Smart energy performance indicators for live historical and normative feedback systems

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Abstract

Communicating building energy performance to building users has been identified as a significant opportunity to support behaviour change. This research pursues the concept of continuous, automated feedback designed to support motivated building users to learn how their behaviour impacts building energy performance.

Automated energy consumption data collection presents an opportunity to develop approaches for continuous feedback systems. However, energy performance is a complex notion and consumption data alone are not suitable to convey performance. In order to be of use, performance indicators designed specifically for providing feedback to building users must reflect changes in user behaviour which may be small relative to total consumption.

A new building energy performance indicator is proposed based on the concept of continuous improvement. The indicator combines the benefits of historic and normative feedback by producing a normalised index of improvement or deterioration over time. The indicator is also well suited to communicating building energy performance in a user-friendly way.

The indicator is based on a predictive consumption model fitted to data for a rolling baseline period. The scale of the indicator is defined in terms of the variation in baseline model residuals. This allows for a direct comparison between buildings on the basis of improvement or deterioration from the baseline performance. A direct comparison can be made even between very different buildings.

A case study of five university buildings is presented. Consumption is predicted at half-hourly resolution using a variation of a standard variable degree day model. The indicator is calculated for each half hour beyond the initial 365-day baseline period on a rolling basis with a new baseline model being calculated each week.

The indicator reflects even small changes to regular consumption patterns, both persistent and transient. Persistent changes are absorbed into the rolling baseline model after a few months. Critically the indicator is sensitive enough to detect small changes in consumption patterns and can be compared between buildings. As a feedback tool the indicator has the benefit of having a common scale and being comparable across buildings.

Introduction

In recent years there has been much interest in the use of feedback systems to encourage energy behaviour change but very little literature on the design of feedback systems in the non-domestic setting. Energy consumption is largely invisible to building users [1] and energy feedback is primarily useful because it makes energy “more visible and more amenable to control” [2].

The behaviour of building users has an important influence on energy consumption. Very often simple, low-cost or zero-cost changes to occupant behaviour can have a significant effect on building energy consumption. These so called **low-hanging fruit** are a great opportunity for motivated building users to take meaningful, autonomous action to save energy [3]. However, if a space is comfortable and equipment is working, the effects of energy consumption are not obvious to building users. Only the services provided by energy are visible, if they are removed (e.g. the space becomes uncomfortable or equipment fails) then a user will notice the impact immediately. Information about the energy consumption required to deliver these services is usually not available.

Half-hourly consumption data from automated meter reading (AMR) systems and smart meters are becoming ubiquitous in larger public buildings and modern building energy monitoring systems collect data at least every half an hour. These 'live' data provides a valuable resource for energy management. They can be used to diagnose problems as soon as they occur, to identify opportunities to reduce energy wastage and to measure and verify the savings from energy efficiency interventions. They can also be used as a means to communicate energy performance to building users and the wider population of stakeholders.

It is desirable to provide feedback systems that enable building users to benefit from these high quality datasets and to directly see the impact of their behaviour on energy performance in more or less real time. In this work "continuous energy performance feedback systems" are defined as continuous information loops in which information about the energy performance of a building in the past and present is used to influence present and future energy performance. A feedback system allows users to learn the impact of their behaviour and enables them to adjust their behaviour to reduce energy consumption. Users can experiment with modifications to their behaviour and see the impact of these changes directly and immediately.

The methodology presented in this paper was developed as part of the EU-funded SMARTSPACES project [4]. The SMARTSPACES project is developing ICT-based services at eleven pilot sites across Europe, each designed to save energy in public buildings. The methodology presented underpins the SMARTSPACES services provided in the Leicester pilot site in the UK [5].

The Leicester pilot site services are designed as a continuous energy performance feedback system, a schematic of this is provided in Figure 1. The main components provided by the system are a metering and communications system, a data modelling and analysis system and web-based visualisation and user engagement tools.

The metering and communications system in Leicester has been in place for over a decade providing high quality, high resolution (half-hourly) electricity, gas and water consumption data. The final link in the feedback loop is user engagement which is delivered primarily via a modern, open source online discussion forum. A detailed discussion of these aspects of the system is outside of the scope of this paper.

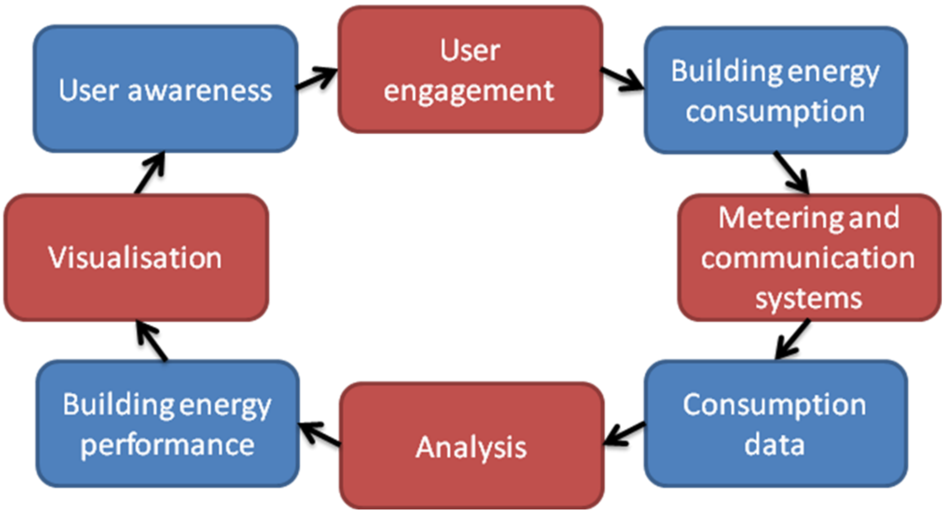

Figure 1: Schematic of data and information flowing in an energy performance feedback loop

The primary subject of this work is the data treatment components including analysis and visualisation. Automated modelling and analysis tools process historical raw data as a way to provide context for recent consumption and to extract the most salient information from the available data. Another critical and carefully designed component is the web-based user interface which provides visualisation tools necessary to deliver useful information directly to the building user in a usable form.

Modeling and analysis

Feedback resolution and timing

For a continuous energy performance feedback system to be effective, it must provide information at a temporal resolution suitable to allow users of the system to distinguish between different behaviours. For example, a feedback system that worked on a daily resolution would provide a single feedback report representing the entire day. If the user required feedback on overnight energy performance then this will be aggregated with daytime performance and difficult to resolve. Similarly, feedback provided at weekly resolution would obfuscate the effects of weekly occupancy cycles. In this case the system is based on half-hourly data and is designed to provide feedback at this resolution. That is, users are provided with information at half-hourly resolution.

