Profiling Energy Use in Households and Office Spaces

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ABSTRACT

Energy consumption is largely studied in the context of different environments, such as domestic, corporate, industrial, and public sectors. In this paper, we discuss two environments, households and office spaces, where *people* have an especially strong impact on energy demand and usage. We describe an energy monitoring system which supports continuous and tailored energy feedback, and assess the level of information (energy awareness) that can be gained from time-series energy profiles. Our studies pointed to similarities between households and office spaces and motivated us to profile energy in the same way for both settings. As result, an individualized energy metric is introduced which assists (a) public sharing of energy use, (b) aggregation and combination of energy use across different environments, and (c) comparison among individuals.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous; H.1.2 [**Models and Principles**]: User/Machine Systems—*Human factors*

1. INTRODUCTION

Recent reports[13] indicate that energy demand is rising, natural resources are limited, and renewable green energy sources are far short of meeting our energy needs. Energy saving is seen as an effective solution which not only reduces this demand, but also lowers our carbon emissions.

To date, energy usage has been largely discussed in the context of different operational environments, such as domestic, corporate, industrial, and public domain. Researchers have began to relate energy demand to high-level objectives and operational settings in these environments [2]. The similar goals, objectives, and resources at these locations has naturally divided the problem space into different operational environments, and suggested an *environment-centric* approach to energy research.

A key contributing factor to the differences between industrial (e.g., data-center) and domestic (household) environments is the *human* element. Human behavior is diverse, and while aggregate human behavior (for a large number of users) in an industrial setting (e.g., data centers) converges and becomes predictable, the aggregate behavior of a relatively small number of people in domestic and corporate environments remains unpredictable. Human involvement complicates the modelling of energy demand and affects the decision/action process which is often automated at the industrial setting.

Inspired by these observations, we have adopted a *human-centric* approach to addressing the energy saving problem, and studied energy demand and usage across two different but complementary environments: domestic (households) and corporate (office spaces). These environments have seemingly different objectives, tasks, and resources. However, they actually have much in common, due primarily to significant human involvement in both settings. Modern life and habits, such as "flexible working hours" and "work-at-home" options, have also contributed to this similarity.

In this paper, we focus on electricity usage as the first measure of energy consumption, and investigate the role of people in energy utilization at homes and office spaces. We measure aggregate electricity use at several households and office spaces, and target "energy awareness" as the key driving component for sustained energy savings. Our energy monitoring platform (*CSK Energy*, described in Section 3.1) uses continuous and tailored feedback to enhance energy awareness, and offers a suitable platform for developing automated control solutions at households and office spaces.

This paper studies several daily energy profiles from households (Section 3.2) and office spaces (Section 3.3), and discusses the information that is conveyed to users, as well as the input that users can provide to enhance energy profiling. An important finding is that an energy baseline is apparent across both environments, and that total energy consumption can be expressed as the combination of environment-specific baseline energy use (Section 4.1) and human-driven energy consumption (Section 4.2).

In an attempt to centralize the role of the human, Section 4.3 provides an energy usage summarization scheme, *API*, which individualizes energy (i.e. attributes energy consumption to individuals). This metric holds users accountable for their share of energy usage, and provides a simple and intuitive measure of personal energy use for public sharing, comparison among people, and aggregation across different environments (i.e. households, office spaces, transportation, etc). Finally, Section 5 presents an energy saving experiment which measures the true baseline energy usage of an environment, assesses the effectiveness of a voluntary energy saving scheme; and provides an estimate of obtainable energy savings with an automated control solution.

2. RELATED WORK

Energy conservation has become important since energy demand and cost is increasing, and natural resources are limited. Reports[13] indicate that UK, like many other developed countries, spends over one-third of its total energy on domestic and business sectors. Energy saving in these sectors can have a significant impact. These sectors are often studied separately by researchers and policy makers.

Psychologists have already studied the problem of behavioral change and energy awareness, and shown that with proper feedback, real-time information, and goal setting abilities, house-holds can reduce their energy consumption by up to 10% with small behavioral changes[10, 11, 17]. For the workplace, psychologist Holmes[8] has looked at creative ways of increasing energy awareness. Others[4] have highlighted the limitations of current energy tracking methods, such as the utility bills, in providing energy awareness.

System researchers are still at the early stages of exploring these problems and delivering adequate solutions. Technical research, in this area, is largely primitive and pursued in an ad hoc fashion. Initial work has looked at new ways of conserving energy through context-aware power management[6] and adaptive controls within the households[12]. Beckmann et al.[1] investigate the use of sensors and their installation at the households for an energy tutor system. Widen et al.[16] have explored a modelling approach for generating energy profiles for households. Individual appliance monitors, like Kill-A-Watt[1] or Watts Up[2] , have also emerged which monitor energy use at a finer detail.

There is also a range of commercial consumer devices, like CurrentCost, DIY KOYOTO, and eco-eye, that monitor household's total energy consumption via a clamp meter that acts as a current transformer. The Energy Saving Trust does not recommend these devices, because they do not inherently reduce energy usage, but only help indirectly. Fitzpatrick and Smith[5] have conducted surveys on several of these devices and their feedback mechanisms, and concluded that more useful information is needed than just the aggregate total energy usage. A simple approach, pursued by WattBot[14], is to use multiple clamp meters where each meter monitors a separate electricity circuit.

Clamp-on electricity meters precede the nation-wide smart meter installations that link accurate energy usage monitors to the utility providers for remote and dynamic billing purposes. Accurate electricity meters, like Autometers[3] (suitable for billing), have long been available to the corporate and industrial sectors, but these are too expensive for households. It is also unclear if the frequency of readings (by smart meters) would be sufficient for deducing useful high-level information or implementing automated control solutions at homes. Understanding individual needs and activities is important as Peter Crabb similarly points out that "people do not use energy, they use devices and products"[3].

