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ORIGINAL ARTICLE

The use of sub-hourly primary meter data to identify electricity savings in municipal buildings

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Abstract Sub-hourly electricity consumption data is being routinely collected from non-domestic buildings in European countries, yet there is little published guidance on how to analyse this data. A new analysis technique is described that produces electricity load profile indicators to help identify potential electricity savings from 81 municipal buildings of six different types: commercial and public offices, libraries and museums, sport centres, schools, community centres and care homes/hostels. This approach is different from conventional energy management analysis techniques since it uses total electricity consumption data in half-hourly periods rather than annual or monthly data. The analysis enabled the detection of buildings with consumption profiles that differ significantly from the typical profile for that building type. This provided a systematic and rapid procedure to identify potential energy saving opportunities in multiple buildings. The new approach introduces a standard statistical technique, independent of energy manager judgement, to help identify energy saving opportunities in buildings.

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Introduction

Policy

It is estimated that 30 to 40 % of worldwide energy consumption occurs in buildings and that this figure is increasing (United Nations Environment Programme 2007). Since buildings often last over 100 years, the importance of reducing the energy demand of the existing building stock should play a key part in the strategy to mitigate the impacts of climate change in the medium and long term. Buildings account for approximately 36 % of the EU emissions (Official Journal of the European Union 2012) and therefore represent a significant opportunity for targeting emission reductions. EU energy policy recognises the importance of smart meters in the reduction of building energy consumption. In fact, the European Parliament in the resolution *Towards a new Energy Strategy for Europe 2011–2020,* (European Parliament 2010), suggest a policy goal for Member States to achieving at least 80 % of consumers equipped with smart metering systems by 2020. The Energy Efficiency Directive (OJEU 2012) and the recast of the Energy Performance in Building Directive (Official Journal of the European Union European Parliament and the European Council 2010) both address the need to promote the use of energy metering and monitoring to assess buildings' performance and induce energy savings. The EU Energy Efficiency Directive in its article 8 goes even further and clearly states the need to roll out smart metering to all energy users. It says that final customers should have access to indicators of energy cost and consumption and utilities should be able to bill individual users in regular intervals, based on actual consumption.

Energy data

The availability of sub-hourly energy metering, in particular for electricity consumption, can have a very positive impact on the promotion of more efficient energy use in buildings. However, in order to achieve its full potential, there is a need to improve data management and data analysis methods. As more energy consumption data becomes available, it will be important to have "automatic" tools to quickly analyse large quantities of data. These tools need to be able to rapidly identify uncommon characteristics in building energy consumption patterns that may be indicative of potential savings. The analysis of energy consumption time series data based on annual and monthly periods is a well-established procedure (Fels 1986; MacDonald and Wasserman 1989; Haberl et al. 1996; Harris 1999; American Society of Heating, Refrigerating and Air-Conditioning Engineers ASHRAE 2001; Lee 2008); however, techniques to analyse half-hourly energy data are still in their infancy. Previous research on the analysis of building energy consumption data in hourly or smaller intervals has tended to focus on manual and automatic diagnostic techniques applied to Building Energy Management Systems (BEMS) data (Liu et al. 1997; Claridge et al. 1999; Pakanen and Sundquist 2003; Piette et al. 2001). This has also included the visualisation of time series data, a relatively well-researched area (Ferreira 2009). These techniques have been applied successfully to the analysis of sub-hourly data; however, they can often be compromised by the subjective interpretation of the analyst. Automated diagnostics tend to be applied to data generated by BEMS, rather than metered energy data, because they collect energy, temperature, lighting, ventilating and air conditioning data. However, the amount of data is often overwhelming and it is difficult for the user to know which data are significant. Automated diagnostics systems using fewer data inputs are therefore required (Katipamula and Brambley 2005).