The data collection infrastructure which provides the energy consumption data is configured to generate half-hourly data. However, the system only communicates these data at three-hourly intervals. As such the information available can be up to three and a half hours out of date. This is a critical aspect of any such system. Were data provided less frequently (e.g. once a week or once a month) then the users would need to remember what they were doing last week or last month in order to map the feedback to their knowledge of activities in the building. More frequent updates provide timely feedback and remove this barrier to information flow. In this respect, providing feedback at sub-daily resolution has a huge advantage.

Context-free information

The aim of the smartspaces project is to create a feedback system to provide all building users including visitors, staff and energy professionals with usable information. Feedback systems rarely provide simple raw consumption figures. Indirect feedback, where the data have been processed in some way, is more common [2]. In this paper we describe a somewhat extreme approach to data processing.

For most building users, we must assume that energy is not an important issue. As such it is unlikely that users will commit significant time and effort to interpret any feedback provided. Ideally, the information delivered should be context-free, requiring as little prior knowledge and interpretation as possible. Providing information that requires sophisticated interpretation is a major barrier to feedback. Reducing the context improves the flow of information around the feedback loop. For example, providing information about energy consumption in units such as kilowatt hours (kWh) is meaningless unless the audience is also aware of the context (i.e. what is a kWh).

There are many examples of attempts to communicate in more familiar units (e.g. “enough energy to make x cups of tea”). This is an example of contextualizing the information. In this case the context is moved from knowledge of kWh to knowledge of tea. By combining information with its context a modified version of the information is produced with a reduced or modified contextual requirement. When manipulating data in this way it is important to consider what context an audience will be aware of in order to produce a suitable form of information. The audience no longer needs to know what a kWh is, but are expected to be familiar with tea.

In this research a more esoteric context of building energy consumption is explored. Providing absolute energy consumption information is reliant on knowledge of how much energy a building ***should*** be consuming under the current circumstances, which in turn requires knowledge of the current circumstances. Without this information, the consumption data alone cannot be easily interpreted. Put another way, energy consumption (the dependent variable) depends on circumstances such as weather and occupancy (independent variables). To determine whether the current consumption is high or low requires knowledge of weather and occupancy and a knowledge of how the building typically responds to these variables.

Contextualizing consumption in this way might involve placing the value within a range of expectation. But it is desirable to provide more than simply raw data. We can reduce the complexity of the message and provide higher-level information. This can be done by converting consumption to a simple message reflecting performance on a scale from good (lower than to be expected under the circumstances), through neutral to bad (higher than expected). This context-free information can be interpreted without prior knowledge of the building. The remainder of this section describes a method based on a statistical model of historical consumption data for creating a robust indicator of energy performance that can be used in a continuous feedback system.

An instantaneous performance indicator

Raw consumption data offer little to the casual observer. Time and effort is required to look closely and understand the patterns. Figure 2 shows two years of half-hourly electricity and gas consumption for four university buildings (outside air temperature is also indicated in red). The data are relatively complicated. Several patterns can be observed in the data, consumption varies seasonally with temperature affecting heating and availability of natural light affecting demand for artificial lighting. At a shorter timescale there are weekly and daily cycles relating to occupancy.

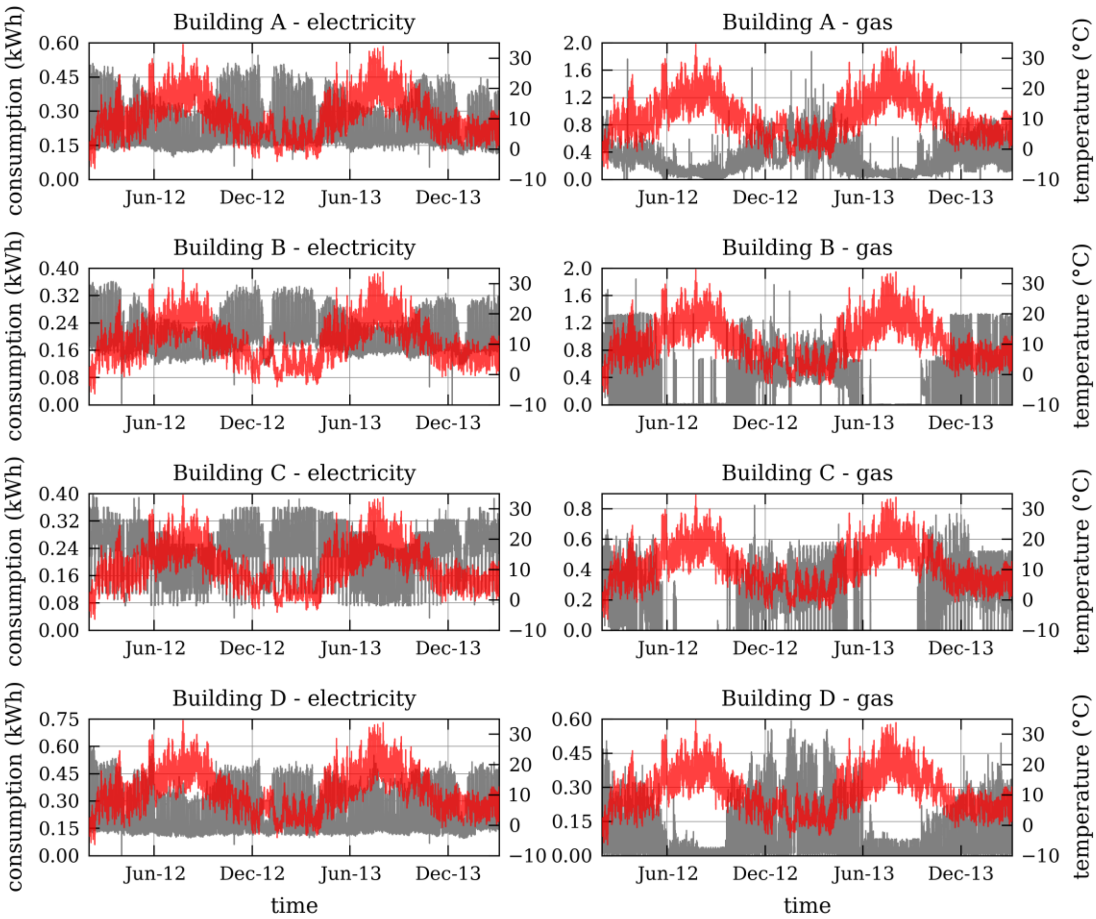

Figure 2: Raw energy consumption data for four buildings (outside air temperature in red)

It would be very difficult for a user unfamiliar with energy data to extract any useful information from a graph of energy data. In any case, as discussed above, energy consumption is not the information we want to communicate. Even for an experienced analyst, an assessment of current performance would require time and effort to produce.

To communicate energy performance we need to define it. For the purposes of this paper, "energy performance" is defined simply as the absence of energy wastage. The energy consumption of a building comprises consumption necessary to deliver useful energy services plus energy wastage. Whilst absolute energy performance is difficult to establish from raw consumption data, relative performance from one period to another is not so difficult if we make certain assumptions. A historical comparison can be a useful proxy for changes in energy wastage. If consumption falls below the historical norm then savings can be said to have occurred. Conversely, wastage is indicated by an increase in consumption above historical norms. A historical comparison is used as the core measure of energy performance or more accurately "energy saving performance".