None of the highlighted studies have attempted to understand individuals energy needs and current ways in which people manage their energy consumption. Chetty et al.[2] have initiated to answer some of these questions, but their work is limited to qualitative observations. In this work, we use a quantitative approach to understand individuals energy needs across two environments, and use clamp-on electricity meters to measure electricity usage at 12 different experimental sites.

3. ELECTRICITY USAGE AND REVIEW

Energy measurement is pivotal to understanding energy demand and usage. Only few (off-the-shelf) systems provide data-logging facilities and almost none provides an adequate interface for real-time feedback, energy review, and control mechanisms. In this section, we present *Cambridge Sensor Kit (CSK) Energy*, an energy monitoring system for energy measurement and review at households and office spaces. This presentation is then followed by examples and discussions of real energy data, collected using CSK Energy at different households and office spaces.

3.1 Cambridge Sensor Kit (CSK) Energy

The objective of an energy monitoring system is to quantitatively measure one's energy consumption and provide adequate feedback to raise energy awareness. Advanced systems would also aid control and automation, but little has been done and implemented in this space for the domestic and corporate environments. A review of the existing (off-the-shelf) domestic energy monitors indicated that they often provide limited feedback in time and space. For example, CurrentCost and DIY KYOTO only provide real-time information about energy usage, and their feedback is limited to a display unit that is situated at the deployment site. We refer to such systems as *localized* systems in which the feedback coverage is limited to the deployment site.

Other systems, such as AlertMe, Google PowerMeter, and Andy Stanford-Clark's (IBM's) power[4] , require internet access to provide feedback. These systems strongly depend on the user's internet service or an external service (e.g., GPRS) to establish connections to their online servers and provide feedback. We refer to these systems as *internet-based* systems where standard operation depends on internet access and connectivity and a stand-alone service is not possible.

We believe feedback should not be limited (in time/space) and not solely dependent on external services. This has motivated us to develop an energy monitoring system that would provide feedback at the local deployment site without the need for an internet connection, and feedback at the external sites via the internet service. This development

[1]http://www.p3international.com
[2]https://wattsupmeters.com
[3]http://www.autometers.co.uk

[4]http://stanford-clark.com/power

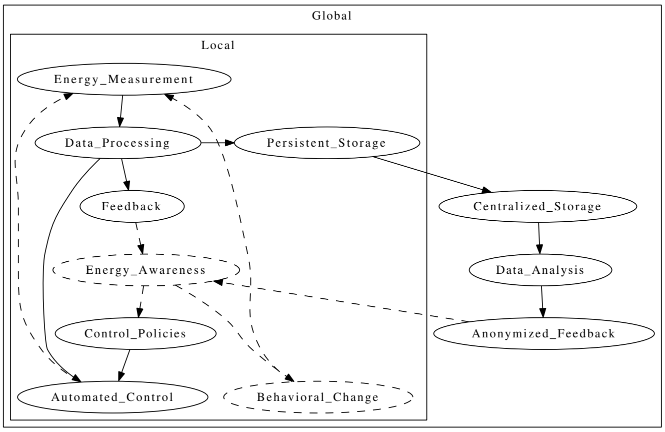


Figure 1: CSK Energy: System Architecture

has also enabled us to quantitatively measure the human engagement and involvement with the feedback mechanism. A quantitative measure of this engagement is important for assessing and evaluating feedback mechanisms, and unfortunately none of the existing systems provide this feature. The following sections briefly describe the overall architecture and the implementation of the CSK Energy system.

3.1.1 Architecture

The CSK Energy system needs to support feedback at two different environments: the local deployment site (i.e. home/ office space) and the external site (i.e. outside home/office space). As we shall see later, the nature of this feedback depends on the underlying environment due to (a) different levels of data, and (b) different security and privacy implications. Thus, it is best to describe the CSK Energy system architecture across two domains: *local* and *global*.

These domains correspond to the spatial coverage of the local deployment and the external sites, respectively. They also confine the operation (coverage) of each system component that is shown in Figure 1. In practice, there exists n such local domains, each corresponding to a different deployment site, and a single global domain covering all local domains and the external sites.

Figure 1 shows three elements of the architecture: (a) the scope of the domains, (b) the components of the system, and (c) the flow of information in-between the components. Solid lines represent data flow that is contained within our system, and dashed lines represent flow of information that is external to our devices. The role of the human user is also highlighted with dashed components. The combination has produced three energy saving information cycles:

1. Localized feedback and behavioral change
2. Localized feedback and assisted control (automation)
3. Global feedback through information sharing and comparison

As illustrated, "energy awareness" is central to our strategy and directly supported by the "feedback" and "anonymized feedback" system components. The next section describes each system component in detail.

3.1.2 Implementation

Our implementation philosophy was centered around three principles: (a) use of established Standards for increased inter-operability (which helps interface plugins for enhanced feedback), (b) use of Open-Source software for increased flexibility, and (c) exploitation of off-the-shelf components for rapid development and prototyping.

Energy Measurement We initially used the CurrentCost clamp sensors to measure electricity usage at the aggregation points (such as meters and fuse boards). These clamp sensors do not require professional installation and do not disturb the electricity circuit, but they only provide estimates of the energy use; current is estimated and voltage is assumed fixed at 235V. High error-margins and unreliable communications motivated us to use CR3110-3000[5] clamp sensors which are more accurate and compact for installation within the fuse boards. Sensor readings are taken every 6 seconds (on continuous basis) for fine energy measurement.

Data Processing The sensor produces substantial data for analysis and visualization. The data processing component aggregates sensor readings to provide summary values for display and actuation. In future, we plan to exploit the fineness of this data to automatically identify individual appliances as suggested in [15]. The initial prototype used a Viglen MPC-L (running the Ubuntu 8.04 server edition with 17-20W of power usage) as the local server, but the latest prototype uses an embedded device, Bifferboard, with the emdebian distribution and less than 1W power usage.

