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ORIGINAL PAPER

Can analytics software measure end user computing electricity consumption?

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Abstract
The purpose of this research is to answer the question, 'can analytics software measure end user computing electricity consumption?' The rationale being that the success of traditional methodologies, such as watt metres, is limited by newly evolved barriers such as mobility and scale (Greenblatt et al., in Field data collection of miscellaneous electrical loads in Northern California: initial results. Ernest Orlando Lawrence Berkeley National Laboratory research paper, pp 4–5, 2013). Such limitations significantly reduce the availability of end user computing use phase energy consumption field data (Karpagam and Yung, in J Clean Prod 156:828, 2017). This causes computer manufacturers to instead rely upon no-user present energy efficiency benchmarks (Energy Star, in Product finder, product, certified computers, results. Washington, D.C.: United States Department of Energy. https://www.energystar.gov/productfinder/product/certified-computers/results, 2021) to act as baseline data for product carbon footprint reports. As the benchmark approach is previously tested to cause scope 2 greenhouse gas emissions quantification to be inaccurate by −48% to + 107% (Sutton-Parker, in Determining end user computing device Scope 2 GHG emissions with accurate use phase energy consumption measurement, 1877-0509. Amsterdam: Science Direct, Elsevier B.V., 2020), testing a new methodology that includes the impact of human–computer interaction is arguably of value. As such, the proposed method is tested using a distributed node based analytics software to capture both computer asset and human use profile data sets from one hundred and eleven computer users operating in a subject organisation for 30-days. The simple rationale is that the node, unlike a watt metre, is not restricted by location, can be deployed and monitored globally from a centralised location and can move with the computer to ensure constant measurement. The resulting data sets are used to populate a current use phase electricity consumption calculation data flow (Kawamoto et al., in Energy 27:255, 2001; Roth et al., in Energy consumption by office and telecommunications equipment in commercial buildings: energy consumption baseline, 2002) in order to examine for omissions. Additionally, to test for data accuracy, one computer user acts as a control subject, measuring electricity consumption with both a watt-metre and the analytics software. The rationale being that the watt-metre data is extensively proven to be accurate (Energy Star, in Energy star computers final version 8.0 Specification, Washington D.C., United States Department of Energy. https://www.energystar.gov/products/spec/computers_version_8_0_pd, 2020) and will therefore expose errors produced by the software in relation to power draw, on-time and resulting kilo-watt hours (kWh) values. Further to the data capture period, the findings are mixed. Positively, the new method overcomes the barriers of numerous, assorted devices (scale) operating in ever changing locations (mobility). This is achieved by the node reporting in real-time make and model asset data together with device specific electricity consumption and location data via internet technologies. Negatively, the control subject identifies that the electricity consumption values produced by the software are inaccurate by a relatively constant 48%. Furthermore, data omissions are experienced including the exclusion of computer displays caused by the node requiring an operating system to collect data. This latter point would exclude the energy consumption measurement and therefore concomitant greenhouse gas emissions of any displays connected to desktop or mobile computers. Consequently, whilst the research question is answered, the identification of the software exaggerating use phase energy consumption by 48% and excluding peripheral devices, determines the analytics methodology to be in need of further development. The rationale being that use phase consumption quantification is key to lifecycle assessment and greenhouse gas accounting protocol and both require high levels of accuracy (WBCSD and WRI, in The greenhouse gas protocol. A corporate accounting and reporting standard, Geneva, Switzerland and New York, USA. https://ghgprotocol.org/corporate-standard, 2004). It is therefore recommended

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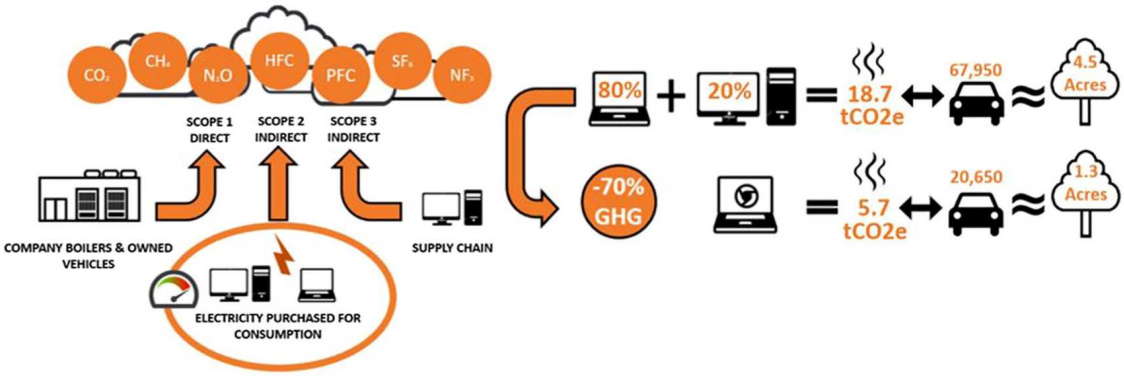
that further research be undertaken to specifically address omissions and to reduce the over reporting aspect identified as caused by algorithms in the software used to calculate hardware power draw.

Graphical abstract



Keywords Human–computer interaction · Use phase energy consumption · Computing scope 2 greenhouse gas emissions · Sustainable end user computing · Computing carbon footprints