Energy saving performance

The International Performance Measurement and Verification Protocol (IPMVP) (EVO 2007) defines a methodology for carefully and precisely quantifying change in consumption patterns due to energy interventions. In particular the protocol defines a baseline period before the intervention and a test period, after the intervention. The baseline is used to establish the pattern of consumption before the intervention was implemented. IPMVP can be implemented with simple regression models fitted to data collected in a baseline period. The standard model is the variable based degree day model, Figure 3 shows this model and several variants.

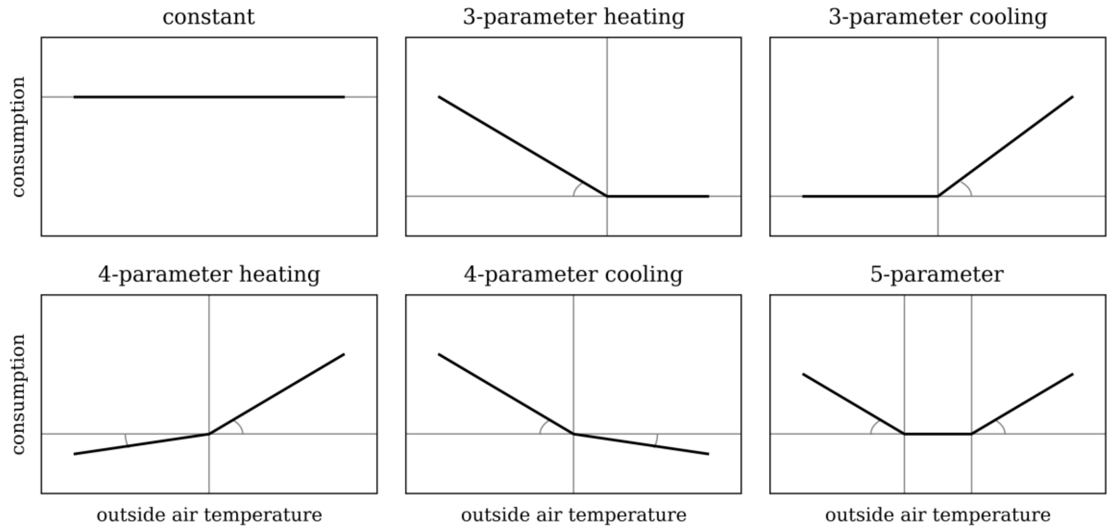

Figure 3: Common variations of the variable-base degree day model

A common IPMVP approach is to fit an appropriate model to data collected in a baseline period and to use this baseline model to forecast forwards into the test period (the period in which savings are to be verified). This is typically done as a one-off calculation where the baseline period is the period covering several months before an intervention was implemented and the test period covers several months after the implementation.

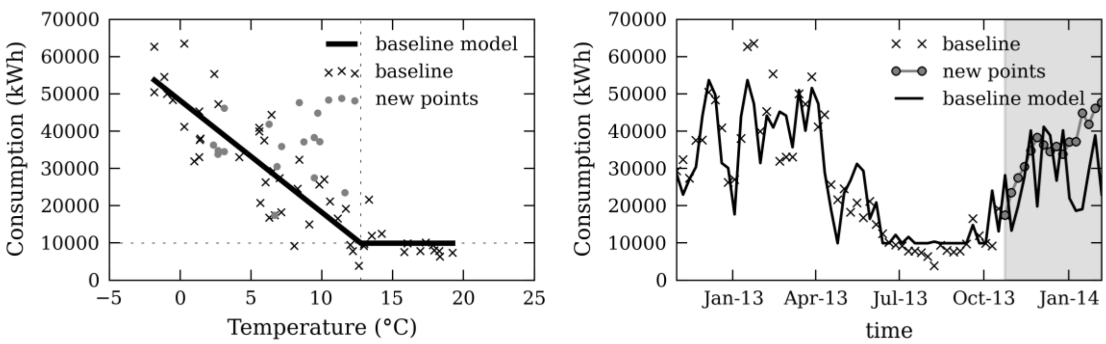

Figure 4: Example energy saving calculation with baseline model and forecast into test period

Savings are calculated as the difference between measured consumption in the test period and the forecast consumption which provides an estimate of what consumption **would have been** without the intervention. Figure 4 shows an example calculated with weekly data. The chart on the left shows a three parameter heating model (the black line) fitted to baseline data (the black crosses). Data from the test period are also plotted as dots. The right side of the figure shows the same model and data transferred onto the time axis. It can be seen that the data collected in the test period (dots on grey background) are above the forecast consumption. This indicates an increase in consumption presumably caused by either increased energy wastage or an increased demand for energy services.

The same approach can be extended to a continuous monitoring scheme where every half-hourly data point is compared to a consumption model fitted to the previous 12-month baseline period. To reduce the computational overhead, this can be simplified to a scheme where a model fitted to a 52-week baseline period is used to forecast one week of half-hourly consumption. Before discussing this method in any more detail, it is useful to describe the actual models used in a concrete implementation of the scheme.

A simple, half-hourly consumption model

In order to model half-hourly consumption patterns it is necessary to extend the consumption models described above by taking occupancy into account. At half-hourly resolution the main feature of consumption data is the daily and weekly occupancy patterns. Figure 5 shows a single week of data for each of the example datasets. Consumption patterns are dominated by the effects of occupancy. The occupancy pattern shown is broadly consistent for each building as changes to opening hours are rare. This pattern of consumption must be predicted accurately for the scheme to be useful.