Feedback This component is also supported by the local server. It provides time-series energy usage information (comprised of last day's and last month's energy consumption) via webpages, and summarized real-time and historic values (via web services) for a network of pluggable visual and audio feedback mechanisms. An Apache server hosts the webpages and the web services. The rrdtool is used for generating graphs of last day's and last month's energy consumption, and the awstats tool is used to analyze accesses to the webpages and the web service; this measures the level of human engagement with the feedback mechanism. Currently, an RSS feed and a RESTful web service support a digital photo frame and a 3-colored LED globe for additional feedback.

Control Policies We are still at the early stages of defining our control policies. Early work has looked at presenting simple choices for selecting appropriate duty-cycling schemes for desktop machines and displays. Section 5 discusses this in detail.

Automated Control We have developed a set of scripts that implement a set of duty-cycling schemes for personal desktop machines. This work is still at its early stages and is briefly discussed in Section 5.

[5]http://www.crmagnetics.com

Persistent Storage The transfer of sensor data to a centralized server requires an internet access at the user's site. Households and office spaces often have broadband services available. The current implementation supports a DHCP-based Ethernet or WiFi connection to the user's broadband router at the local server. Experience has shown that such services should not be readily assumed; thus, persistent storage is required at the local site to protect data. A local MySql database stores the data and reliably uploads a compressed version of the data when external access becomes available.

Centralized Storage A central server collects compressed raw sensor data from deployed sites for subsequent data analysis and global feedback. Clients are authenticated by an RSA key scheme, and upload files to a central MySql database. Data import is unordered since client's access to the internet (and hence the upload time) is unpredictable.

Data Analysis The collected data, at the central server, is fused and correlated across different deployment sites to deduce useful information. Our initial analysis focuses on baseline and human-driven energy usage information. These are compared across time and deployment sites using the "baseline inefficiency factor" and the "API" metrics which are described in Section 4. These metrics provide additional insights into people's energy demand and usage, and provide goal setting and competitive objectives that can improve energy awareness among people.

Anonymized Feedback The global feedback presents the high-level data analysis results. This is a web-based feedback mechanism that provides global and continuous access, via the internet service, about the latest uploaded energy data. In addition to the high-level data, the time-series energy usage information is also made available. People can access their own or others energy usage profiles, and observe similarities and differences about their consumption behaviors. Privacy and security concerns are preliminarily addressed through (24 hours) delayed data access, and anonymization of the deployment site identifiers. Global access to the latest uploaded energy data is supported through obfuscated web links for the privileged and authorized users (e.g., owners of the data).

3.1.3 Deployments
Over the past six months, we deployed twelve CSK Energy systems in Cambridge, UK. These deployments were carried out in stages with the first one in May, and the last one in September 2009. To increase diversity in our data, systems were installed in residential houses and office spaces with varying numbers of users. Tables 1 and 2 provide the relevant details. The number of occupants (residents) varied from one (single person living in a flat) to over 30 (people sharing an office floor at the Computer Laboratory, CL).

3.2 Households
Figure 3.2 shows two examples of image-based energy feedback, used as part of the local time-series feedback information. These plots illustrate the energy usage of two households over a day. They are annotated by the users, describing the devices and appliances which have contributed to the electricity usage at various times.

Site	p1	p2	p4	p5	p6	p7	p10	p11	p12
Type	F	F	H	H	H	H	H	H	H
Count	2	1	3	2	5	2	4	2	6
Heating	G	E	G	G	G	G	G	G	G

Table 1: Residential deployments; 'F' is for 'flat', 'H' is for 'house', 'E' is for 'electric', 'G' is for 'gas'.

Site	p3	p8	p9
Floor	1	2	2
Side	N	N	N
Circuit	S	S	L
Offices	13	15	15
Count	34	28	28

Table 2: Office space deployments; 'N' is for 'north', 'S' is for 'sockets', 'L' is for 'lights'.

This information (data annotation) can be used to train and evaluate automatic appliance-use detection algorithms in the future. In immediate terms, however, this practice has two benefits: (a) it demonstrates that the time-series energy information is sufficiently rich to enable users annotate their activities throughout the day, and (b) it allows users to assign energy usage (in coarse terms) to individuals or shared groups of people. The former provides an argument in support of cheap energy measurement at the aggregate points as opposed to expensive individual appliance monitoring at the power sockets, and the latter supports our proposed individualized energy metric (described in Section 4.3). The following sections discuss these energy profiles in detail.

3.2.1 House p11
House p11 has two residents who were working from home on the day under review. The CSK Energy system shows a 'baseline' energy consumption level of about 200W, which the users have attributed to the computer systems, servers, and the refrigeration appliances. Figure 3 shows a detailed break-down of these appliances and their individual daily energy use, measured by a plugin socket monitor.