European projects

The EU Intelligent Energy Europe projects have been testing the use of sub-hourly energy data from primary meters (i.e. total consumption) of non-domestic buildings and businesses. The ENERinTOWN (Ferreira et al. 2008) and Intelligent Metering (Webber et al. 2007) projects dealt specifically with municipal buildings. In the first, different types of meters and communication systems were used to collect electricity and gas consumption data from around 77 buildings from 32 municipalities in Europe. Data was analysed using visual analysis techniques (such as bar charts, graphs and contour plots) available in specialised monitoring software and spreadsheets packages. The conclusion was that significant savings, up as much as 50 %, could be achieved through the use of sub-hourly electricity and gas consumption from the municipal building's primary meter. The main energy efficiency measures implemented were related to the reduction of equipment and lighting being used during non-occupied periods and from improved time and temperature control settings. The training of energy managers and information campaigns towards building occupants' using collected data contributed to the high level of savings achieved. The Intelligent Metering project looked at data from 70 municipal buildings in four countries, and arrived at similar conclusions. Significant savings were possible using the smart metering, analysing data, discussing results with the building manager and occupants in order to agree on corrective energy efficiency measures. A pilot study conducted by the UK Carbon Trust on the use of sub-hourly data from smart metering systems from SMEs concluded that it was possible to identify about 12 % of carbon savings through the use of energy metering and monitoring systems (HMSO 2007). The aIM4SME project, which conducted a study in about 75 SMEs in Europe, concluded that the applications of the smart metering systems were as follows: reduction in overnight and weekend consumption, reduction in daily peak consumption, very early identification of faults that caused excessive consumption and quantification of savings arising from investment in new plant and equipment (Webber et al. 2011). All the above results were attained using sub-hourly energy data from primary meters analysed using conventional software packages equipped with simple visualisation techniques. In all the above projects, a relatively small number of facilities (typically less than 100) were analysed since it is relatively time consuming to visual inspect bar charts, graphs and contour plots of each building's sub-hourly data.

New technique

The new technique described in this paper takes at least 1 year's half-hourly data for different classifications of buildings and rapidly produces a series of load profile indicators from which energy managers can then identify buildings where there are potential energy savings. The introduction of such an automated approach to primary meter data analysis could improve the cost-effectiveness of the smart metering systems, by quickly providing the information on which energy managers can compare and benchmark the consumption profiles, and promptly detect energy saving opportunities. This would also enable an assessment of the potential for energy saving that is independent of the analyst's experience, using readily available accurate energy consumption data. Data analysed were total electricity consumption collected directly from the primary meter every half hour. The data are collected using a proprietary system, which combines hardware for collecting the metered data and a software package for processing data. This system is described in the Energy Efficiency Best Practice Programme—General Information Leaflet 49 (HMSO 1996). The system is similar to what has been generalised as Automatic Meter Reading (AMR) (Vasconcelos 2008). Leicester's approach is described in more detail in Ferreira et al. (2007) and a detailed technical presentation is available in Brown and Wright (2008).

This paper contributes to the debate on automated building diagnostic tools by presenting the results of the analysis of half-hourly electricity data from over 80 municipal buildings in the city of Leicester, UK. It introduces a standard statistical technique, independent of energy manager judgement, to help identify energy saving opportunities in buildings.

Smart metering data analysis

The Leicester City Council half-hourly electricity consumption data covers a wide range of non-domestic buildings and premises: offices, schools, libraries, leisure centres, administration offices, elderly persons homes, warden-assisted accommodation, etc. These are shown in Table 1. A total of 81 municipal buildings were analysed in detail. Data were supplied in text format, then converted and stored in a Microsoft® Standard Query Language (SQL) Server™ 2005 database. Whilst the SQL Server incorporates basic data analysis functions, this was not able to carry out the complex analysis, therefore Matlab® software, from Mathworks, was used to analyse the data. The building classification adopted was derived from the Pclass codes presented in Bruhns et al. (2000). This is a classification based on the activities conducted in non-domestic buildings. The database consisted of commercial and public offices (CO), hospitality buildings devoted to leisure (HL), schools (SE) and social community buildings (SQ). HL buildings were divided into libraries and museums (HL1) and sport centres with and without swimming pool (HL3). Similarly for SQ buildings, a division between community centres (SQ10) and hostels and care homes (SQ21) was introduced. The following table presents the Pclass codes used to classify selected buildings from Leicester half-hourly utility metering database.

The buildings vary in size, most are less than 5,000 m^2. The smallest building is 136 m^2 (library) and the largest building is 22,166 m^2 (school). However, the school is not just one building, but a collection of buildings and the metered energy (electricity and gas) consumption is for the total school premises.