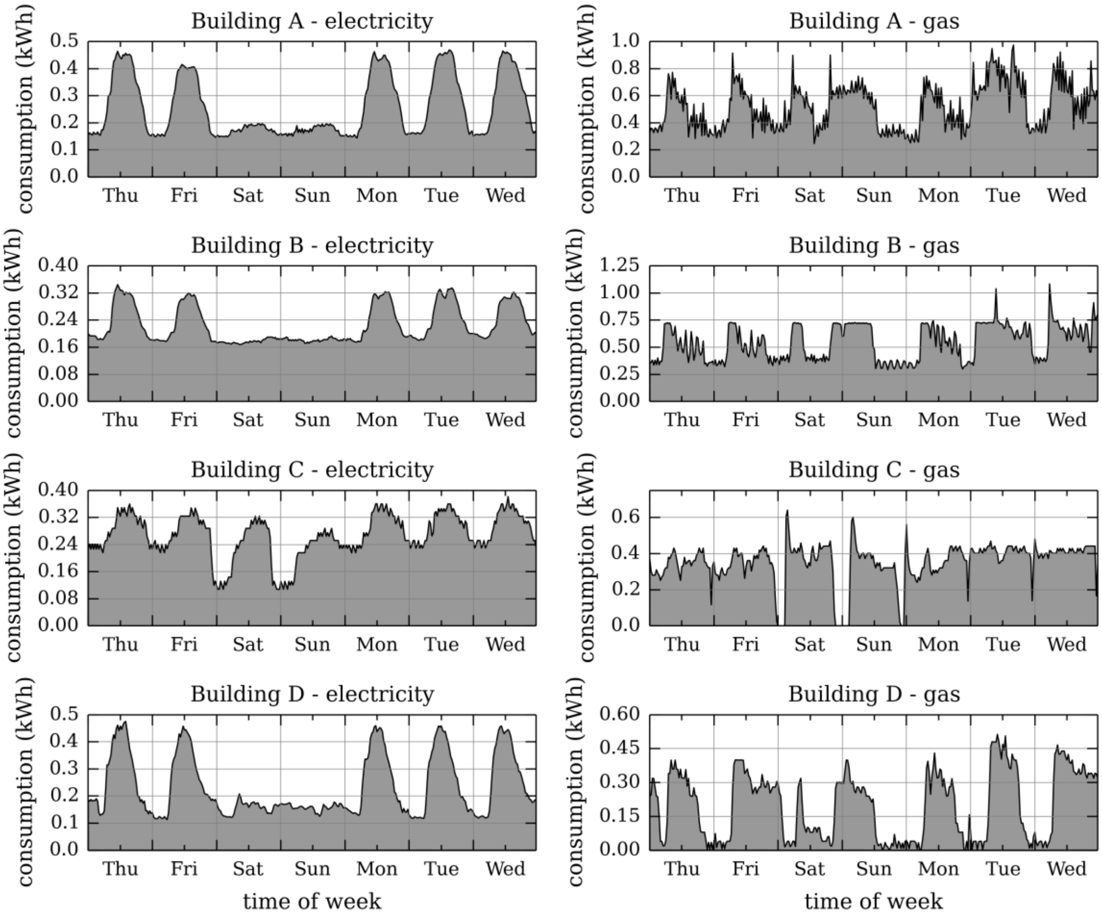

Figure 5: A single week of electricity and gas consumption data for the example datasets

To model this pattern, baseline data are split into 336 subsets, one for each half-hour period in the week (i.e. a combination between time of day and day of week, e.g. one subset only contains data from Mondays at 09:00). Each subset contains 52 data points. The baseline model is created by fitting an independent model to consumption data within each of the subsets. This generates 336 individual sub-models. To generate a prediction from a data point in the test period, the appropriate sub-model is identified and used to generate the prediction.

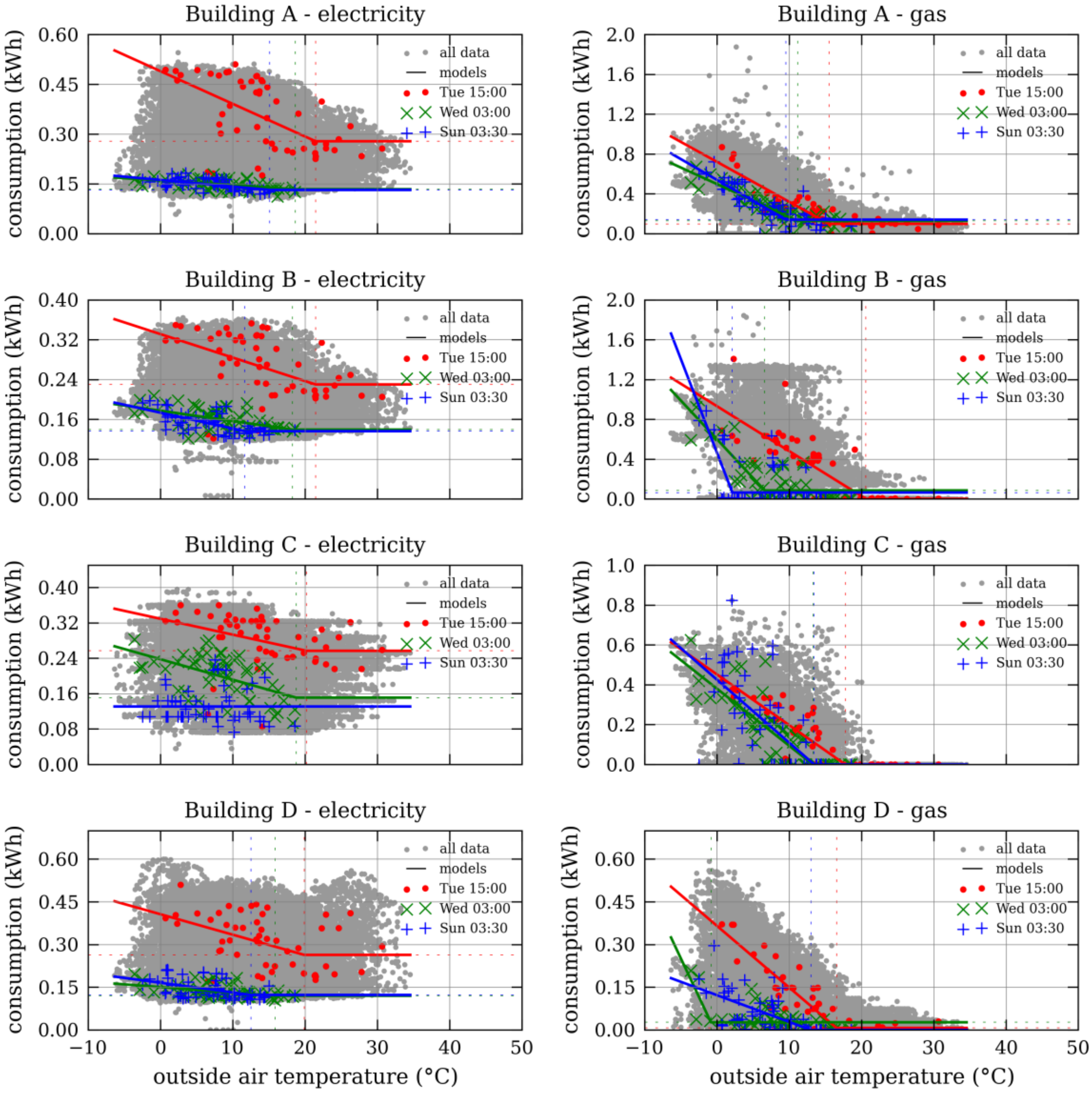

Figure 6: Three sub-models (Tue 15:00, Wed 03:00 and Sun 03:30) for the example datasets

Figure 6 shows how the model fits to data from different buildings. Only three periods are shown to avoid confusion (the full set of 336 models would be difficult to visualize in this way). The blue line and points indicate a weekend overnight period (03:30 on Sundays) when the buildings are expected to be unoccupied. In most cases this period is shown to be the lowest consumption period with lower values for the model parameters. The green line and points indicate a mid-week overnight period (03:00 on Wednesdays) when the buildings are also expected to be unoccupied. In most cases this model is very similar to the weekend equivalent but some buildings show systematically higher consumption during this time indicating different control strategies and possibly occupant behaviour. The final period highlighted in red shows an occupied period (15:00 on Tuesdays) and shows a clear difference in model parameters during occupied and unoccupied periods for most buildings. Interestingly, the gas consumption shows a far smaller difference. This is likely due to high setback temperatures and relatively poor heating control.