The greyed-out bars in Figure 3 show energy consumption

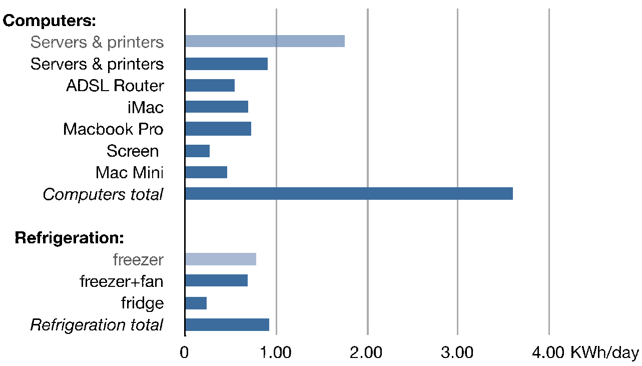
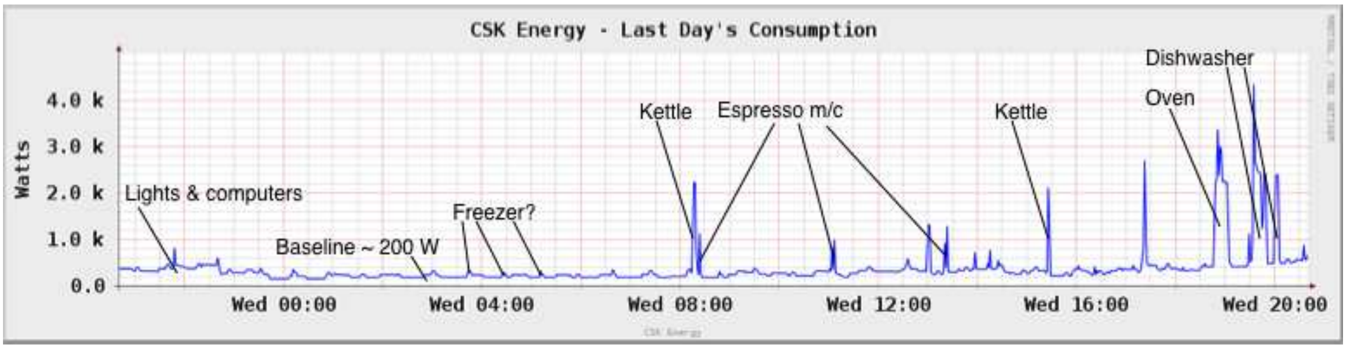
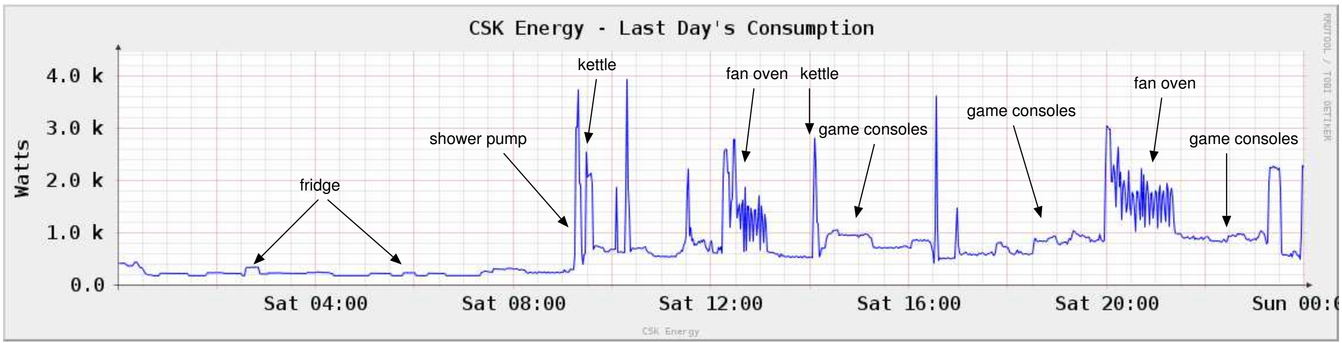


Figure 3: House p11's baseline appliance usage



(a) Aggregate energy usage at house p11



(b) Aggregate energy usage at house p12

Figure 2: Annotated daily energy consumption at two houses

levels before the residents adopted suitable energy-saving measures. For the computer systems, this action consisted of merging two network file servers (a shared file server and an archive server) onto a single hardware platform and adopting a policy of switching off printers at night. For the refrigeration, the action consisted of installing very low-power fans to provide additional air circulation to the external coils of the refrigeration units. We have aggregated the daily energy use at this home, and realised that it uses (on average) about 9.28kWh of energy per day.

3.2.2 House p12

House p12 has six residents. Figure 2(b) shows that this house also has a baseline power usage of about 200W. This is similarly attributed to computer systems, standby multimedia systems and refrigeration units. Naturally, due to the higher number of residents, this house has a higher energy consumption throughout the day with more appliances and more frequent usages. Interestingly, users have still been able to identify the devices and the appliances from this time-series graph, even on a busy day like Saturday. This house's average daily energy use is about 13.58kWh per day.

3.3 Office Environment

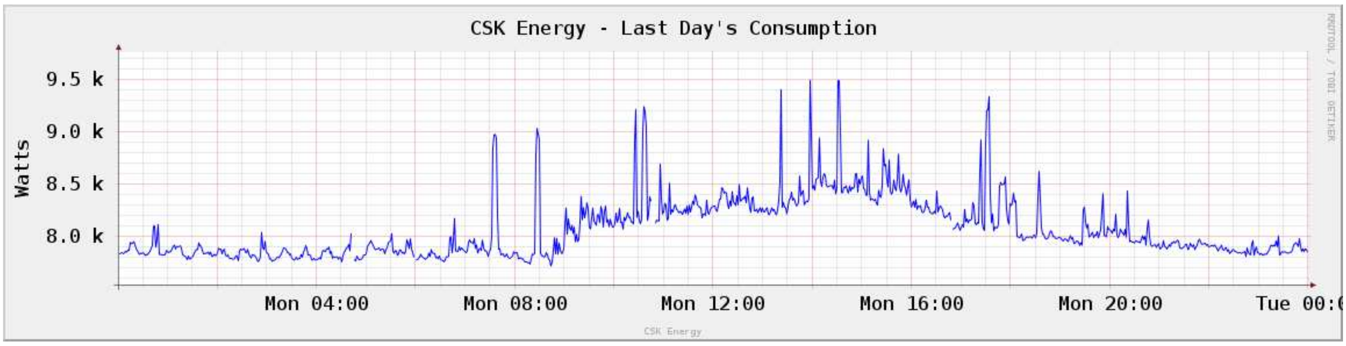
Figure 4 shows two plots of daily electricity use at two office floors. These plots exclude electricity usage of the lighting infrastructure, since lighting is on a separate circuitry and switch board. Typical to an office space, there is a high base-load electricity use for both floors which correspond to the server rooms, desktop machines and the basic infrastructural systems like the air conditioning unit.