Half-hourly electricity indicators

The metrics used for the analysis of half-hourly electricity consumption consisted of indicators that described the buildings' daily and weekly load demand profiles and can be described as load demand shape indicators. The indicators were calculated using the average 24-h electricity demand profiles for weekdays (Monday to Friday), for weekends (Saturday to Sunday) and for the full week (Monday to Sunday). For example, the annual mean weekday load demand profile is calculated as the mean value of the 48 data points (one for each 30-min interval) for 1 year of data. These three average profiles were then used to calculate the indicators, which model the building occupancy patterns, intensity of energy use and baseload consumption.

Previous research on electricity grid load demand forecasting by Nazarko and Styczynski (1999) and Chicco et al. (2001, 2002 and 2003) identified 12 load demand shape indicators. Following an extensive literature review, no evidence was found that these indicators had been applied to building energy management. These indicators have characteristics that could be relevant to model energy consumption in buildings. They are ratios, calculated using the weekdays (Monday–

Table 1 Number of datasets and building types

Building type	Pclass	Activity classification	No. of buildings
Commercial/office	CO	All type of commercial, local and central government office activities	19
Hospitality/leisure	HL1	Museums, art galleries or libraries	9
Hospitality/leisure	HL3	Leisure centres, sports halls, swimming pools, etc.	5
Schools	SE	All type of schools, from kindergartens to universities	11
Social/community	SQ10	Community centres, neighbourhood centres or social clubs	8
Social/community	SQ21	Social hostels, children homes, elderly people homes, warden-assisted accommodation	29

Friday), weekend (Saturday–Sunday) and week (Monday–Sunday) demand profiles. Average (AV), minimum (MIN) and maximum (MAX) values presented in Fig. 1 are then calculated for the different periods of the day (d, o, n):

- Day (d): the 24 h of the day,
- Night period (n): period from 2200 to 0600 hours,
- Office working hours (o) from 0800 to 1800 hours,

The night (n) and office working hours (o) periods model the times when the buildings are non-occupied and occupied, respectively.

Table 2 presents the 12 load demand shape indicators initially calculated in the study (Ferreira 2009). For example, the first daily indicator, the weekday load factor, α_{D1}, is the load factor for weekdays (Monday to Friday). It is calculated by dividing the daily (d) average (AV) energy use ($E_{d.\mathrm{AV.weekdays}}$) by the daily maximum (MAX) demand on weekdays ($E_{d.\mathrm{MAX.weekays}}$).

An analysis of the results of the initial set of 12 indicators (Ferreira 2009) found that these could be reduced to five indicators. In fact, it was concluded that some indicators reproduced the same information, for example α_{D1} and α_{W1} were strongly correlated. Similar conclusion was reached for α_{D2} and α_{W2}. So α_{W1} and α_{W2} could be removed. It was also found that other indicators presented similar results for all the buildings, and therefore did not contribute to differentiating demand profiles and identify opportunities to save energy.