It should be noted at this point that the type of sub-model applied is determined by an intelligent algorithm [6] which selects either the constant model or the three-parameter heating model (see Figure 3) based on the Bayesian Information Criterion. This allows for a more parsimonious fit to the data and helps avoid spurious effects of over-parameterized models. This can be seen in the electricity consumption of building C where a constant model has been chosen for the data from Sundays at 03:00. An automated method is necessary when working in a live information system.

Figure 6 only shows three sub-models for each dataset. To visualize the complete model requires some more innovative design work. To create a visualisation, each model was used to generate a matrix of predictions covering each of the 336 time periods and a range of temperatures from -5°C to +35°C at 0.5°C intervals. This grid of predicted data was then converted into a false colour image. The resultant visualisations are shown in Figure 7.

Figure 7 reveals some interesting features that are not easily visible in the raw data. The model represents a simplification of the pattern of consumption in each building. It is clear that there are similarities between the buildings in both their electricity consumption pattern and their gas consumption pattern. Building C stands out as using electricity both on the weekends and into the evenings. This is expected as it is a Library and is occupied almost 24 hours a day, 7 days a week. As in Figure 6 we can see a strong correlation between electricity consumption and outside temperature in all buildings. This may be due to pumps and fans of the heating systems or may be mostly the impact of seasonal availability of natural light.

During warmer periods electricity consumption maintains a strong correlation with occupancy, this is likely to be mainly due to occupants turning on equipment and lighting but also timer controls. Gas consumption during warmer periods tends to have a flatter profile though not necessarily at zero consumption as some buildings have gas powered hot water (which seems to be independent of occupancy). Interestingly, there is electricity consumption later into the evening during colder periods. This indicates that the consumption may be due to lighting and that there may be some lighting control based on available natural daylight which decreases in a seasonal pattern closely matching temperature. If the consumption pattern during warmer periods is a proxy for occupancy (i.e. variation above the base-load is the sum of occupants actions) then it may be that lighting in the colder (and presumably darker) evenings is serving very few people.

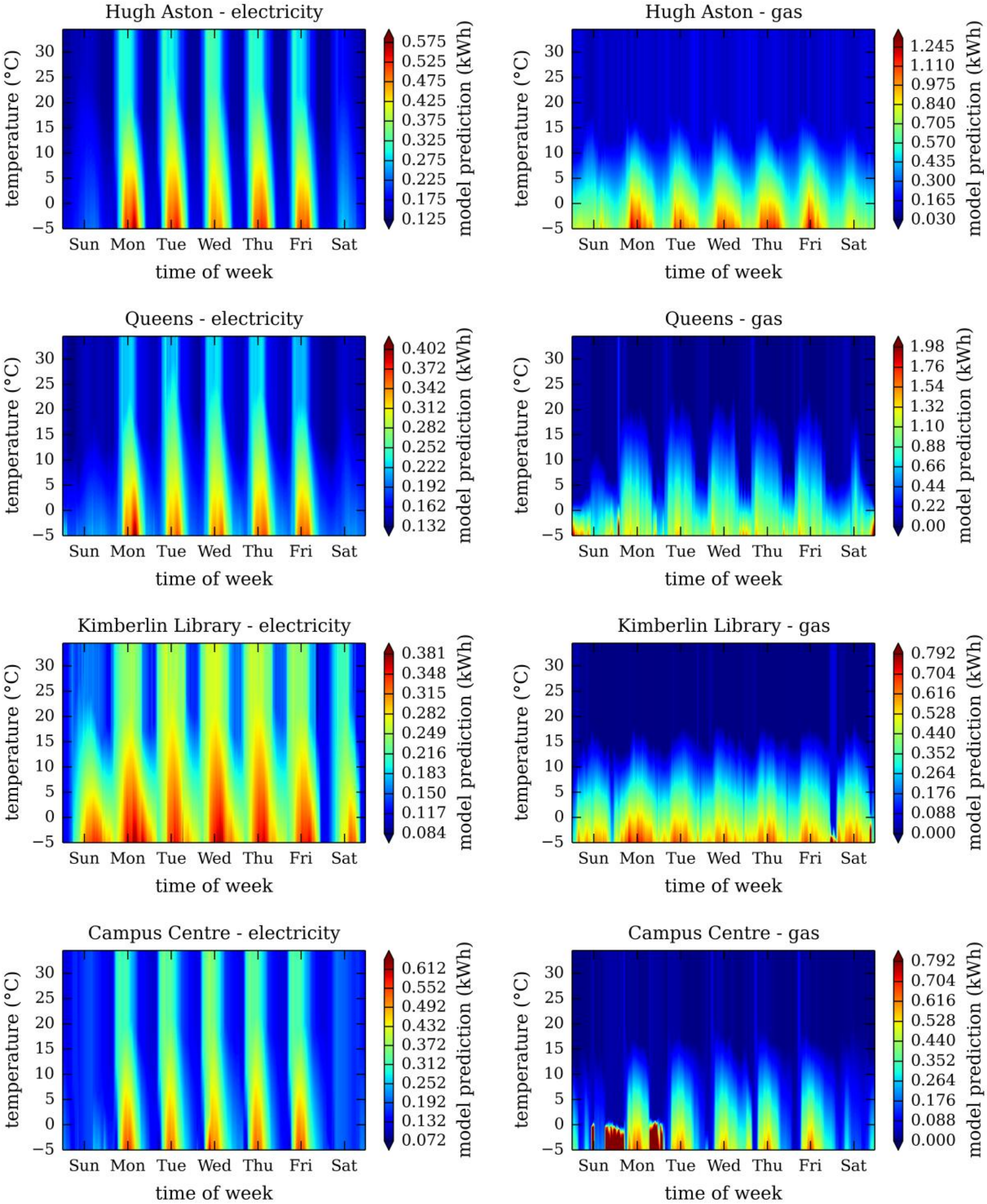

Figure 7: Full consumption models visualised for the example datasets

The model is clearly effective at establishing a realistic pattern of consumption in the baseline period. It is also capable of generating a reliable estimate of consumption under given conditions. This is simply a matter of identifying the time of week and the outside air temperature for which a prediction is required and using the model parameters to produce a predicted value. The following section describes how the model was used.

