demand that is always "on". It represents the invariable energy consumption in buildings, i.e., the portion of energy consumption that is independent of weather variations. The base load is a key target of building energy management. This load is made up of service lighting, emergency and parking lights, HVAC system idling, standby plug loads, etc. A higher base load reduces the sensitivity of the overall energy output to variations in weather, since the weather-driven component of load is a smaller portion of the overall

figure. The first efficiency factor calculated in this study is the base load per square meter. Quantifying the proportion of base load provides a benchmarking system to evaluate the level that occupants' behaviour and usage of equipment and appliances (e.g., computers, printers, washers, refrigerators, etc.) contribute to energy use. A bigger base load indicates constant operation of building systems and equipment and translates to wastage during night-time or unoccupied hours. The next two efficiency factors are the peak load per unit area and base load-to-total-consumption ratio. These factors can be used for benchmarking by comparing the values among peer buildings, i.e., offices, primary/secondary classrooms, college laboratories, college classrooms, and dormitories. The base load-to-total-consumption is independent of the building size. This is useful when the information on the floor area is not available. An example for this is when energy meters cover a portion of a building rather than the whole building. This ratio enables a good evaluation of the relevance and significance of base load to the building type. The peak load per unit area is also used to compare a building to its peers since there is no clear way to determine what a building's peak load *should* be. In LR models the intercept in the regression equation represents the base load. However, in case of the PR and GBR, the base load in each building is defined as the median of the minimum hourly electricity consumption data every day (i.e., median of the daily minima of the hourly consumption curve). The peak load in each building is defined as the median of the maximum hourly electricity consumption data every day (i.e., median of the daily maxima of the hourly consumption curve).

Results

Augmenting temperature-based regression

Figure 1 shows a boxplot of the mean absolute error for all buildings in scenarios 1 and 2, i.e., fitting monthly consumption to HDD/CDD using linear and polynomial regression models, respectively.

Figure 1: Box plots of mean absolute errors (%) fitting linear and polynomial models to monthly consumption data. The dataset is too small to fit a nonlinear model like Gradient Boosted Regression trees. The bulk of errors are small (less than 20%) for both model types, but there is a small number of large errors; when a model is trained on a very small amount of data (one year monthly consumption), it is unable to predict unusual new cases (months with unusual HDD/CDD)

In these scenarios the number of observations is equal to twelve (monthly consumption) and the linear fit uses two variables while the polynomial fit uses five. The linear model fits the data better in this case, though both models provide acceptable results: 75% of the buildings show MAE less than 15%. As is to be expected, using so little data meant that the models failed for unusual months, i.e., a month with significantly different HDD/CDD from the norm for that location. This explains the long tail of errors for both models (up to 100%).

Next, models with more data and additional features, i.e., using hourly values for each building and including solar radiation, relative humidity, and a variable for "weekends", are tested. Figure 2 presents the MAE for scenarios 3, 4, and 5 by building types. By increasing the number of observations (i.e., one year of hourly consumption data), the more complex models (GBR) performs slightly better. All models provide acceptable fits, except for the primary/secondary classroom. This highlights a major issue with a regression based mostly on weather: the seasonal nature of classroom usage results in large errors during school holidays. The effect of occupancy on energy consumption is considered in the models with a simple categorical variable differentiating weekdays from weekends. However, the change in occupancy pattern due to, for instance, holidays is not considered. Thus, the schools, with a substantial number of holidays compared to the other building types presented here, have the worst fits. Comparing the median MAEs resulted by each model across all the buildings in each category, GBR works best for college laboratories and primary/secondary classrooms, and polynomial regression (PR) for college classrooms, dormitories and offices.