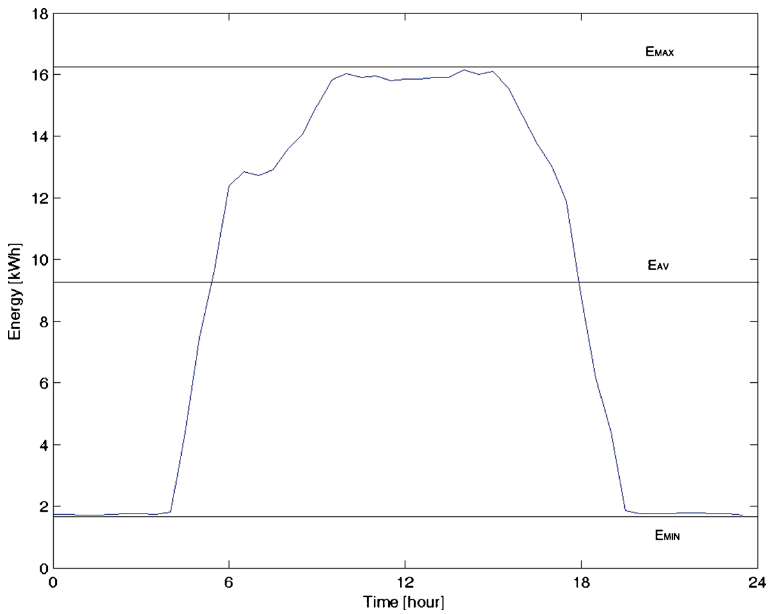

Fig. 1 Electricity load profile model with energy variables

Table 2 List of electricity indicators

Indicators	Short name	Equation
α_{D1}	Weekday load factor	$\alpha_{D1}=E_{d.\text{AV.weekdays}}/E_{d.\text{MAX.weekdays}}$
α_{D2}	Weekday baseload	$\alpha_{D2}=E_{d.\text{MIN.weekdays}}/E_{d.\text{AV.weekdays}}$
α_{D3}	Weekday office hours load factor	$\alpha_{D3}=E_{o.\text{AV.weekdays}}/E_{o.\text{MAX.weekdays}}$
α_{D4}	Weekday office hours baseload	$\alpha_{D4}=E_{o.\text{MIN.weekdays}}/E_{o.\text{AV.weekdays}}$
α_{D5}	Weekday/weekend peak demand	$\alpha_{D5}=E_{o.\text{MAX.weekdays}}/E_{d.\text{MAX.weekdays}}$
α_{D6}	Weekday/weekend baseload	$\alpha_{D6}=E_{d.\text{MIN.weekdays}}/E_{o.\text{MIN.weekdays}}$
α_{D7}	Weekday night	$\alpha_{D7}=E_{n.\text{AV.weekdays}}/E_{d.\text{AV.weekdays}}$
α_{D8}	Weekend night	$\alpha_{D8}=E_{n.\text{AV.weekend}}/E_{d.\text{AV.weekend}}$
α_{D9}	Weekday lunchtime	$\alpha_{D9}=E_{l.\text{AV.weekdays}}/E_{o.\text{AV.weekdays}}$
α_{W1}	Week load factor	$\alpha_{W1}=E_{d.\text{AV.week}}/E_{d.\text{MAX.week}}$
α_{W2}	Week baseload	$\alpha_{W2}=E_{d.\text{MIN.week}}/E_{d.\text{AV.week}}$
α_{W3}	Weekend/week	$\alpha_{W3}=E_{d.\text{AV.weekend}}/E_{d.\text{AV.week}}$

In summary, the five load demand shape indicators considered were as follows:

- Weekday load factor (α_{D1}) is the average load on weekdays (Monday–Friday) divided by the peak load on weekdays. This indicator varies from 0 to 1. A high load factor means that power usage is relatively constant over the weekdays average 24-h demand profile. However, a constant power usage over a 24-h period in an intermittently occupied building might be indicative of excessive intensity of energy use (α_{D1}), which could be reduced. Nevertheless, this conclusion can only be derived after comparing buildings of the same type and/or similar use, as presented in "Results per building type" section.
- Weekday baseload (α_{D2}) is the minimum load divided by the average load on weekdays. For the building under study, this indicator also varies between 0 and 1. A high baseload factor (α_{D2}) means that minimum power usage, which for the type of buildings in the study occurs during periods for which buildings are not occupied, might be excessive, and therefore the causes for high baseload consumption need to be investigated and could be potentially reduced.
- Weekday night (α_{D7}) is the night (2200 to 0600 hours) average load on weekdays divided by the day (full 24 h) average load, also on weekdays. For the buildings under study, this indicator also varies between 0 and 1. A high weekday night (α_{D7}) indicator means that energy consumption, on weekdays, and during the night period, is similar to the consumption during the day and therefore might be excessive.
- Weekend night (α_{D8}) is the night (2200 to 0600 hours) average load on weekends divided by the day (full 24 h) average load, also on weekends. This indicator might be above 1 for some building types (e.g. buildings that are closed during weekends but have security lighting during the night time). A high weekday night (α_{D8}) indicator means that energy consumption, on weekends, and during the night period, is similar to the consumption during the day.
- Weekend/week (α_{W3}) is the average load on weekends divided by the average load of the week (Monday to Sunday). This indicator (α_{W3}) should be below 1 for most of the buildings in the study. It models the load demand during weekends compared with the overall load demand for the 7 days of the week.

Table 3 provides an overview of the aggregated results of the calculation of the five indicators for the six different building types under analysis, including the standard deviation values.

Results per building type

Different buildings types have distinct consumption profiles, due to different occupancy patterns and use. For example, the load factor for SQ21-type buildings (homes/hostels) is expected to be consistently higher than for other buildings since these are usually permanently occupied. However, this does not necessarily mean that SQ21 buildings perform "better" or "worse" than other buildings because of their relatively high load factor.