Introduction

End user computing generates in excess 1% of global greenhouse gas annual emissions (Andraea and Edler 2015; Bekaroo et al. 2014; Belkhir and Elmeligi 2017; GeSI 2008, 2012, 2015, 2019; Malmodin et al. 2010) and therefore potentially represents a rich source of pollution abatement in order to tackle global warming. Life cycle assessment research indicates these greenhouse gases are predominantly generated by embodied emissions created by raw material extraction and manufacturing plus use phase emissions generated by electricity consumed by the devices during operation (Andrae and Andersen 2010; Andre et al. 2018; Arushanyan et al. 2014; Subramanian and Yung 2016). Whilst this is agreed, the proportionate representation of each value varies considerably between findings. As an example, the embodied phase ranges from 12 to 97% of the total and conversely use phase emissions from 3 to 88% (Atlantic Consulting and IPU 1998; Choi et al 2006; Duan et al. 2009; Hart 2016; IVF 2007; Kemna et al. 2005; Kim et al. 2001; Lu et al. 2005; PE International 2008; Sahni et al. 2010; Socolof et al. 2005, 2017; Tekawa et al. 1997; Teehan and Kandliker 2012; Williams 2004). From an embodied perspective, incongruity is caused by differences in the way lifecycle inventory data sources are calculated (Sonderegger et al. 2017; Steen 2006) meaning that depending on which database is accessed during calculation, the embodied value may change in prominence whilst remaining theoretically accurate (Finnveden et al. 2016; Peters and Weil 2016; Rigamonti et al. 2016; Rorbech et al 2014). From a use phase perspective, unlike the embodied emissions the total electricity consumed during a device life span is not fixed and can vary between identical devices. This is due to the use profile generated by each user and the location of use. As an example, whilst power draw measured in watts differs between device types due to component specification, the resulting kilowatt hour value used to measure energy consumption is influenced by human–computer interaction. Specifically, the type of computing activities conducted and the regularity and duration of those activities will alter the energy consumption result. Additionally, the use phase emissions are calculated by multiplying the electricity consumed value (kWh) by the greenhouse gas conversion factor published annually by each government where the energy is consumed (DoBEIS 2021). The factor is created to reflect the carbon intensity of the electricity supply grid. As such it is reasonable to state that the same research conducted in different geographies will generate different proportionate emissions results. As an example, in North America, where transition to solar, wind and water sourced energy has been slow, a conversion factor of 0.45322 exists (Carbon Footprint 2020). Comparatively, where adoption of green energy has proved faster, such as the UK, the resulting conversion factor is 0.21233 (DoBEIS 2021). As such, 10 kWh of electricity consumed in the former will create 4.5 $kgCO_2e$ greenhouse gas emissions compared to the latter of 2.1 $kgCO_2e$, thus increasing or decreasing the percentage contribution of end user computing use phase emissions.

Legacy sources of use phase electricity consumption data from the late twentieth century exist in relative abundance due to the fact that the majority of end use computers were desktop bound. As such, large user samples could be measured in situ using watt metre methodologies pioneered

by prevailing researchers to capture the kWh values (Piette et al. 1985, 1991, 1995; Yu et al. 1986; Norford et al. 1988; Nguyen et al. 1988; Dandridge 1989; Lovins and Heede 1990; Norford et al. 1990; Newsham and Tiller 1992; Johnson and Zoi 1992; Smith et al. 1994; Szydlowski and Clivala 1994; Koomey et al. 1995, 1996; Routurier et al. 1994). However, current use phase data sets are recognised as highly limited (Greenblatt et al 2013; Karpagam and Yung 2017; Malmodin et al 2010) due to 86% of end user computers becoming mobile (Gartner 2021; Statistica 2020, 2021) meaning that the immobile watt metre can no longer track the influence of human interaction. Greenblatt et al. (2013) emphasise that consequently, widespread use phase field measurement is now avoided due to scale and mobility creating unsurmountable logistical complexities. Such is the limited availability of contemporary field data, Karpagam and Yung (2017) note that whilst conducting end user computing device lifecycle assessments their work was made all the more difficult by what is described as a field that is 'data starved'. Belkhir and Emeligi, (2017) concur, conceding that electricity consumption findings are subject to error as validity of use profile variations is sought from sources predominantly tied to the desktop era between 1988 to 2002 (Norford et al 1988; Koomey et al. 1995, Kunz 1997, Komor 1997, Hosni et al. 1999, Roth et al. 2002). Intellect (2016) consequently echo Malmodin's et al. (2010) concerns concluding that using legacy source data to calculate modern day end user computing emissions is unreliable due to data being obsolete.

To compensate for the recent limitation, a second source of use phase electricity consumption data offers a contemporary baseline value in the form of pre-sale energy efficiency Energy Star benchmarks (Energy Star 2021). Conducted under strict test set-up and conduct regulations, the programme accurately measures newly manufactured computing devices for power draw in no-user present operational modes such off, sleep and idle (Energy Star 2020). The results are published online (Energy Star 2020) and include a typical energy consumption value to represent an anticipated annual kWh value. Whilst used as the basis for manufacturer carbon footprint publications (Apple 2021; Dell 2021; HP 2021; Lenovo 2021; Microsoft 2020) the values are ultimately without validity in the context of a life cycle assessment as they do not include the active operation mode when a user is interacting with the device. Prior research determines (Sutton-Parker 2020) that this causes the typical energy consumption value to be inappropriate as a substitute for field measurements as the additional power required as the device carries out useful work is excluded from any calculations (Sutton-Parker 2020). Specifically, the inaccuracy ranges from −48% to + 107% (Sutton-Parker 2020) consequently causing calculations reliant upon the benchmark method to under estimate the proportionate representation of use phase electricity consumption by an average of 30%.

Whilst the issue of embodied emissions incongruity is beyond the scope of this research, previous research designed to address key issues such as scale and mobility affecting the accuracy of use phase consumption values have been undertaken. Notably, in response to increasing legislation and policy to reduce scope 2 emissions in the public sector, Cartledge (2008) and Hopkinson and James (2009) produced the SustIT/JISC tool. Essentially an end user computing device specific version of the use phase emissions consumption input tables from the Kenma et al. (2005) life cycle assessment energy consumption calculator, the tool enables any organisation wishing to complete computer use phase emissions quantification to do so following a few simple steps. First the organisation simply conducts an asset profile exercise and then inputs the high level results (e.g. 20 × notebooks) into the tool. An annual energy consumption value is then applied to each device type, having been generated by use profile field data measured within the relevant universities where the original research was conducted. The resulting value is then multiplied by the relevant carbon emissions factor and a $kgCO_2e$ unit value is produced. Whilst logical, again the limitation of the imposed use profile based upon a fixed seventy active hours per week may address the inclusion of an active value, it does introduce error of non-specificity raised by Malmodin et al (2010). The issue lies within the uniform use phase electricity consumption value applied to device types (e.g. notebooks) rather than the specific notebook used by an organisation. As an example, the field measured annual electricity consumption in the workplace for an Acer Chromebook is 11.93 kWh (Sutton-Parker 2020) generating 2.53 $kgCO_2e$ of annual scope 2 emissions if used in the UK (DoBEIS 2021). Conducting the same calculation using the estimation tool (Hopkinson and James 2009), an average electricity consumed value of 30 kWh is applied (JISC 2019). This value is translated to scope 2 greenhouse gas emissions of 6.37 $kgCO_2e$ per device. As such, the inaccuracy introduced is equal to + 152%.

To overcome this non-specificity and the mobility barriers software has previously been trialled to achieve the similar action of a watt metre. The approach was called Joulemeter (Kansell 2010) and was capable of measuring and reporting real time energy consumption of both physical information technology hardware, virtual machines (VM) and software applications. Whilst the idea of moving to software based measurement would have offered scope for wide scale end user computing and use phase electricity consumption data to be generated, the tool suffered a setback for two reasons. Firstly, it required a watt meter for a calibration phase, thus re-introducing the issue it was designed to overcome plus upon scrutiny (Bekaroo et al 2014) it proved to only achieve 59% accuracy. Subsequently, the software failed to progress

and is noted only by Microsoft as no longer publicly available and deprecated.