The utility of including new weather parameters can be quantified by evaluating the sensitivity of the modelled consumption to solar radiation and relative humidity in addition to, and compared with, outdoor temperature. Sensitivity to the "weekends" input is presented as well. The sensitivity is quantified as "weights" for each feature (Figure 3), where a larger weight for an input implies that the output is more sensitive to that particular input. Note that the PR model includes the features together with their squared values and combinations, while the other two do not. The results presented in Figure 3 confirm that the model outputs are sensitive not only to temperature, but also to occupancy (for now, represented only by differentiating weekends from weekdays), solar radiation, and, to a lesser extent, humidity. That is, their respective weights are consistently non-zero. In the polynomial fits, higher order effects, e.g., temperature squared, and interactions, e.g., temperature times solar radiation, have much smaller weights. When the information about the fuel source for heating and cooling is not available, the feature's weight could be used as an indicator: higher weights for outdoor environmental parameters indicates greater correlation of electricity consumption to weather, which could indicate that electricity is being used for space heating/cooling.

Estimating efficiency factors from base and peak loads

Area Normalised Base Loads by Primary Space Usage

Figure 2: Mean absolute errors (%) of each model fit to hourly consumption data. The performance of each model is similar for each building type. At this level of simplicity, the building type dominates the fit quality

Figure 5: Area normalized peak loads [kWh.m⁻²] by primary space usage

Figure 6: Base load to total consumption ratio by primary space usage

Figure 6 shows box plots of the ratio of the base load to the total load in each building, by building type. Higher values here may indicate that the building may not shut down during non-occupied hours. This is especially relevant if the building does not already have a high-performance envelope or is not located in a mild climate. In this case investigating internal and plug loads is a priority instead of envelope improvements.

One way to demonstrate that each of these efficiency factors quantifies a different aspect of the building's energy characteristic is to see the order in which the same group of buildings is arranged based on the value of each parameter. Table 3 presents the three buildings, from each

building type, corresponding to the minimum, median, and maximum of each metric. Conventional metrics for comparison, including the building size and annual energy consumption per square meter are presented alongside the efficiency factors proposed in this paper. According to Table 3 the rankings are different considering different metrics. This indicates both that the metrics describe different aspects of the building, and that each metric is not necessarily correlated to another. The choice of the efficiency factor should be guided by the motivation for benchmarking. For example, estimating peak loads would help target demand-response measures.

Table 3: Building ranking based on size, annual electricity consumption, base load, and peak load per square meter, as well as base load to total load ratio

Building usage	Ranking	Building size		Annual consumption per square meter		Base load per square meter		Peak load per square meter		Base load to total consumption	
		ID	Value [m ²]	ID	Value [kWh.m ⁻²]	ID	Value [kWh.m ⁻²]	ID	Value [kWh.m ⁻²]	ID	Value [%]
Office	Min	Javon	689	Elizabeth	2.79	Elizabeth	9.76E-05	Ellie	0.0006	Scottie	2
	Med	Ashanti	6581	Asher	95.47	Gustavo	0.007	Max	0.0162	Garman	8
	Max	Evelyn	155679	Cameron	786.14	Cameron	0.0773	Cameron	0.1038	Louise	24
Primary/secondary classrooms	Min	Angel	960	Everett	2.13	Elisabeth	0.0001	Everett	0.0003	Ulysses	0.08
	Med	Everett	9804	Eva	8.34	Ervin	0.0005	Ellen	0.0019	Edwin	8
	Max	Eoghan	29302	Angel	145.02	Angel	0.0062	Angel	0.0313	Elijah	15
College laboratory	Min	Audra	426	Paul	17.05	Paul	0.0017	Paul	0.0022	Allison	2
	Med	Albert	8480	Suzette	201.47	Annabelle	0.0192	Marie	0.0275	Mario	11
	Max	Tracie	60210	Aoife	909.98	Aoife	0.0994	Allison	0.1231	Aoife	29
College classroom	Min	Conor	399	Clifford	2.33	Clifford	0.0002	Clifford	0.0003	Tamra	2
	Med	Allen	5782	Serenity	96.14	Peter	0.0078	Ciara	0.0158	Alfredo	7
	Max	Tammy	32547	Caitlyn	357.82	Caitlyn	0.0366	Abby	0.0524	Nelly	23
Dormitory	Min	Candace	1697	Una	16.95	Una	0.0012	Una	0.0030	Leonard	4
	Med	Cathal	7287	Mitch	78.69	Alonzo	0.0075	Alyssa	0.0119	Cathalina	15
	Max	April	51395	Cecilia	591.18	Cecilia	0.0622	Cecilia	0.0826	Carter	26