The five indicators were calculated for the 81 buildings and typical electricity indicators for each of the six

Table 3 Indicators per building type and standard deviation

Building type (Pclass)	Activity classification	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}
CO	All type of commercial, local and central government office activities	0.50±0.08	0.38±0.12	0.41±0.12	0.90±0.11	0.51±0.14
HL1	Museums, art galleries or libraries	0.46±0.10	0.22±0.14	0.26±0.13	0.43±0.16	0.65±0.10
HL3	Leisure centres, sports halls, swimming pools, etc.	0.76±0.12	0.53±0.23	0.61±0.24	0.67±0.22	0.89±0.13
SE	All type of schools, from kindergartens to universities	0.47±0.07	0.40±0.11	0.45±0.12	1.03±0.08	0.47±0.10
SQ10	Community and neighbourhood centres or social clubs	0.51±0.07	0.34±0.12	0.48±0.22	0.82±0.20	0.62±0.21
SQ21	Social hostels, children/elderly people homes, warden-assisted accommodation	0.78±0.09	0.78±0.12	0.87±0.09	0.90±0.09	0.98±0.02

building types presented in Table 3. The typical electricity indicators were defined as the mean value of each indicator and were calculated for each building type. These are the values against which buildings of a similar type can be compared in order to identify uncommon profile characteristics and these can be considered the typical electricity profiles for these building types.

Table 3 shows that commercial and public offices (CO) buildings average consumption on weekdays is 50 % of the peak load (weekday load factor−α_{D1}= 0.50). For these buildings, the weekday baseload indicator (α_{D2}) is 0.38, i.e. the baseload is about 38 % of the average demand on those days of the week. The impact of night-time electricity consumption on weekdays (when compared to "normal" office hours consumption) is 41 % (α_{D7}), which is surprisingly high, and might be indicative that most office buildings under analysis have excessive night-time electricity demand. On weekends, the night-time electricity consumption impact is 90 % (α_{D8}), meaning that night and day have similar power demands, as expected over the weekend. The average electricity consumption on weekends (α_{W3}) is about 51 % of the average demand on the 7 days of the week.

When compared to office buildings (CO), libraries and museums (HL1) have lower weekday load factors (α_{D1}), lower baseload consumption (α_{D2}), but higher electricity consumption on weekends (α_{W3}).

Load shape profiles for sports centres (HL3) have higher indicator values because these are open for longer hours than offices and libraries. Sports centres' weekday load factor (α_{D1}) is 0.76, the weekday baseload indicator (α_{D2}) is 0.53 and weekend/week indicator (α_{W3}) is 0.89, all higher than offices, libraries and museums.

Schools (SE) and community centre (SQ10) are similar to other intermittently occupied buildings, such as commercial and public office buildings. However, SQ21 are permanently occupied buildings, so have higher load factors, baseload and consumption over night and on weekends.

Benchmarking using electricity indicators and standard scores

The results above enable the 12-month average electricity load demand profiles for each building to be calculated. The next stage of the analysis compared these profiles against a typical/mean profile for that building type characterised by the five indicators to identify any major differences.

The mean and standard deviation values identified the distance from the mean value of each calculated indicator (Urdan 2005). The *z* score−z_i associated with each indicator value x_i is given by the following equation, where x_i is subtracted by the mean value (x) and divided by the standard deviation of all observations in the group (i.e. buildings of the same type).

$$z_i = \frac{(\overline{x}_i - x)}{\sigma}$$

Eq. 1 Standard score calculation

This standardisation process compared the indicator results for the different buildings of the same type. A standard score of 1.00 is a result that is above the mean by exactly 1 standard deviation. If the values follow a normal distribution, a standard score of 1.00 is equivalent to 84.13 % of the values (84th percentile). Standard scores above 1.00 were considered "outside the expected" in terms of a "normal" energy consumption profile, and therefore were indicative of the potential for energy savings. Standard scores below −1.00 are also considered "outside the expected", but, conversely, these mean that the consumption profile is better than the average.

This therefore introduces a standard statistical approach to energy management, which is independent from the traditional manual visual interpretation of graphs. Whilst the standard score method was selected in preference to percentiles due to the (small) number of buildings of each type, when data is available for a larger number of buildings the use of percentiles for benchmarking would be more appropriate.