Setting up a monitoring regime

The model described above can be used to estimate savings using a similar approach to that shown in Figure 4. It can be fitted to 52-weeks of baseline data and used to forecast one or more points into the future using measured outside air temperature and the known time of week for data in the test period. A simplistic approach would then be to directly compare the forecast with the actual measured consumption. This is a very useful approach for calculating savings but requires some interpretation and does not provide a complete picture. The variation in the data around the model (shown for example in Figure 6) is in some cases approaching the scale of consumption being predicted. If this is not communicated as part of the feedback then there is a real danger of misinterpretation. Absolute deviation from the baseline model is not a direct measure of relative energy performance and needs to be presented in context.

For example, in a particular building a deviation of 1kWh during peak occupancy periods may be minor and considered well within the normal variability of consumption. The same deviation of 1kWh may be drastic and noteworthy during unoccupied periods. Similarly, a 1kWh saving may be insignificant in one building but very significant in another. Our aim is to communicate deviation in terms of what is normal for a particular building. As discussed above, it is ultimately desirable to present energy performance as a context-free normalised scale from 'good' to 'bad'. This would then require no special knowledge to interpret the feedback. Such a simple message is likely to be picked up by more users, even those with no experience of the building seeing the feedback for the first time.

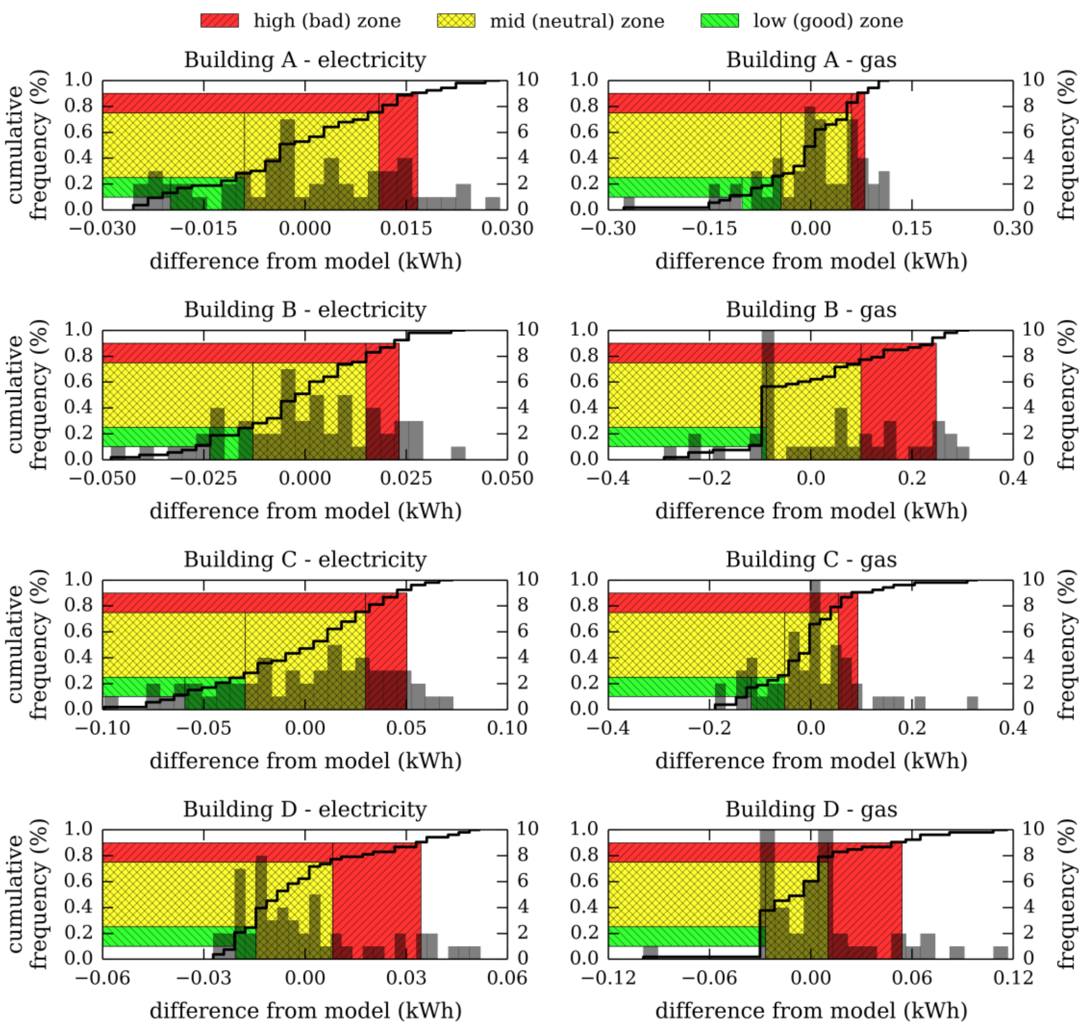

Figure 8: Example sub-model residuals and zones for example datasets (Wed 03:00)

The variability of consumption around the baseline model is seen as scatter in Figure 6. Model residuals are defined as the deviation of consumption from the baseline model prediction for each data point in the baseline period. Model residuals are recorded for each sub-model, Figure 8 shows the residuals for the sub-model fitted to data from 03:00 on Wednesdays. Residuals are presented as both a histogram (grey blocks) and a cumulative histogram (black line). The inter-quartile range and the ranges from 25^{th} – 10^{th} and 75^{th} – 90^{th} percentiles are also highlighted.

A context-free indicator

To calculate our performance indicator, the residual data are used as context for the absolute deviation of the test data point. More specifically, the deviation in the test data is converted into a percentile value within the population of baseline residuals. That is, the proportion of baseline residuals above the test data deviation is determined and this value (which necessarily sits between 0 and 100%) is used as a normalized measure of performance for each half-hourly data point.

The performance indicator can be interpreted as follows. A value of zero implies an extreme negative deviation from the model greater than any experienced in the baseline period. In other words, consumption is further below the model than any of the scatter in Figure 6. A value of 100 implies the opposite case where consumption is further above the model than any of the scatter in Figure 6. A value of 50 implies a non-remarkable deviation from the model, half of the baseline data deviated in a positive direction and half in a negative direction relative to this value. These values are therefore very easily converted into an essentially linear scale from 'good' (a value of zero) through 'neutral' (a value of 50) to 'bad' (a value of 100).

Visualisation

Direct visualisation of the indicator is described later in this section. First we will consider the construction of various composite visualisations which takes the raw energy consumption data and place it directly in the context provided by the modelling approach described. By providing data in context it is very easy to infer energy performance.

A further way in which baseline model residuals can be used is to compute useful values to provide visual context for the test period data. For example, it is useful to identify the inter-quartile range of the residuals as a 'normal' or 'neutral' range of consumption values. Any consumption in the test period that falls within this range is 'normal' in terms of the baseline data. We can also define a 'bad' and a 'good' zone as the 90th - 75th percentile range and 10th - 25th percentile range respectively. To calculate these zones is trivial. The zones are shown in Figure 8 extending from the appropriate cumulative frequency levels (i.e. percentiles on the left y-axis) and mapping to concrete residual values (the x-axis). The mapping is directly related to the cumulative histogram.