Although the identification (or annotation) of the graphs is difficult due to the combined energy use of a large number of people, a consistent and identifiable baseline energy use can be seen for both graphs outside the normal office hours. Floor 1 has a baseline power usage of about 7.8kW, and floor 2 has a baseline power usage of just under 14kW. The additional energy use (throughout the day) is attributed to 34 and 28 people for floor 1 and floor 2, respectively. The next section further describes these numbers in an effort to relate and combine energy usage across the households and office spaces.

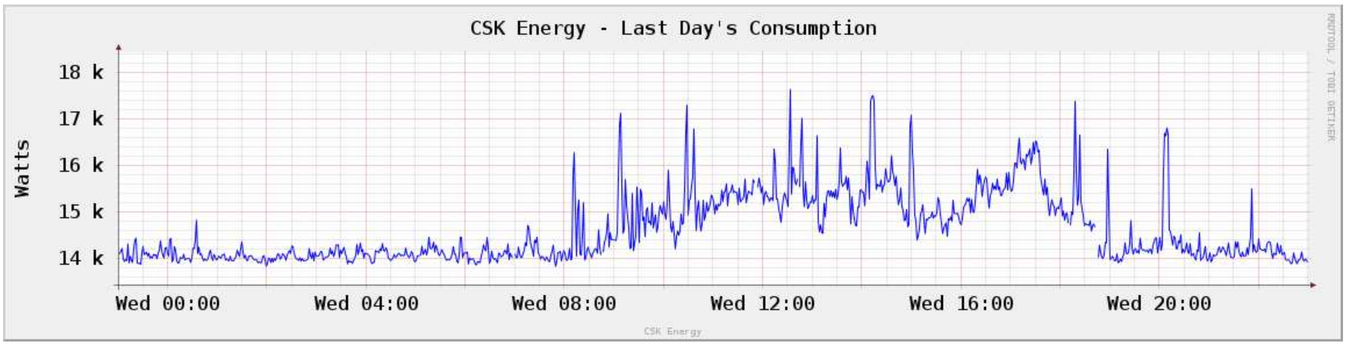
4. ENERGY PROFILING

Home users found the time-series presentation of their energy data helpful. A brief survey (among our users) indicated that real-time and historic (time-series) energy usage data helped them to relate their activities and experiences to energy use, and provided a better measure of their appliances' electricity consumption.

This time-series data, however, provided little information to external users and non-experts. Experience has shown that the provision of the annotated data is more useful, but people still can not relate and compare energy use among households or across households and office spaces. Provision of this fine-grained data can also pose security and privacy risks if it is made publicly available for sharing and comparison. Finally, without this time-series plot at hand, there is little or no means of communicating energy use, trend, or profile to other people.



(a) Aggregate energy usage at floor 1, p3



(b) Aggregate energy usage at floor 2, p9

Figure 4: Daily energy consumption at two office floors (excluding lights)

These issues highlighted the need for a summarization scheme that would encapsulate an individual's or a groups' energy use into a simple and intuitive format that is easy to understand, combine, and compare across people. Ideally, this metric should also be independent of the environment and account for individual's energy use at home and office space alike. Existing metrics, such as "kWh per day" or "kWh per day per person" (proposed by David Mackay[9]), are often too simple and inadequate for easy aggregation or comparison across diverse human-involved environments. This section introduces a new metric, API (Aggregated Power Index), which can easily be understood and related across people and environments.

We broadly observe energy as a combination of two factors: *baseline energy use* and *human-driven energy use*. These two need to be separated as people often have little or no control over the baseline energy consumption at their environments. The following sections describe these, and provide real-life measures and examples.

4.1 Baseline Energy Use

The *observed* baseline power usage is the minimum power value that is observed (using a CSK Energy system) at an occupied house or an office space. In households, this figure often corresponds to the appliances' stand-by power usage, home's security and alarm systems, heating systems, refrigeration units, and some IT infrastructure (e.g., broadband router). Some of this usage is justified for the security and safety of the environment; others are as a result of individuals behavior, living and possibly cultural habits.

We define the *correct* baseline power usage as the aggregate power use of all appliances and systems in the first category, which need to be continuously operating for the safety, security, and well-being of the home and its users. The difference between the correct and the observed power value is labeled as the *baseline inefficiency factor* and accounted for in the human-driven energy use (discussed in the next section).

$$\Delta_{bl} = b_{observed} - b_{correct} \tag{1}$$

where Δ_{bl} is the baseline inefficiency factor, and $b_{observed}$ and $b_{correct}$ are the observed and the correct baseline power values, respectively.

Initial observations have indicated that the correct baseline power value, $b_{correct}$, for houses can be very similar. We instrumented two houses with the CSK Energy system, and unplugged all devices from the mains to measure this value. Results indicated that 30W may be a reasonable estimate for the $b_{correct}$ of an average household. Figure 5 shows the baseline inefficiency factor of 9 houses that are monitored by the CSK Energy system. A key challenge is to reduce the inefficiency which is continuously contributing to the overall energy use. Some initial insights into how this can be achieved was discussed at Section 3.2.1.