The results of the standardised scores for all the buildings are presented in the tables below for each building type. The bold emphases indicate standardised values that are outside what is considered to be the range of common consumption profile, i.e. above 1 standard deviation from the mean value of the building type. The calculation of the electricity load demand indicators for the 81 buildings and the application of standard scores resulted in the identification of 26 buildings with potential energy saving opportunities. The following tables present the results of the analysis for each of the six building types. The results were discussed with the municipal energy management team to identify the causes of the "atypical" consumption.

Table 4 Standardised load shape indicators for office buildings

Building name	Standard scores				
	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}
CO_1	0.25	−0.85	−0.95	0.71	−1.15
CO_2	0.08	0.24	0.35	−1.73	**1.20**
CO_3	−1.04	−0.96	−1.08	0.97	−1.44
CO_4	**2.60**	**2.24**	**2.30**	−0.32	**2.46**
CO_5	−1.48	−0.40	−0.56	0.21	−0.66
CO_6	0.00	0.19	0.35	−0.15	0.11
CO_7	−1.13	−1.38	−1.49	−2.16	−0.93
CO_8	−0.63	−0.13	−0.26	**1.22**	−0.53
CO_9	−0.50	−0.63	−0.66	−1.07	−0.05
CO_10	−0.24	−1.18	−1.29	0.55	−1.49
CO_11	0.29	0.65	0.67	0.92	0.36
CO_12	**1.80**	**1.83**	**1.66**	0.37	**1.29**
CO_13	0.22	−1.00	−0.72	−0.81	−0.58
CO_14	−0.51	0.67	0.47	0.71	0.22
CO_15	−0.36	−0.71	−0.44	0.06	−0.32
CO_16	−0.56	0.03	−0.16	−1.41	0.42
CO_17	−0.30	−0.32	0.10	0.91	−0.15
CO_18	**1.30**	**1.07**	**1.05**	0.14	0.78
CO_19	0.20	0.63	0.66	0.89	0.47

Office buildings

Table 4 shows that the CO_4, CO_12 and CO_18 buildings have high weekday load factor (α_{D1}), high energy use intensity (α_{D2}) and high night-time energy use on weekdays (α_{D7}), when compared with similar buildings. These buildings have different consumption profiles from the "typical" office building for different reasons. The CO_4 demand profile is different because in this building there is also a snooker bar in the ground floor, which is open until midnight. CO_12 demand profile is an office air-conditioned building, which was not being controlled properly. CO_18 is an old office building with inefficient lighting systems.

In addition, it was detected that CO_2 had high weekend consumption, which was caused by lights and equipment left on by occupants. CO_8 building night-time consumption was also found to be uncommonly high. This was caused by the building night security lighting, which could be reduced with the installation of motion sensors.

The indicators were able to identify several uncommon characteristics of load demand profiles; some were related to untypical uses of office buildings, others were related with opportunities to save energy. Similarly results were found for other building types, as presented in the following tables.

Conversely, CO_6 present a "normal" demand profile, with indicators close to the mean values of CO-type buildings. The differences between the profiles are clear, particularly in terms of the occupancy hours, differences between baseload and peak demand, night-time and daytime consumption, and weekday and weekend consumption.

Libraries and museums

The indicators identified HL1_1 building as having high weekend consumption (α_{W3}), which was caused by the poor programming of lighting controls that resulted in lights being turned on weekends when the library was closed. HL1_7 indicated high night-time consumption during weekends (α_{D8}) that was caused by security lighting. HL1_5 was found to have a rather different profile. This building is the only museum in the group; an air-conditioned building with very precise control of temperature and humidity for artefacts, resulting in a relatively high electricity use (Table 5).

Table 5 Standardised load shape indicators for libraries and museums

Building name	Standard scores				
	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}
HL1_1	−2.19	0.15	−0.07	−1.01	**1.90**
HL1_2	0.13	−0.63	−0.49	−0.38	−0.50
HL1_3	0.86	−0.38	−0.01	−0.02	−0.51
HL1_4	−0.28	−0.61	−0.75	−1.06	0.07
HL1_5	**1.07**	**2.55**	**2.45**	**1.88**	**1.33**
HL1_6	0.88	−0.22	0.36	0.54	−0.43
HL1_7	0.07	0.13	−0.06	**1.04**	−1.05
HL1_8	−0.66	−0.48	−0.70	−0.88	0.10
HL1_9	0.12	−0.51	−0.74	−0.11	−0.91

Sports halls

The electricity indicators did not identify any excessive consumption in the sports halls. This sample had a small size of only five buildings and the buildings were quite different. Some sports halls had swimming pools and others did not (Table 6). A narrower breakdown of buildings classification and a large sample size is therefore necessary to complete the analysis, which was not possible with available data.