These values can then be added back onto the model to produce a predicted range of consumption. The range covers the same percentiles and so will necessarily cover 80% of all consumption data in the baseline period with 10% falling above and 10% falling below. By design, 50% of the baseline data fall in the neutral yellow zone. The zones calculated for the period at 15:00 on Tuesdays are shown in Figure 9 with the original baseline model and data shown for reference. Since the baseline period includes 52 weeks we can expect around 5 points to be located above and 5 points below the highlighted ranges.

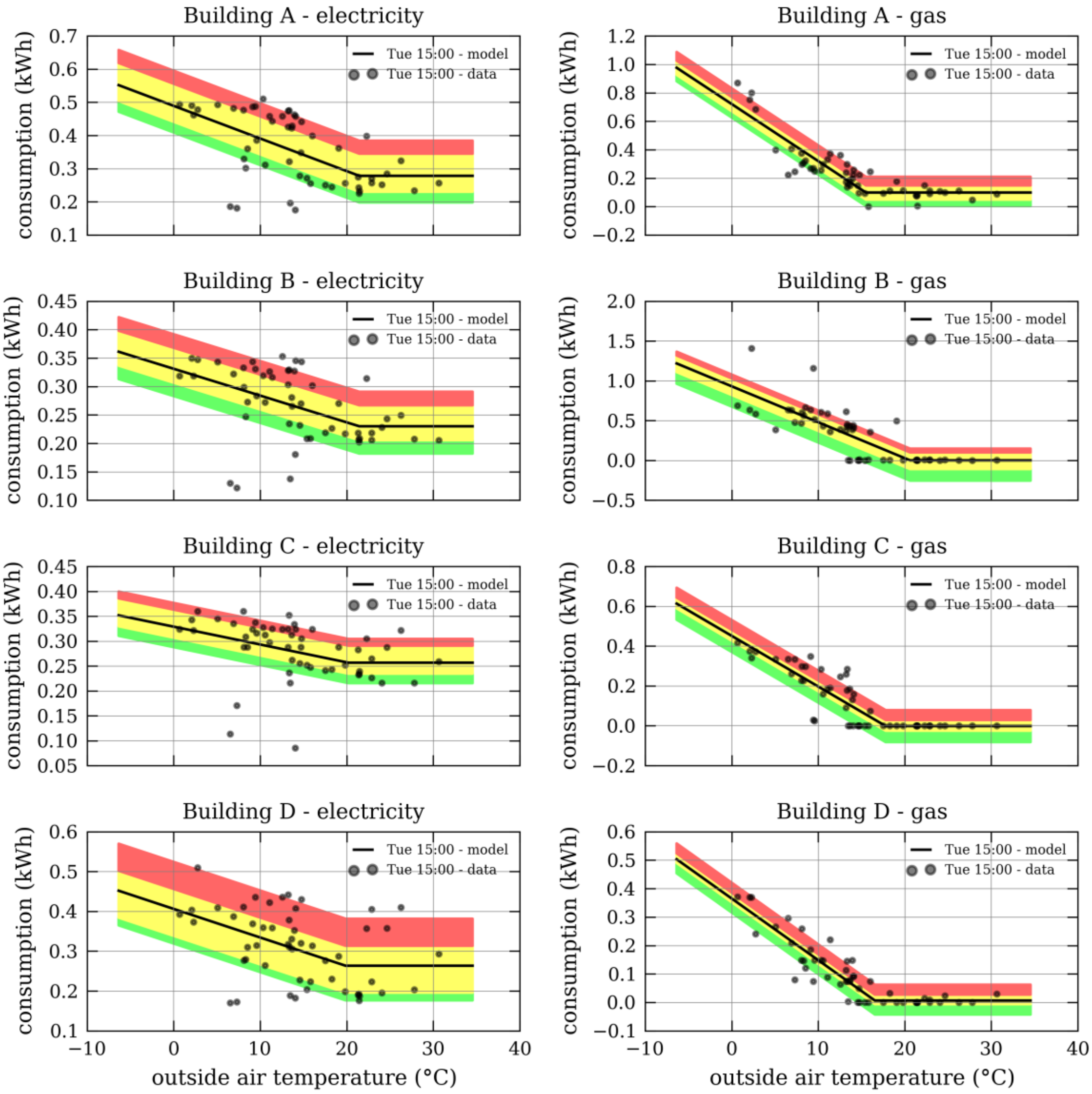

Figure 9: Sub-model (Tue 15:00) with percentile bands included for the example datasets

Taking the first complete week after the baseline (shown in Figure 5) as our test period we can now produce a visualisation which includes this contextual information alongside the actual consumption. It is a simple matter to compute a prediction and to add the calculated ranges. Figure 10 shows the resulting visualisation.

The coloured zones represent the expected range based on data from the baseline period. The raw data can now be easily equated to performance by observing into which of the zones consumption falls. In fact, performance relative to the baseline period can be determined very accurately by observing how deeply the black line falls into the appropriate zone. High values of the indicator are associated with consumption falling deep into the red zone. Low values of the indicator are associated with consumption falling deep into the green zone. Values around 50 fall centrally in the yellow zone.