Consequently, the objective of this research is to test an alternative method of capturing end user computing use phase data regardless of scale, mobility and location parameters. This is attempted by using remotely deployed analytics software. The rationale being that the reliance upon fixed position watt metering that has continued since the late 1980s may be overcome by utilising such a node based distributed data base approach that allows for mobile energy metering. In doing so, the holistic value of the research is that contemporary computer use profile field data can be generated by researchers or manufacturers without restriction and in abundance. Such untethered capability would produce data that both reflects the electricity consumption efficiency of today's end user computers and captures the real time evolution of emerging human–computer interaction that may affect power draw, such as video conferencing. If proven feasible, a field described as data starved (Karpagam and Yung 2017) and consequently reliant on aged data (Belkhir and Elmeligi 2017) could once again be populated with contemporary data. The impact of this will potentially enhance substantiation and accuracy for future research papers attempting to quantify the impact of end user computing upon global greenhouse gas emissions. The rationale being that it is accepted that the data currently used for the use phase energy consumption and concomitant pollution is difficult to validate due to the lack of available field data (Andraea and Edler 2015; Bekaroo et al. 2014; Belkhir and Elmeligi 2017; GeSI 2008, 2012, 2015, 2019; Malmodin et al. 2010). At a product level, achieving the objective will also refine quantification as to the contribution of electricity consumption to the total carbon footprint of end user computing devices that is subject to divided opinion (Atlantic Consulting and IPU 1998; Choi et al 2006; Duan et al. 2009; Hart 2016; IVF 2007; Kemna et al. 2005; Kim et al. 2001; Lu et al., 2005; PE International 2008; Sahni et al. 2010; Socolof et al. 2005, 2017; Tekawa et al. 1997; Teehan and Kandliker 2012; Williams 2004). This improvement may in turn speculatively, support emerging government procurement policy and legislation created to abate the environmental impact of information technology in the workplace (HM Government 2020, 2021; European Commission 2021a, b). As an example, the new legislations require evidence to be delivered that increases accountability and reporting related to the procurement and subsequent carbon footprint of information technology. As such, validating the use phase contribution with widespread field data may potentially act as a vehicle to enable compliance in relation to this requirement.

As such, in order to achieve the objective and prove the value of the research, the following sections describe the methodology used to conduct the field experiment and the results and discussion generated by the undertaking.

Methodology

The objective of the experiment is twofold. Firstly, to test the feasibility of using analytics software to capture both asset and use profile data regardless of scale, mobility and location. Secondly, to measure the accuracy of the resulting use phase electricity consumption values. To achieve this the following structure is used:

1. Identify a candidate organisation
2. Determine a suitable time horizon
3. Determine a test set-up and conduct for the organisation
4. Determine a test set-up and conduct for the control user
5. Determine a comparison test for the asset profile data collection
6. Measure the electricity consumption of end user computing devices for both the organisation and control subject
7. Document the results
8. Discuss the results
9. Summarise and conclude
10. Make recommendations and state limitations.

Selecting the subject organisation

Three considerations influenced the selection of the subject organisation. Firstly, more than fifty mobile users were required to test the capability of the software in relation to scale and mobility. The rationale being that the number is sufficiently significant to produce both device type and model variety. Secondly, operations within multiple countries was preferable to enable location capture to support the feasibility of identifying national based greenhouse conversion factors. Thirdly, a company already using the software for its intended use of digital experience management to avoid reluctance or delay related to the installation of new software that may be perceived as an unplanned cost or network security issue. To meet the criteria, the analytics software vendor was contacted and asked if they could propose a customer willing to participate in the research. The rationale being that Lakeside has over three thousand active customers and the likelihood of a positive response was high. Perhaps surprisingly, Lakeside themselves agreed to be the test organisation as they obviously use the analytics software as part of their business operations and were highly interested in exploring sustainability options both internally and to promote to customers. The profile of the candidate organisation subsequently met all proposed criteria.

Time horizon

The time horizon of the experiment is thirty days. This is determined by certain predefined reporting aspects built into the analytics software that offers both a daily and monthly cumulative report. Additionally, 30 days represents one month and as such can be extrapolated during the results and discussion to create annual values. It is recognised that the optimum duration would be one year although this experiment is to test feasibility plus the accuracy of the control subject. As such, it proved unfeasible for the control subject to remain in one location and connected to a watt metre for a period any longer than one month.

Test set-up and conduct for the organisation

The test set-up was relatively simple as Lakeside already use the analytics software and as such analytic database nodes resident on the end user computing devices were pre-installed and already collecting the required data at ten second intervals. To ensure that the asset and use profile data inputs identified as critical to the use phase consumption and concomitant greenhouse gas quantification were captured, a specific dashboard was created within the software's visualizer capability. As such, data sets including computer name, device manufacturer, model, serial, chassis format and age, power average in watts, energy consumption in kilo watt hours (kWh), on time (OT) observed, and location were able to be extracted at the end of the 30-day period. The format is a simple Microsoft.xls Excel binary file.

The conduct for the main body of users required no intervention or awareness. This was decided upon to ensure that the automatically captured data reflected the extraneous variables such as a multitude of unique user profiles experienced in a real life setting. The rationale being, that if the user was made aware that measurement was occurring, then this may change natural use patterns. However, as the control user was required to adhere to certain conditions to ensure comparison between the active time and watt metre readings, the following approach was employed in this instance only.