As explained before, the base load is separated out as the intercept in the linear regression, and as the median of the hourly consumption curve minima in the case of PR and GBR. Figures 7 and 8 illustrate the distribution of base load minima and peak load maxima in an office and a university classroom using box and violin plots. We see two types of distributions between Figures 7 and 8: unimodal and bimodal. If the operation of a building was regular and consistent, then we would expect unimodal distributions for both base and peak loads. That is, the building reverts to the same base line every day.

Figure 7: Distribution of base load minima and peak load maxima in an example office, illustrated with box plot (top) and violin plot (bottom)

Figure 8: Distribution of base load minima and peak load maxima in an example university classroom, illustrated with box plot (top) and violin plot (bottom)

The peak load has a seasonal component; hence we expect the distribution to be less strongly unimodal. Many of the buildings in the database do indeed have this kind of data, like the building in Figure 8. These figures provide a simple way to identify buildings that require further investigation. To study the unusual, bimodal, distribution of base and peak loads in "Office_Louise" (Figure 7), we plotted the time series values in Figure 9. Based on this graph, in July the base load shifts down from nearly 40 to about 20 kWh.m⁻². This might happen when another fuel is used for heating, but in the case of this building, the drop does not coincide with the heating season. Thus, a simple plot identifies whether a building needs to be investigated further for faults or energy-saving opportunities.

Figure 9: Hourly electricity consumption in Office_Louise from Figure 7. The sudden change in July indicates the necessity of further exploration.

Figure 10: Hourly electricity consumption in UnivClass_Peter from Figure 8

Conclusion

In design and renovation of buildings, benchmarking helps contextualise the evolution of simulated or measured performance of a building through comparison with similar buildings. A given design modulates the effect of weather and human usage, and variation in these boundary conditions creates variation in the energy usage. Since these boundary conditions cannot be controlled by a designer nor known with perfect accuracy, this paper presents a benchmarking method that judges buildings based on the efficiency with which they modulate weather conditions to provide indoor conditions suitable for their usage. Meter data and weather conditions were used to build simple black-box models of the thermo-physical characteristics of a building and identify inefficiencies suitable for investigation. The power of this method is that minimal knowledge is required about the building

geometry and physical properties as compared to white- or grey- box models. Since the benchmarking system is based on time series, it can be used with both measured and simulated data. And since it is based on measured data from a building and its site, it is global in application. These models open up the possibility of identifying the biggest retrofit opportunities with minimal specialist time requirement over large building stocks. Through the black-box models proposed here, we extend the utility of the well-established degree day concept and present useful new efficiency metrics that can be empirically estimated from the data at hand. The results present that the choice of the regression model depends on the resolution of the available data: simpler models require less data to fit but, conversely, provide less information. Based on the best fit calculated for each building, the future consumption may be predicted against predicted future weather along with the impact of potential improvements. Similarly, it is possible to quantify the effect of actions taken by comparing the energy consumption of the building predicted by a regression model based on the "old" building against the consumption of the "new" building. Quantifying the ratio of base load to the total consumption provides a benchmarking system to evaluate the priority areas and potential effects of improvements. For example, lower ratios indicate energy consumption is driven by the weather conditions and the building envelope and that the behaviour of occupants, heat gains from equipment, etc., do not contribute; while a high proportion of base load indicates that addressing internal and plug loads should be a priority over envelope improvements. This could be because the building already has a high-performance envelope or is in a mild climate. The efficiency factors proposed in this paper demonstrated the potential to use simple factors to identify energy-efficiency opportunities from benchmarking measured energy performance. The efficiency factors or graphs do not themselves indicate *what* the problem is, if any. They simply indicate where further resources should be committed to investigation.

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