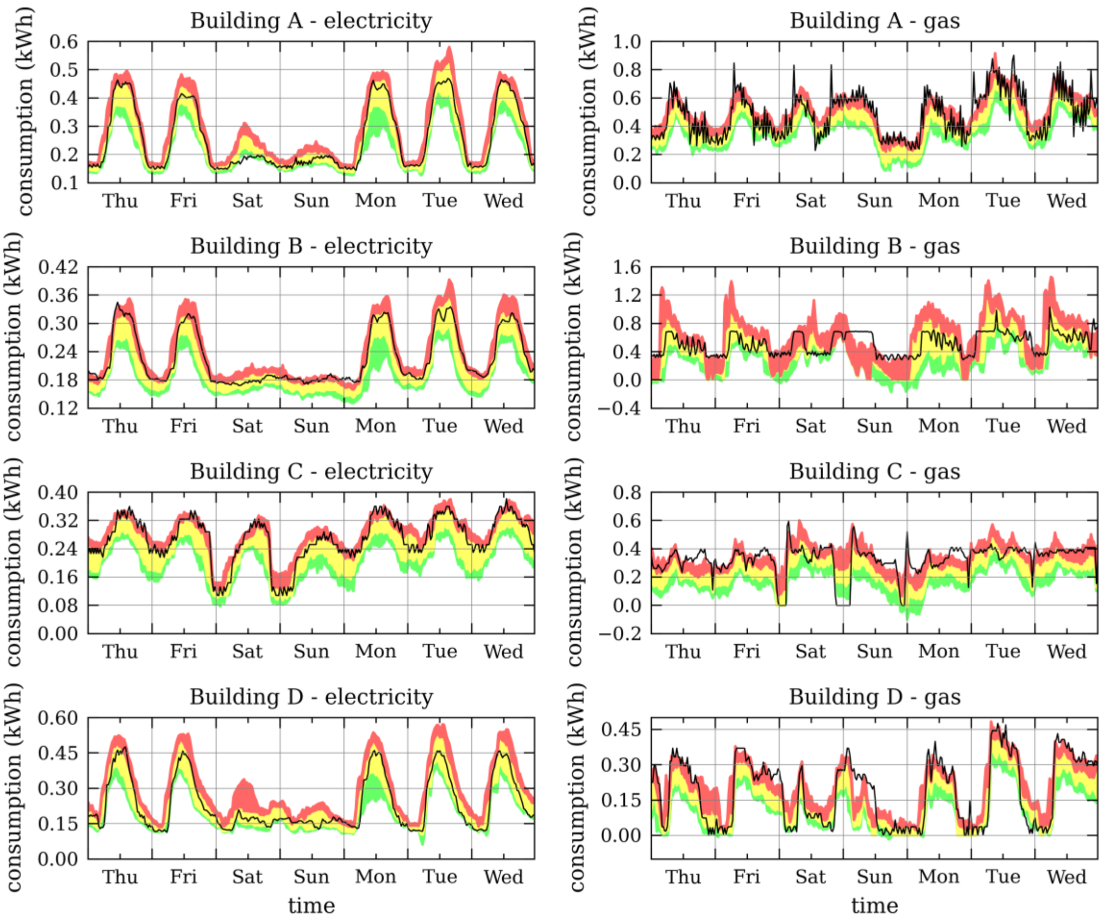

Figure 10: One week period with expected zones calculated from baseline model

This provides a robust visualisation of the model forecast and is an effective way to express the meaning of the indicator. The boundaries between zones from green to red correspond exactly to indicator values of 10, 25, 75 and 90 respectively. Expressing the derivation of the indicator in this way is useful to communicate the nature of the indicator to energy professionals and those building users who want more detail. It also serves as a powerful and intuitive diagnostic tool. Small deviations become very obvious and the predicted effect of outside air temperature is clearly expressed in the modelled zones.

The indicator itself is highly suitable for visualisation in innovative, interesting ways. The indicator is unit-less and ranges linearly from 0 to 100. As such it is possible to map it directly to any set of images representing good, neutral and bad performance. This is a major benefit of the context-free indicator, no special calibration is necessary. It can also be aggregated, for example by averaging to produce values representing daily or weekly periods and it can be compared directly across commodities and even merged across datasets to show overall performance.

Figure 11 includes two example visualisations. The first shows composite visualisation across electricity, gas and water consumption for a single building. The indicator is converted to coloured smiley faces with low values reflected as happy green faces and high values as sad red faces. Intermediate, neutral faces are yellow. The largest face represents an average of the three main indicators. Each of these is an average of 48 values covering the latest 24 hours of available data for the relevant utility. Underneath the main display is a smaller version of the four faces for each of the previous seven days. It is easy to see that performance in all categories has improved over the last week and is still being maintained at a good level. The second visualisation shows a comparison between buildings where the weekly average indicator is used as a more stable measure of overall performance.

Figure 11: Screenshots of example visualisations using aggregated performance indicator

Discussion

The approach described in this paper produces an indicator of energy performance relative to a baseline period. The indicator provides a robust comparison between data in the test period with a model fitted to data from a 365-day baseline period. The indicator ranges from 0 to 100 where zero indicates lower consumption (and presumably, better performance) than any experienced in the baseline period. A value of 100 indicates higher consumption (and presumably poorer performance) than any experienced in the baseline period.

Consumption is compared to the ***baseline model*** and the comparison is made with reference to the scatter around the model produced by the baseline data. This makes the indicator normalized for occupancy patterns and outside air temperature. This normalisation makes the indicator effectively context-free and allows it to be easily interpretable with no special knowledge of the building or the method. This approach also allows the indicator to detect relatively small increases and decreases in consumption against the baseline when the model fits closely to the baseline data.

When implemented in a continuous energy performance feedback system the indicator tracks improvement and deterioration of performance over time. This is ideal for a general purpose, objective energy performance feedback system. A simple monitoring scheme would create a baseline model with the first 12-months of available data and use this model to compute an indicator for one time-step. The next time-step would be calculated using a baseline model fitted to the 12-month period ending on the previous time-step and this would roll forwards one time-step at a time.

In practice this is computationally expensive. The computational requirements can be reduced by rolling the baseline one week at a time. Far fewer model fitting operations are conducted by using a single baseline model instance fitted to 12 months of historical data to forecast values for a full week of consumption. This way each week, rather than each half-hour of consumption has its own baseline model and the effectiveness of the scheme is not affected.

The indicator is designed to be sensitive to changes in building base load (the minimum consumption during unoccupied periods). By considering each ‘time of week’ independently it is possible to identify the variation in the base-load (which is often quite small) and so any reductions or increases in the base load are identified easily. The base load is often responsible for a large proportion of total consumption. Base load consumption occurs 24 hours a day and so a 1kW reduction in these loads represents a greater saving than a similar reduction in occupancy-related loads. A problem identified during unoccupied periods may indicate an opportunity to reduce the baseline.

The indicator provides a very convenient index for visualisation. A normalised value which is guaranteed to fall between 0 and 100 can easily be transformed onto any visual scale, in particular user-friendly scales which indicate good, neutral or bad performance. Examples of these include common metaphors such as traffic lights, thumbs up or down and smiley faces. It can also be aggregated over time by taking a simple average of multiple indicators.

For example the Leicester smartspaces pilot system [5] employs smiley faces to communicate the value of the indicator to building users on public screens within the building. Figure 11 shows a screenshot from the system. The electricity, gas and water performance indicators are averaged together to produce an overall figure. The screenshot also indicates the average of the latest 24 hours of indicators and seven figures for seven complete days. The half-hourly performance indicator allows user interface designers great flexibility in what can be presented by simply aggregating indicators over time and across datasets.

The system also has the benefit of being entirely objective. There are no special targets set, the indicator can be calculated for any building that responds well to modeling in the way described. In principal it would be possible to apply the same methodology and fitting the baseline data to any suitable consumption model. The indicator will always respond in the same way, providing a measure of improvement or deterioration.

It is important to recognize trust issues in a feedback system. Simply presenting smiley faces without providing a path back to the baseline model and raw data could erode trust in the system. Providing more detailed visualisations such as shown in Figure 8, Figure 9 and Figure 10 ensures transparency and can help more enthusiastic users understand their building in greater detail. To provide this as part of a user interface it is desirable to start with high-level interpretation (e.g. smiley faces representing a week) and drill deeper with each click, eventually reaching the most complex visualisations.

A great benefit of the approach is that it can be implemented with minimal input data, commonly available via AMR or smart meters. The example datasets include half-hourly energy consumption data (gas and electricity, although the approach has also been used with water data) and outside air temperature (also half-hourly). With these data and appropriately configured software it is possible to implement a complete system.

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