Test set-up and conduct for the control user

The control user was a single mobile user measured by both the analytics software and an accurate watt meter for use profile values to enable future comparison of results. This extra measure is undertaken to determine whether the electricity consumption values produced by the analytics software matched the accurate watt metre kWh results. Similar to the main cohort of users, the software was previously loaded and automatically reporting whereas the watt metre required specific set-up. To ensure that the notebook energy consumption measured by the watt meter was not altered by any additional power demands such as plug sharing or peripheral devices, elements of the Energy Star benchmarking test set-up (Energy Star 2020) were incorporated in the test set-up as they are proven to enable accuracy. These include:

A. The 'Input Power' using alternating current (AC) mains supply must be connected to a voltage source appropriate for the intended market (country). In this case the UK where nominal supply voltage is 230 V + 10%/ − 6% to accommodate transformer settings of 240 V
B. Connected to a watt meter meeting the IEC 62301 standards plugged in between the input power and the mains supply.
C. No peripheral devices were used or attached during the experiment
D. The notebook was connected to the power source for 24 h per day for the duration of the experiment

It is noted that as per the Energy Star recommendations the notebook remains connected to a power source. This is undertaken to ensure the watt metre continues to collect energy data. The rationale being that unplugging the device from the power source will register a pause in power draw by the watt meter but not by the software. As such, removing the device from the power source would invalid the comparison of both data sources. As such, the notebook can be considered the equivalent to a desktop in this instance by the fact that it is required to remain static throughout the process. To safeguard that the notebook energy consumption measured by the software was not affected by the loss of Wi-Fi signal during the experiment a local area networking (LAN) cable was connected directly to the broadband router via the Ethernet port. It was confirmed by the software vendor that the network interface card (NIC) is included in power monitoring. The notebook was operated by one consistent user throughout. To mirror real world use, no restrictions were placed upon when the notebook could be used during each twenty-four-hour measurement period with the exception noted below. As both the watt meter and software are capable of measuring the time per day that the notebook is 'on' and drawing energy the following modes were measured.

A. 'On Time' (OT) representing the period of time in hours and minutes that the notebook was 'on' and drawing electricity. This is not to be confused with the 'active' measurement used in experiment 2 as it also includes periods of time when the notebook has transitioned to other modes such as short or long idle.
B. 'Off' representing the period of time that the notebook was either switched off or had powered down and was potentially no longer drawing energy.

To enable comparison to existing TEC and active use comparative research, Energy Star recommendations were used for most part of the experiment as follows:

C. Display Sleep Mode was to initiate after 15 min of user inactivity as per Energy Star recommendations.
D. Sleep mode was set to initiate after 20 min of user inactivity as per Energy Star recommendations.

Deviations to this test set-up were included in the experiment on certain days to test the capability and accuracy of the software. These included changing the power settings for the device to disable the sleep and/or 'turn off the display function'. The rationale was to test if certain aspects of the software required the user to be actively logged in and working for energy consumption reporting to occur. This is explained in full in the results discussion.

Whilst the software data collection is automated, the watt meter daily energy consumption (kWh) values and on time (hours and minutes) were noted manually from the LCD screen at the same time to maintain consistency.

Asset profile test comparison

As the experiment include testing both the use phase emissions data capture and the asset profile data capture capabilities of the software a comparison of capability for the latter is required in addition to the electricity consumption control user. The rationale being that without alternative methods of asset profile capture against which to compare the results to, any findings may prove less meaningful. As such, two further asset profile exercises are undertaken at two separate large organisations using existing survey and asset management techniques. The results of all three approaches are then compared for ease and accuracy.

Measurement

The measurement occurred during March 2021 following the conduct previously documented, and the results are discussed in the following section.

Results

The results are discussed in two categories of feasibility and accuracy. As such the following sections firstly document the ability of the analytics software to capture asset and use profile data in relation to the majority of users, before discussing the accuracy of the use profile data as determined by the control user.

Feasibility testing asset and use profile data capture

The data flow created by Kawamoto et al (2001) and refined by Roth et al (2002) defines inputs required to calculate the use phase consumption of computer device types within large install bases such as companies, sectors and geographies. Effectively the model creates two data sets called asset profile data and use profile data. The first data set determines the types and number of devices used by various user types to create a stock unit quantity. The second captures user usage time and computer power demand in watts to calculate a unit energy consumption (UEC) value. The two values are then multiplied by one another to create a total end user computing device use phase electricity consumption value. As an example, Fig. 1 shows the data flow utilised to enable

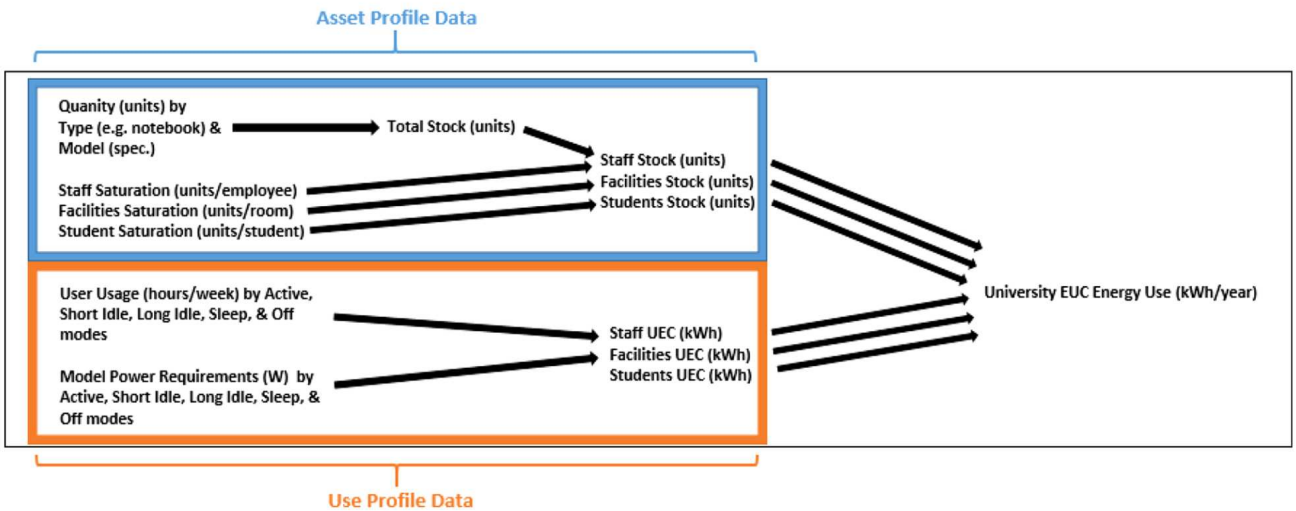


Fig. 1 Modified Kawamoto et al (2001) and Roth et al (2002) end user computing kWh data flow

the kWh consumption quantification of all end user computing devices within a University. In this instance, the educational establishment is able to not only understand the total energy consumption caused by devices such as notebooks, tablets and desktop computers but also sources of specific consumption such as student or staff notebooks further to population of the data.