Office spaces have diverse baseline power consumption, but that can also be categorized in a similar way. The baseline power consumption is often dominated by the electricity use of servers and business equipment that need to be operating continuously. Similarly, we define the observed baseline

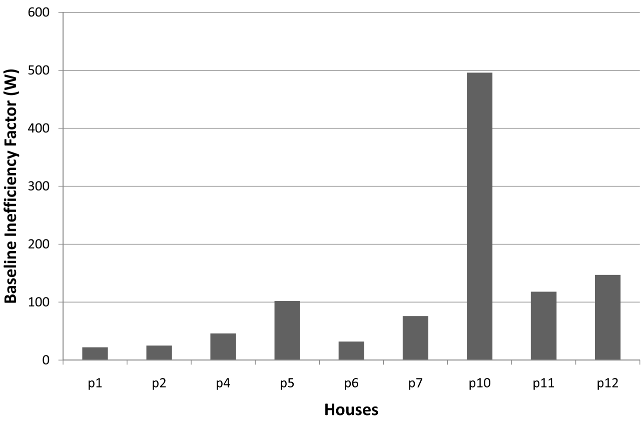


Figure 5: Baseline inefficiency factors for 9 houses

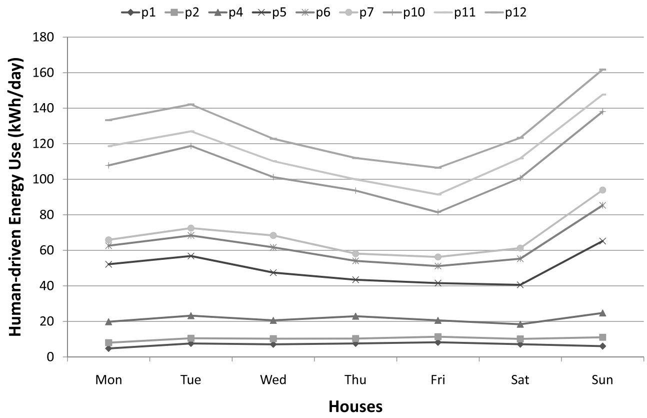


Figure 6: Human-driven energy use for 9 houses

power value as the minimum observed power value by the CSK Energy system, and the correct baseline power value as the base-load essential for safety, security, and key objectives of the business. Observations, based on monitoring 2 office floors, indicated that the correct baseline power value varies across time and environment. Variation across time, however, is infrequent since business objectives and resources change gradually and unpredictably.

Measurement of the correct baseline power usage, even at the office spaces, is not difficult. In Section 5, we describe an experiment in which the correct baseline power use of a floor is measured by asking users to turn-off and unplug any electric appliances at their control for an hour - this duration can be as small as the measurement interval (6 seconds for the CSK Energy system). Such experiments pose no risks to the users, households and/or office spaces, since the correct baseline power usage accounts for the essential safety, security, and well-being of the environment and its users.

4.2 Human-driven Energy Use

The human-driven energy use is the most variable and unpredictable element of the energy consumption. In households and office spaces, this element is composed of the baseline inefficiency factor, individual's use of appliances (e.g., personal desktop machines) and the shared use of appliances (e.g., washing machines at homes, and printers at office spaces). These appliances may be pre-programmed for use (e.g., timer-based heating control) or operated on demand (e.g., turning on a kettle). The human-driven power use, at any point in time, can be accurately measured by the difference between the total power use (i.e. real-time power measurement by the CSK Energy system) and the correct baseline power use (estimated or measured for an environment),

$$h = p - b_{correct} \tag{2}$$

where h is the (momentary) human-driven power usage (in watt), p is the total power use (in watt), and $b_{correct}$ is the correct baseline power usage (in watt).

At home, many appliances are used on demand and their time of use can not be predicted. This can be observed by strong temporal variations over a day or in-between different days. Since the human-driven power usage value, h, is quite variable, it is reasonable to measure the total human-driven energy consumption over a day or a week,

$$e = \int_{24Hr} h \, dt \tag{3}$$

where e is the human-driven energy use for a day. This energy value, e, represents the area under the time-series power curve which excludes the correct baseline power value over a 24-hour duration.

Figure 6 shows the human-driven energy consumption value for the 9 households over a week. This data shows strong ties between the energy use and the human behavior, and can be used to deduce high-level information such as "people are probably most active at their homes on Sundays". In addition, this data may still pose security and privacy concerns since less energy active days and perhaps days with lower house occupancy can be detected over time. These measurements and profiling should be continued over at least a year to reflect the effect of external parameters such as seasonal changes on human behavior and energy use. Over short durations, the human-driven energy use for households seems to vary insignificantly between weeks, and can be reasonably predicted if holidays are excluded.

In office spaces, however, the human-driven power usage is more predictable than at homes. This is because the human-driven power value represents the collective behavior of a large number of people and is less sensitive to individual change or behavior. The human-driven energy use at office spaces reflects the working culture and behavior and depends on the working schedule of the people (i.e. low energy use over the weekends, similar energy use over the week days). Since the number of occupants at an environment has a strong influence on the human-driven energy use, we discuss a new metric in the next section which (a) factors out the number of people and is attributed to individuals, (b) poses little security or privacy risks when shared among people, and (c) can be easily understood, combined, and compared across people and environments.

4.3 Aggregated Power Index (API)

The *Aggregated Power Index (API)* is an individualized energy metric that can be intuitively understood, related, ag-

Individuals	PI_{home}	PI_{office}	$API_{\{home,office\}}$
Subject A	137.38W	176.34W	**313.72W**
Subject B	156.17W	176.34W	**332.51W**
Subject C	193.37W	50.38W	**243.75W**

Table 3: API for three individuals

gregated and compared across people and environments. Much like the existing appliances on the market, the API indicates how much power (on average) is attributed to an individual for his/her style of living and behavioral habits. For simplicity, we focus on two environments in which people spend most of their time, namely the household and the office environment.