Schools

From the analysis of schools, SE_1 identified potential savings from reduction of intensity of energy use (α_{D1}), baseload consumption (α_{D2}), energy use when building unoccupied on night-time on weekdays (α_{D7}) and reduction of energy use when building unoccupied on night-time on weekends (α_{D8}). However, this is a special school for students with physical difficulties, and therefore there are more energy consumption for wheelchair charging, motors for opening and closing doors. This caused high baseload and overnight consumption. SE_6 is also a special school, but it was found that equipment was left running during weekend when the school was not occupied. SE_3 and SE_9 were found to have unusually high night-time consumption during weekends (α_{D8}) caused by night security lighting (Table 7).

Table 6 Standardised load shape indicators for sports halls

Building name	Standard scores				
	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}
HL3_1	0.42	0.40	0.52	0.42	0.70
HL3_2	0.63	0.56	0.57	0.66	0.33
HL3_3	0.14	0.59	0.48	0.43	0.43
HL3_4	−1.76	−1.77	−1.77	−1.77	−1.77
HL3_5	0.56	0.22	0.20	0.26	0.31

Table 7 Standardised load shape indicators for schools

Building name	Standard scores				
	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}
SE_1	**2.15**	**1.78**	**2.17**	**1.38**	0.21
SE_2	−0.46	0.55	0.08	−0.03	0.63
SE_3	−0.84	−0.52	−0.36	**1.00**	0.00
SE_4	−0.01	−1.06	−1.02	−1.47	−0.85
SE_5	−0.58	−0.75	−1.06	−0.57	−0.86
SE_6	**1.33**	**1.24**	0.71	−0.75	**1.10**
SE_7	0.26	0.74	0.82	−0.87	**1.75**
SE_8	0.45	0.51	0.24	−1.01	0.85
SE_9	−0.53	−0.72	0.27	**1.32**	−0.41
SE_10	−1.19	−1.16	−1.01	0.50	−1.30
SE_11	−0.61	−0.60	−0.84	0.50	−1.12

Community centres

Table 8 shows that community centre SQ10_6 had high base-load consumption. It also suggests that there is the potential to reduce night-time and weekend consumption in SQ10_7, since this building presents higher energy use on those periods when compared with similar buildings.

Table 8 Standardised load shape indicators for community centres

Building name	Standard scores				
	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}
SQ10_1	**1.05**	−0.05	0.08	−1.11	0.89
SQ10_2	0.67	0.14	−0.55	0.18	−0.64
SQ10_3	0.65	0.58	−0.25	−0.48	0.07
SQ10_4	−1.69	−1.30	−1.17	0.79	−1.83
SQ10_5	−1.28	0.00	−0.51	−1.29	0.08
SQ10_6	−0.28	**1.81**	0.68	0.05	0.92
SQ10_7	0.27	−1.29	**2.10**	**1.80**	**1.10**
SQ10_8	0.61	0.11	−0.38	0.05	−0.60

Elderly persons homes and hostels

SQ21 buildings are all warden-assisted accommodation (sheltered housing for older people). The lighting systems for some of these buildings were upgraded with more energy efficiency lighting. However, whist more energy efficient lights were installed, the lighting levels are now higher than the previously, resulting in additional electricity consumption. This was the case for SQ21_8, SQ21_12, SQ21_13, SQ21_17 and SQ21_27. It was also found that SQ21_12 building had a large car park that was lit overnight (Table 9).