Simplified, the calculation flow is represented by the equation Asset profile (units) × Use profile (kWh) = Total use phase energy consumption (kWh). Consequently, in order to accurately quantify end user computing device use phase electricity consumption values required for scope 2 greenhouse gas emissions calculation, the analytics software must first capture the following data:

- Asset profile data—quantity (unit), type (description), model (description) and user (description)
- Use profile data—power draw (watts), usage (hours and minutes)

Whilst the asset profile data is self-explanatory, the use profile data arguably requires explanation as to how the quantification of watts and time produce kWh. As such, the energy value (kWh) is produced, as would be the case with any electrical item, by multiplying power (watts) supplied to the device by the length of time (hours) the device is used, divided by equivalent energy used by a 1000 W electrical device for one hour. As an example a 50 W personal computer would take 20 h to consume 1 kWh. Therefore, the same 50 W device would consume 1.2 kWh if left in operation for twenty-four hours. Consequently, measured energy in kWh is expressed as follows:

$$\text{kWh} = \frac{\text{Watts} \times \text{Time (h)}}{1000}.$$

In order to inspect the data captured by the analytics software, three separate reports within the digital experience monitoring solution were accessed including hardware (computer name, manufacturer, model, chassis), computer performance (computer name, user name, location) and power (computer name, power draw, kWh, OT). To eradicate the complexity of cross referencing and possible introduction of error, a browser accessed dashboard was created within the software's visualizer function to isolate and display only the required data sets structured in a.xls format. In order to also ensure anonymity during the experiment, employee and computer names were intentionally obfuscated and replaced with alpha numeric sequenced descriptions (Table 1).

Asset profile data capture—quantity, type, model and user

Documenting the exact quantity of devices by type, model and associated users represents the foundation data required to complete the capture of asset profile data. As highlighted by the discussed JISC methodology (2019) previously, failure to produce device specific results generates inaccuracy. The original Kawamoto et al (2001) research utilised the calculation flow to calculate the number of devices in operation at a national scale generating stock unit quantities for residential, commercial and industrial computer installations. As the asset capture is undertaken within a single company, the market input is replaced with a job role. The rationale being that when examining identified areas of high end user energy consumption and therefore concomitant greenhouse

Table 1 Analytics asset and use profile data extract

Computer name	Power Av. (W)	OT observed (%)	Elec monthly (KWH)	Manufacturer	Model	Chassis	Country location	Role
Computer 1	17	15.9	2	Dell Inc	Latitude E7450	Laptop	NL	Not collected
Computer 2	54	42	17	Dell Inc	XPS 15 9570	Notebook	US	Not collected
Computer 3	Not collected	Not collected	Not collected	Not collected	Not collected	Not collected	US	Technical Support
Computer 4	47	70.5	24	Dell Inc	XPS 13 9370	Notebook	US	Not collected
Computer 5	10	21.4	2	Apple Inc	Not collected	Laptop	Not collected	Not collected
Computer 6	39	33.3	9	Dell Inc	XPS 13 7390	Notebook	US	Not collected
Computer 7	32	69.6	16	Dell Inc	XPS 13 9370	Notebook	US	Not collected
Computer 8	55	31.5	13	Dell Inc	XPS 13 9370	Notebook	US	Not collected
Computer 9	30	91.7	21	Hewlett-Packard	HP EliteBook Folio 1040 G1	Notebook	IL	Not collected
Computer 10	34	24.4	6	HP	HP EliteBook 840 G6	Notebook	PL	Not collected

gas emissions, an organisation is enabled to understand if it is a job role causing excessive OT. Additionally, to ensure appropriate national electricity conversion factors can be applied, an additional input of location is captured by the software. Further to the data capture period, the analytics software collected asset profile data from all one hundred and eleven end user devices. In relation to type, seven manufacturers were noted, consisting a total of forty-six different models of devices. Notably, no categorisation was achieved for 10% of devices, with a further 4.5% being tablets, 10% desktops and 75.5% notebooks. As demonstrated in the use profile section, type is vital to the data flow as a notebook will have a very different power draw to a desktop computer. The user role identified 17 sales people, 6 corporate workers, 1 professional services consultant, 7 technical support representatives and 2 technical services engineers. As such, 78 (70%) of employees were simply listed as 'not collected'. Location was captured successfully in 90 instances across eight countries with 23 entries registered as 'not collected'. Of the captured location data, 43% were based in the USA, 26% in the UK, 10% in India, 2.2% in each of the Netherlands, Poland, and the United Arab Emirates and 0.9% in both Israel and South Africa.

Further to the findings, it is notable that whilst asset data was captured for 100% of devices, the success rate of each metric suffered omissions. The 10% omission of type was discovered to be due to the software application programme interface (API) accessing basic meta-information from the Microsoft Windows Management Instrumentation (WMI) database. The WMI stores definitions of products to work in conjunction with the Windows Driver Model (WDM) to allow for update and management of the device by acting as a repository of software drivers, applications and extensions available in the Windows operating system (OS). As the inventory data populates automatically using the WMI data when the analytics agent is installed on the device, then the issue of type omission would require to be addressed within the WMI and is therefore arguably surmountable. The issue of only collecting 30% of job roles was defined as the role based attributed not being defined within the company's active directory. Consequently, to improve accuracy simply updating the employee role details on the domain network would theoretically rectify the issue. Of location, no definite reason for 21% lacking in data although the hypothesis was suggested that users exhibiting this lack of granularity may be using internet protocol (IP) masking software therefore denying the function access to information identifying which country the device is being used in.

Whilst it is anticipated that each omission may be overcome with additional focus, to gauge if the proposed analytics approach represents an improvement to existing techniques, further asset profiling practices were undertaken at two different organisations using survey and asset management software. The survey technique was undertaken at the University of Sussex, having agreed to assist the research due to an interest in wanting to better understand the environmental impact of the current end user computing estate with regards to use phase emissions. The technique proved highly time consuming from a creation process as it required sixty-eight specific questions to capture the required data via drop down, sliding scale and free type inputs. As the results were populated manually by the information technology manager, there was no ability to identify location of devices and only hardware supplied by the University could be included. As an example it was not possible to account for any student owned devices used in the campus. However, further to completion of the survey online via a supplied quick response (QR) code, the results identified 8,927 end user computing devices and 20,000 light-emitting diode (LED) displays. By type the devices were noted as 5200 desktop computers, 1,840 integrated desktop computers, 960 workstations, 927 notebooks and 20,000 monitors. Excluding the monitors, the devices are dominated by 58% desktops, 21% integrated desktops, 11% fixed workstations and 10% notebooks. Specifically, due to the prominence of monitors within the University estate, the survey technique highlighted that the analytics software failed to capture peripheral devices such as displays. Upon further investigation, it was found that the initial analytics 'hardware' report includes a column indicating the number of monitors detected as connected to the device at any point during the measuring period rather than any associate make, model or size. Further to speaking with the analytics vendor, it was explained that as the condensed SQL node requires an operating system to interface and as such reporting asset or power profile data for peripheral devices, such as monitors, was not achievable currently. Considering that 157 monitors are listed as connected to the devices profiled by the analytics software, the impact is significant as the resulting electricity consumption would be excluded from any calculations due to the lack of asset data. Comparing the two practices, each suffers setbacks. The survey technique lacks the automation of the analytics approach and cannot generate location context. Although positively, the ability to include peripheral devices is arguably essential for complete representation of use phase emissions. From a time to completion perspective, the lack of automation suffered by the survey method is partially passed on to the person tasked to populate the asset profile data as noted by the University information technology manager:

> 'I think the survey was very easy generally. There were a couple of sections I had to go back over because I'd not appreciated the whole breakdown of areas so consolidated initially and then had to separate once I realised, but this wasn't bad and could be addressed

by providing a list of the areas in advance. That would probably help anyway to be honest as there is a fair amount of info to gather which I happened to have but I'm guessing not everyone would.' – P. Collier, University of Sussex.