The API for an individual is the accumulate of his/her Power Index (PI) at different environments.

$$A^x = \sum_V P_v^x \tag{4}$$

where A^x is the API (in watt) attributed to an individual x, P_v^x is the PI for x at environment v (in watt), and V is the set of environments where energy is measured or estimated, $V = \{home, office, \cdots\}$.

The Power Index (PI) similarly describes the average power usage of an individual at a specific environment. Power Index (PI) is defined as the normalized human-driven power usage that is attributed to an individual in an environment. Hay et al.[7] look at PI quantification with respect to billing and personalized incentives. Their study shows that an accurate quantification requires context aware devices and appliances. A simpler approach here is to apportion total human-driven power usage according to user control and device ownership: an individual is accounted for every appliance's (or device's) energy consumption if he/she has control of the device, and if the device's power usage is not covered by the correct baseline power usage of the environment.

$$P_v^x = \frac{1}{T}\int_T h_v^x \, dt \approx \frac{1}{T.n}\int_T (p_v - b_{correct,v}) \, dt \tag{5}$$

where T is a finite duration, h_v^x is the total human-driven power usage value attributed to x at the environment v (in watt), and p_v and $b_{correct,v}$ are the total power and the correct baseline power values at environment x (in watt) for the simplified case of sharing all human-driven power consumption across n occupants (or users).

For illustration, we compute the API for three individuals, Subject A, Subject B, and Subject C, for whom we have real-data available across two environments, home and office space. Subjects A, B, and C reside at houses p2, p4, and p11, respectively. For simplicity, the human-driven power usage at different environments is shared across all occupants, and the API is computed over a typical week. Table 3 shows the results.

In this instance, all users shared the same office environment, but Subject C, as a part-time resident member, was only held accountable for a fraction of the total human-driven energy use at the office. There are also differences across the home PI values for these individuals, ranking them in the order of Subject A, Subject B, and Subject C for the home environment. Subject A has the lowest PI at home due to fewer devices and appliances at his house, and Subject B benefits from sharing his human-driven energy use with two others at his household. Overall, however, Subject C is the most energy efficient, followed by Subject A and Subject B.

Table 3 indicates that on average Subject C is accountable for 243.75W of power usage, or in other words 243.75W of power is used at all time to serve his lifestyle. Similarly, Subject A is using 313.72W of power, and Subject B is using 332.51W. An *effective* change in their behavioral habits or energy usage patterns would be directly reflected in these figures. Thus, people's API could be re-computed and compared over months or years to assess their change.

5. ENERGY SAVINGS

Individuals have access to resources that allow them to live comfortably at their homes (e.g., washing machine and kettle) or perform their duties at work. Such resources include appliances that are either uniquely allocated to individuals (e.g., desktop computers) or shared among them (e.g., freezers at households, printers at offices).

We believe that there are energy savings to be made by optimising the use and sharing of such resources. For instance, a more tight control of the desktop machines, such as switching off computers and displays when they are not in use, should yield improvements in energy use.

Many desktop machines (at work) are left on over night, and this has become a common habit with people's preference of leaving sessions open at the end of the day and resuming work the day after. System administrators have also used this scheme to (a) implement security measures by periodic pinging of machines (at all times), and (b) performing generic software and security updates over night. Energy awareness and increasing costs, however, have motivated users to re-visit their habits and re-consider these working principles. Some key questions surrounding this are:

- How much energy use is at the user's control?
- How much can a simple automated solution achieve in terms of energy saving?

In an attempt to answer these questions, we conducted an experiment on the 26th October 2009 at the CL. We asked members of the 2nd floor to shut down their desktop machines, displays, and disconnect them from the mains (power sockets). The office lights were also switched off before they attended a regular Monday meeting from 1pm to 2pm.

Twenty two people took part in this experiment by switching off their machines, displays, and office lights. Some personal computers and electronic units were also switched off and removed from the mains power supply. In total, 24 desktop machines, 6 servers and 2 network switches (100W each) were disconnected from the mains. The total power consumption value, attributed to these devices, was estimated

Item(s)	Power usage
Desktop machine and LCD display	110W
Server machine	160W
Lights (small office)	200W
Lights (large office)	300W

Table 4: Individual device energy measurements

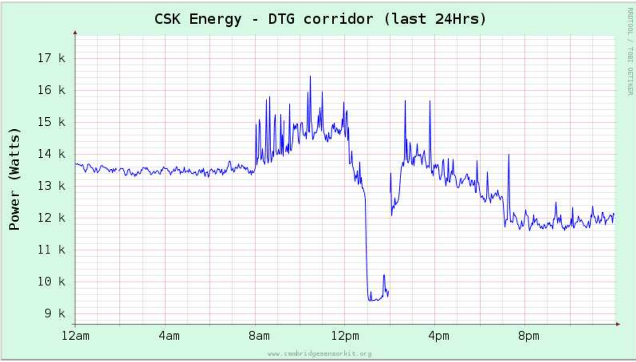


Figure 7: Energy use (sockets) on the 26th of Oct

at 3800W; Table 4 lists our single device power measurements using a portable socket monitor.

Figure 7 shows the measured power consumption drop as result of this experiment; the drop is shown at the interval between 1 to 2pm. Power savings of about 4kW (with respect to the week's baseline of ≈ 13.8kW) was achieved. The reduction in lights electricity usage was ≈ 2kW which included 5 regular offices and 4 large (PhD student) offices (see Figure 8). The estimated power use (for lights) was 2.2kW according to the Table 4. The night-time baseline power use (for lights) is about 700W.

This experiment helped us to identify the observed and the correct baseline power usage values for the sockets and the lights of the second floor as shown in Table 5. The total power usage of lights, during the experiment, did not reach the observed 700W value at night-time because corridor lights (whose control is with the building manager) are brighter during office hours than at nights. Since the building manager did not take part in this experiment and for simplicity, we attributed the difference $1.6kW - 700W = 900W$ to the building's health and safety measures at day-time.