Table 9 Standardised load shape indicators for homes/hostels

Building name	Standard scores				
	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}
SQ21_1	0.15	−1.56	−0.47	−0.84	**1.47**
SQ21_2	−0.23	−0.53	−0.27	−0.30	−0.01
SQ21_3	0.26	−0.20	0.43	0.35	0.14
SQ21_4	−0.52	−0.24	−0.28	−0.26	−0.48
SQ21_5	−0.35	−0.37	−0.57	−0.64	−0.01
SQ21_6	0.95	0.33	**1.63**	**1.46**	**1.47**
SQ21_7	0.19	0.58	−0.13	−0.30	0.77
SQ21_8	**1.84**	**1.71**	**1.23**	**1.11**	0.18
SQ21_9	−1.51	−2.50	−2.68	−2.67	−0.65
SQ21_10	−0.23	**1.10**	0.68	0.82	−0.49
SQ21_11	−0.67	−0.73	−0.93	−1.18	0.80
SQ21_12	**1.16**	0.55	**1.64**	**1.41**	0.95
SQ21_13	**1.73**	**1.60**	**1.16**	**1.03**	**1.81**
SQ21_14	0.10	−0.19	−0.60	−0.74	0.40
SQ21_15	−0.25	0.24	−0.09	−0.20	0.39
SQ21_16	0.61	−0.50	0.01	−0.14	0.47
SQ21_17	**1.69**	**1.33**	0.86	0.71	0.50
SQ21_18	−1.81	0.23	−0.60	−0.05	−2.06
SQ21_19	−0.62	−0.55	−1.21	−0.77	−2.10
SQ21_20	0.50	0.09	−0.46	−0.59	0.25
SQ21_21	0.27	−0.16	0.68	0.67	−0.43
SQ21_22	−1.81	−0.71	−0.45	−0.53	0.47
SQ21_23	0.80	**1.36**	0.99	0.82	0.77
SQ21_24	−1.02	−1.37	−1.08	−0.98	−0.57
SQ21_25	−0.31	−0.29	−1.24	−1.33	0.10
SQ21_26	−0.98	−1.13	−0.78	−0.53	−0.37
SQ21_27	**1.05**	**1.32**	**1.07**	**1.21**	−0.46
SQ21_28	0.25	0.91	0.89	**1.31**	−2.22
SQ21_29	−1.24	−0.34	0.60	**1.14**	−1.08

The development of the electricity load profiles have identified buildings with load demand profiles that differ significantly (i.e. 1 standard deviation from the mean) from "typical" electricity load profile for that building type. This "benchmarking" analysis identified of buildings that by their intrinsic or/and operational characteristics differ from similar buildings. Not all the features were related to energy efficiency measures, rather to different uses of the building. The indicators offer a systematic and automated procedure to analyse sub-hourly time series data from a primary electricity meter.

These indicators could be easily integrated in energy analysis and billing software packages to help identify those buildings to investigate further and to provide tailored advice for building managers and users on profile characteristics that are not "typical" and that therefore might be related to potential savings.

Conclusions

A new approach to identifying more specific information about the building's performance by comparing it with similar buildings of the same type has been developed. It can readily identify:

- High intensity of energy use,
- High baseload consumption,
- Energy use when building unoccupied on night-time on weekdays,
- Energy use when building unoccupied on night-time on weekends, and
- Energy use when building unoccupied on weekends.

The five indicators, based on half-hourly electricity consumption, provide a more detailed understanding of the typical electricity consumption patterns in different building types. They identify uncommon profile characteristics that can then lead to action to implement energy savings. The technique can be used for a large number of buildings and so allows building occupiers to identify potential energy saving opportunities for different building types. That is, peak, daytime, night-time and out of hours electricity consumption compared with typical consumption for that type of building. Overall, the new approach provides a level of detail not available through traditional monthly or annual analysis or through conventional visualisation techniques.

The analysis is relatively quick and straightforward to carry out on large numbers of buildings. It can be automated and it helps to eliminate the subjectivity of the conventional data analysis using visualisation of plots and graphs. However, local knowledge is vital to identifying whether they are real savings or untypical buildings. Discussions with the building's energy management team are essential to then lead to on-site investigations that result in the detection and correction of electricity wastages.

There is great potential to use this approach to achieve improved building operational energy efficiency and contribution to EU targets. With Member States investing in the rollout of smart meters to all electricity users, the availability of sub-hourly data will no longer be a barrier to energy management. The analysis techniques described in this paper have the ability to analyse a large volume of data and provide useful tailored advice and feedback to electricity consumers in non-domestic buildings, and can also be applied to the analysis of other utilities measured in sub-hourly periods for example gas and water consumption.

Future work

The approach has been successfully used for electricity consumption on over 80 municipal buildings. The next steps are to expand the number and types of buildings and to use the approach for gas consumption.

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