The comment highlights, however, that unless some form of asset list already exists then, unlike the analytics approach, the process may become unfeasible. Consequently, in order to offer an automated comparison to the analytics method, the same asset profile process was undertaken using automated asset management software at a prosthetic limb manufacturing company, Ossur. The company is an active participant in the United Nations Global Compact working towards sustainable and socially responsible goals and, similarly to the University, wished to assist the research in testing methodologies. As asset management software called Lan Sweeper was already installed at the company, a similar Microsoft Excel file extension spreadsheet was extracted using the software report structuring capability. As before, asset profile inputs such as quantity, manufacturer, model and location were generated with the exception of chassis (type) and role. This first exclusion was caused because the type of device, such as notebook, was not available within the report function as a criterion. To overcome this, a look up table was created to compare the captured device brand and model data with type data extracted from the Energy Star (2021) online data base. With regard to role, it is feasible within the software, although similar to the analytics software the function had not been configured at the active directory level. In order to overcome this in the short term, the captured location data was used to create role based context. Although not conclusive, this was achieved because each Ossur site has a specific function such as manufacturing and clinics. As such, a further lookup was created to generate a 'role' defined by location column including support, manufacturing and clinician. With the exception of the additionally created functions, unlike the survey method, the data extraction was instantaneous thus mirroring the time saving capabilities of the analytics solution. Arguably more importantly, the asset management software also identified peripheral devices such as monitors excluded by the analytics tool. Specifically, the asset management software method identified 3,928 end user computing devices. Of these 30% (1,160 units) were desktop computers, 67% (2,643 units) notebooks, 1% (43 units) integrated desktop computers and 2% (82 units) workstations. A further 2,579 monitors were identified ranging from 14″ mobile screens to 92″ presentation and information displays. From a role perspective, 20% of devices were used by prosthetic, bracing and supports business units, 20% by clinicians, 14% by manufacturing and operations, 5% by research and development with 41% unable to identify a specific role. Location data was captured for 97.5% of the devices with only 95 devices indicating neither region nor country. Proportionately, the devices were located 62% in Europe, 32% in the Americas, and 6% in Asia and Pacifica.

Summarising the asset profile data capture capability of the analytics software, it is reasonable to state that when compared to the existing methods of survey and asset management software it is certainly a more efficient approach in terms of time spent. Contrarily, it is also reasonable to suggest that having created the survey and the look up tables, this advantage diminishes when conducted for a second time. Undoubtedly, the survey method would fail if no prior records existed and as such the asset management software perhaps offers the ideal solution to populate the first half of the Kawamoto data flow. With regard to accuracy, to collect the key inputs of type, make, model, user and role analytics again outperforms both options from a granularity perspective by achieving the chassis categorisation and location without intervention. However, the oversight of not specifying peripherals such as monitors causes it to be highly flawed considering that such devices consume often higher electricity values annually than notebook devices. Specifically, in both cases of the University and the medical manufacturer monitors constituted 69% and 40% of all end user computing devices, respectively. Although arguably not always utilised by mobile device users operating notebooks and tablets within an organisation, considering too that fixed thin clients, desktop and workstations cannot operate without a monitor and represent 14% of all devices manufactured, ignoring this category is not feasible if accuracy is sought.

Use profile data capture—power draw, on time

Unlike the survey methodology and asset management software practice, the analytics software has the ability to collect use profile data required to populate second half of the Kawamoto et al (2001) data flow. Leveraging a distributed database architecture that is stored on the endpoint, the software captures thousands of end-user data points at five second intervals. The results are transmitted by networking technologies for compilation by a Microsoft SQL database operated by a master server situated either on-premises at the organisation's data centre or in a cloud computing data centre. The graphical user interface offers a configurable dashboard that when configured, enables selected metrics to be displayed either in summary or by detail such as a single user device at any selected time. Among the available metrics, the power reporting function captures power draw (watts) per device and OT observed (hours and minutes) in order to generate a kilowatt hour (kWh) calculation. As discussed in the methodology, this capability is effectively mimicking the actions of a watt metre without the restriction

of being bound to a static power source. Consequently, the use profile data captured for the subject organisation's devices is examined for completeness and tested for accuracy. Data quality assessment is achieved by ensuring the use profile data generated by the organisation's workforce is complete and where appropriate the kWh data can be converted to display location specific use phase greenhouse gas emissions, whereas accuracy is validated using a single user as a control subject measured by both a watt metre and the analytics software's power capability.

Data completeness was high with regard to capturing the use profile values as only 7% of devices were excluded. Examining these exclusions revealed that only the egress IP location had been captured suggesting that the device had been used at some point during the last year but not during the measurement period. The rationale being that this data is retained until refreshed. Whilst not confirmed in this specific case, this may be because the devices are surplus stock awaiting assignment to new employees. Consequently, 103 devices reported power and OT observed metrics required to complete the electricity consumption (kWh) calculation. The power draw is represented as a watt (W) average value for the entire period. This ranged from 10 W registered by an Apple MacBook Pro notebook to 145 W for the HP EliteDesk 800 G5, which is a tower form factor desktop similar to a small server. This created an average power draw of 49 W for the entire end user estate. The demand was elevated specifically by the desktop category, as would be anticipated due to the component architecture of the devices. As an example, the desktop power draw ranged from 59 W required by a small form factor HP EliteDesk 800 G1, rising to the noted 145 W, creating a desktop computer category average of 88 W. Comparatively, the notebook estate ranged from the noted 10 W value to 93 W registered by a Dell Latitude 5285 convertible notebook. As such, the measured notebooks averaged 39.66 W and 55% lower than the desktop estate. Examining existing research (Sutton-Parker 2020), the notebook values in particular appear relatively high adding emphasis to the examination of the control data discussed below.