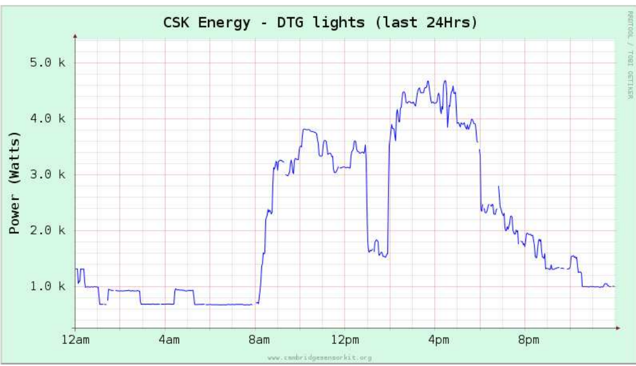


Figure 8: Energy use (lights) on the 26th of Oct

Environment	$b_{observed}$	$b_{correct}$	Δ_{bl}
Lights (9 to 5pm)	3kW	1.6kW	**1.4kW**
Lights (5 to 9am)	700W	700W	**0W**
Sockets	13.8kW	9.3kW	**4.5kW**

Table 5: Baseline power usage for floor 2

State	Power	Current Cycle	Proposed Cycle
Disconnected from mains	0W	0%	67%
Switched off	12W	0%	0%
Stand-by	60W	75%	8%
Switched on	110W	25%	25%
Total power		72.5W	32.3W

Table 6: Desktop and monitor duty cycling at CL

Users were asked to voluntarily repeat this experiment for outside office hours for one week, 26th Oct to 2nd Nov. System administrators were notified of this and they implemented a circumventing system update solution for the duration of this week. Figure 9 shows a month's duration of electricity usage (2nd of Oct to 2nd of Nov), with the experimental week situated at the far right. The minimum spike point (on the graph) corresponds to the 1 to 2pm experimental hour which was conducted on non-volunteer basis. As evident, energy saving on volunteer basis works (at least for short-term) but it is not as effective as the involuntary scheme. The energy saving (during this week) was about 15% from the power sockets, and 10% from the lights. These results also show that simple and coarse-grained power duty cycling schemes can be effective.

Following these observations, an automated duty cycling scheme was proposed to assist users in saving energy. Table 6 presents the current CL duty cycle and the proposed duty cycling scheme. The proposed duty cycling scheme considers disconnecting computers from the mains overnight (8pm-9am) through wireless actuating switches (not implemented yet). It also considers around 2 hours of stand-by time for the machines when users are on short or long breaks throughout the day. Currently, power use related to the machines is at 72.5W per person which amounts to 1.74 kWh/day. The proposed duty cycling scheme reduces this to 32.3W per person or 0.775kWh/day. This amounts to more than 55% energy saving from just the desktop machines and the display units on this floor.

6. CONCLUSIONS

In this paper, we described our energy monitoring system, CSK Energy, which provides tailored feedback for different environments. We illustrated that fine-grained energy measurement at aggregate points in homes is sufficient for energy review, and identification of related appliances by energy users. In future, data annotation and automatic appliance identification shall assist accurate energy assignment to individuals or shared groups of users at the home environment.

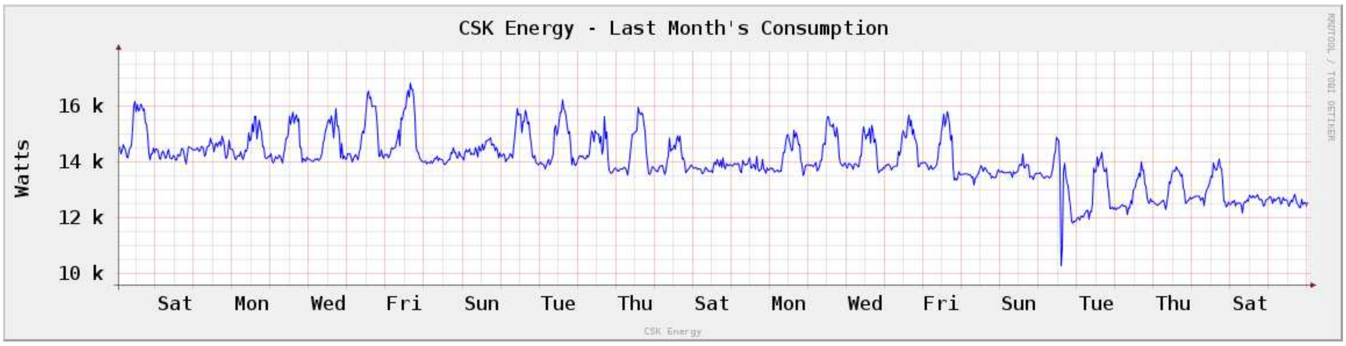


Figure 9: Repeated experiments (26th Oct - 2nd Nov 2009)

We also discussed the energy consumption of two office floors. Although a consistent baseline energy use was visible outside office hours, it was evident that the detection of individual appliances is not easy. In future, we wish to exploit the existing infrastructures at the office spaces (e.g., card accesses, and machine logins) and correlate this information against the aggregate energy consumption to individualized energy use. We also highlighted an experiment (at the office environment) to (a) measure the true baseline energy consumption of the floor, and (b) estimate energy savings through automated duty cycling of desktop machines and displays. Initial findings suggest 55% saving is possible.

Finally, the individualization of energy was discussed, and two metrics (baseline inefficiency factor and API) were introduced. These metrics assist (a) public sharing of energy use, (b) aggregation and combination of energy usage across different environments, and (c) comparison among individuals and environments. Future work towards measurement of energy use in other environments (e.g., transportation), and better assignment of energy use to individuals will help us to derive more accurate figures for these parameters.

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