The second metric of 'OT observed' is represented by a percentage of the 30-day period that the software node registers the computer as being used. As such, a 10% OT reading means that the device is used for 72 h during the available 720-h measurement period. Consequently, if the average power draw is 10 W, such a device would require 0.72 kWh of electricity consumption for one month. As with the W value, all but eight devices registered OT ranging from 2.4% (1 h 45 min) to 100% (720 h). The average for all devices was 41.42% OT during the thirty-day measurement period. As the month in which the measurement occurred included twenty work days this result indicated that the employees were either spending an average of almost fifteen hours per working day operating devices or that other factors were influencing use. These include the possibility of shared use, additional leisure use such as streaming, standard power management settings such as sleep being overridden or software inaccuracy. As accuracy is investigated thoroughly by the control device and leisure time and power management are not tracked, shared use was examined. As such 10% of the devices exhibited between 90 and 100% OT raising the average value considerably. Of these devices, it was revealed that 64% were desktops operated by technical support in shifts that according to the organisation, enable the support team to action requests twenty-four hours per day.

Applying the power average to the OT in the manner previously discussed produces a total of 1592 kWh electricity consumption by the end user computing estate. Specifically, the data determines that eleven desktops representing just 10% of all devices consumed 41% (657 kWh) of the measured energy due to a combination of high W values and extended OT as discussed. Comparatively, one hundred notebooks representing 90% of the estate consumed 59% (935 kWh). By location the UK consumed the highest value of 699 kWh (24 units), followed by the USA 585 kWh (39 units), India 66 kWh (9 units), Netherlands 29 kWh (2 units), Poland 19 kWh (2 units), the United Arab Emirates 23 kWh (2 units), Israel 21 kWh (1 unit) and South Africa 13 kWh (1 unit). The representation by country as displayed in Fig. 2 allows for visual comparison as to the importance of location when determining use phase emissions using national specific electricity conversion factors. Clearly whilst the use profile data determines the UK to be the highest consumer of electricity even though it has 14 less devices than the USA

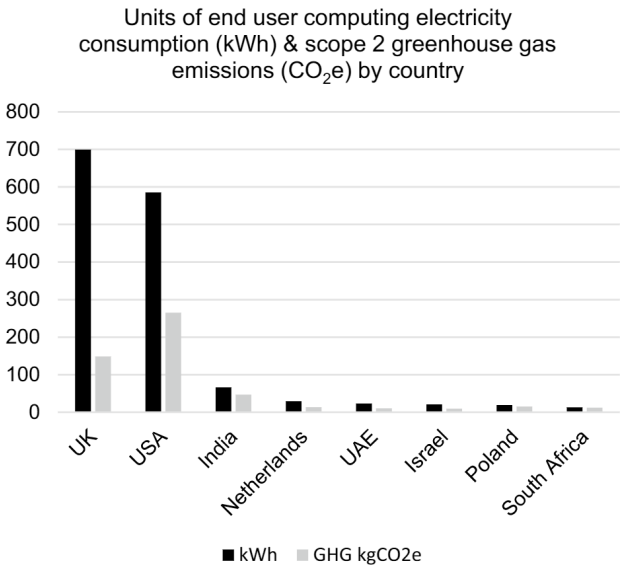


Fig. 2 End user computing use phase electricity consumption (kWh) and greenhouse gas emissions (CO_2e) by country

operations, in terms of actual emissions the USA proves to be the highest polluter. This is as previously described, due to less renewable energy being available in the US supply grid and therefore generating a higher carbon intensity of carbon per kWh consumed.

To summarise, with the exception of the surplus devices, use profile data capture using the proposed analytics methodology proved comprehensive. The key values of power (W) and use (hours and minutes) were captured successfully enabling concomitant greenhouse gas emissions values to be generated. As such it is reasonable to state that the analytics software achieved the same function as a watt metre whilst overcoming the barriers of scale and mobility. The rationale being that 103 devices were measured in near real time across 4 continents, 8 countries, with 90% of the devices being mobile. However, whilst the data is represented cohesively, if proven inaccurate, then the advancement of technique is diminished. As such the next section examines accuracy via the control user results.

Determining the accuracy of analytics software captured use profile data

Following the completion of the 30-day measurement period, the control user results indicate that the analytics software overestimates electricity consumption (kWh) by an average of 48%. The range of error is between minus (+) 29% to 58% with minor anomalies of − 100% caused by long period of 'off mode'. At a summary level, the accurate watt metre measured 4.25 kWh for the single device, whereas the software measured 6.31 kWh of electricity consumed. In order to determine the source of the disparity, the two measured values used to generate the kWh result are examined for inconsistency. As noted in the use profile capture section, these values are the time spent in operation and the power drawn (W) during that period.

On time observed

As noted, 'on time' (OT) is defined as the period of time measured in hours and minutes that the notebook is registered as drawing power and therefore consuming energy. Due to the 30-day duration of the experiment the highest feasible OT would be 720 h (30 days multiplied by 24 h). OT represents one of the key values used to calculate a kWh value. The results highlight that the watt meter reported a total OT measurement of 44.3% or 318.95 h during the 30-day period. Comparatively, the software reported an OT of 40.8% or 293.76 h. The results deliver an error of OT underreporting by the software of − 3.5% or − 25.2 h. Divided by the time horizon, this suggests that the software is not reporting electricity consumption for an average of close to 50 min per day. To identify the source of the OT inconsistency, data relating to 'off' and 'sleep' modes were examined.

'Off Mode' is defined (Energy Star 2020) as when the power consumption level in the lowest power mode which cannot be switched off (influenced) by the user and that may persist for an indefinite time when the appliance is connected to the main electricity supply. In context, off mode is achieved when the user has shut down (not sleep mode) the notebook yet it remains plugged into the power source. In this state no 'OT' should be registered by either the watt meter or the software. The results indicated that the watt meter did not register any OT when the notebook was in off mode. It was however noted that a minimal draw of 0.005 kWh was recorded for a 24-h period. Reversing the kWh equation indicates that 0.2 W 'trickle feed' of electricity occurs when the notebook is in off mode as the battery experiences a minor energy discharge. The standard Energy Star benchmarks are calculated with 'off mode' assumed as 25% of annual use profile. Using this mode weighting and the experiment results, the watt meter measured value would be 0.456 kwh per annum. The official Energy Star published benchmark results for the HP Elite Book notebook is 0.2 W draw and 0.438 kWh. Consequently, the watt meter results confirm that the source is 100% accurate for reporting 'OT' in 'off mode' and 96% accurate with regard to kWh measurement when extrapolated and compared to the typical energy consumed benchmark.

Comparatively, the software also correctly measured no 'OT' when in the 'off mode'. However, it was noted that the software also measured no power draw nor energy consumed. The impact of the software not reporting 'off mode' electricity consumption creates an under reporting disparity ranging from zero to 2% maximum depending on the duration of 'off mode' weightings. As an example, the maximum off time that could be attributed to the experiment's measured 30-day period is 55.7% or 16.7 days (401 h). As such, the total energy not measured by the software in this instance is equal to 0.0835 kWh or 1.9% of the total energy consumption measured. However, as the test set-up and conduct methodology includes a requirement for the notebook to be placed into sleep by the Energy Star governed power settings, there is no influence to the results of this experiment. In relation to 'Time' reported during off mode, it is reasonable to state that both the software and watt meter are 100% accurate and therefore this metric does not contribute to the 48% kWh disparity.

Having discounted 'off mode' as the source of error, the 'sleep mode' results were examined. 'Sleep Mode' is defined as a low power state that the computer is capable of entering automatically after a period of inactivity or by manual selection. As determined by the methodology the sleep mode was set to initiate automatically after 20 min for the predominant duration of the experiment. Exceptions

did occur including setting the notebook to sleep instantly at night and as described below in order to test the software capability. The results indicated that the watt meter registered 90 min of OT during a 24-h period when the notebook was in sleep mode consuming a maximum of 0.020 kWh per full day. The standard Energy Star typical energy consumption benchmarks are calculated with 'sleep mode' assumed as 35% of annual use profile. Using this mode weighting and the experiment results, the watt meter measured value would be 0.895 kwh per annum. The official Energy Star published benchmark results for the HP Elite Book notebook (the equipment under test) is 0.3 W draw and 0.919 kWh. Consequently, the watt meter results confirm that the source is 97.4% accurate with regard to kWh measurement when extrapolated and compared to the typical energy benchmark and within the accepted 5% error range.

Comparatively, the software measured zero 'OT' during sleep mode and no associated power draw nor electricity consumption causing it to be determined unresponsive and therefore inaccurate for all periods of time spent in sleep mode. As the OT registered by the software is 40.8% and the methodology dictates no 'off time', this finding indicates that the notebook entered sleep mode for a maximum of 59.2% of the experiment's duration. This time period is equal to 426 h and 14 min. The watt meter indicated that for each hour the notebook spent in sleep mode 3.83 min were classified as OT as the notebook was drawing a minimal amount of energy. Combining the mode and duration values indicates that 26.64 h of 'OT' has occurred but not been reported by the software due to sleep mode. Consequently, if the OT measured during sleep mode by the watt meter is added to the software OT reading, the result is 320.16 h of OT and is correct to within 0.37% of the watt meter 'Time' reading. As such, it is reasonable to state that the time disparity between the two data sources has been identified and explained.

Power draw

Whilst the difference between 'OT' values was satisfactorily addressed, the finding did not correct the 48% energy consumption (kWh) disparity generated during the experiment. Contrarily, if the additional kWh generated by the extra OT generated by sleep mode (0.1278 kWh) were added to the software results then the disparity would rise a further 3–51%. As such, the second key value of power (W) was examined for inconsistency. Having determined that time reporting was consistent between sources to within an error of -7.9%, and that the watt metre was accurate within less than 3% compared to published TEC results, theoretically the over reporting error must be caused by inflated Watt readings. As Fig. 3 shows the kWh daily reading from both sources is relatively consistent in its disparity across all 30 days. Both data sets follow one another's peaks and troughs across the experiment's time horizon as content switching fluctuated the power draw as various components worked at varying paces. The only exceptions to this are shown on two weekends (days 21, 22 and 28, 29) when the notebook was used for a very limited (and in some cases not at all) period. In these examples, the sleep mode kWh reported by the watt metre exceeded the zero kWh noted by the software as previously validated. Consequently, it is clear that the power draw (W) is being over reported by the software by an average of 51% per day when the four anomalous days were excluded. The full range of error was between + 48% and + 58%.

As the uniform disparity became obvious from the results generated in the first week, a one-day test measure was introduced for the 8th day in the hope that the results generated might indicate the source of the error. As such, specific short-term changes were introduced to the test set-up and conduct. Specifically, for the duration of day 8 only, the power options on the notebook were altered from those described in the methodology to the following:

- Turn off display when plugged in = Never
- Put the computer to sleep = Never

The rationale for the changes being that the notebook would remain in an apparent active work state for 24 h even after the user interaction had ceased. The results would list both the power requirements during working hours when content switching occurred and during the time that the screen was left active but resting during non-working hours (when no content switching occurred). Consequently, anomalies during either active or resting OT period may offer clues to the problem. The results for day 8 highlighted

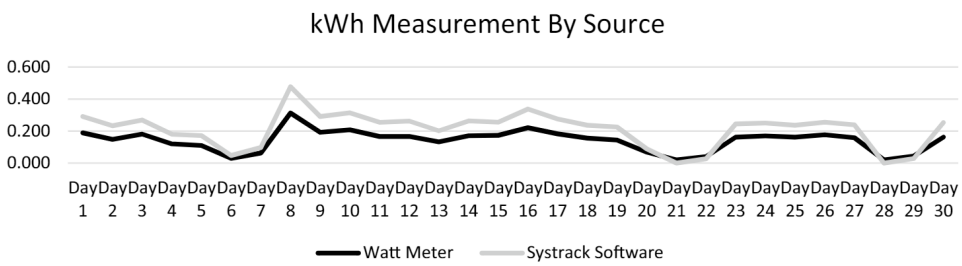


Fig. 3 Energy consumption (kWh) measurement by source (watt metre and software)

that the as expected the OT reported by both the software and watt metre was exactly 24 h and therefore correct. This further validated that the software is accurate with regards to OT measurement. During the 9 h when the notebook experienced user interaction the kWh inaccuracy rose to 63%. Comparatively, during the remaining 15-h period of the notebook being active but without user interaction, the kWh inaccuracy was lessened with a disparity of 46% when compared to the watt metre readings. Examining the watt results for the inactive period revealed that the software recorded a near constant reading of 19 W whereas the watt metre recorded 13 W. As such, it is reasonable to state that when the notebook is in idle or long idle mode (represented by the inactive period) the software is uniformly inconsistent by 46%. Examining the watt results for the active 9-h period revealed that the software recorded a range of 19 W to 26 W. Whereas the watt metre ranged from 13 to 27 W. At the lower end, the results reflected the inactive period results as expected. However, it was notable that the high end readings became almost equivalent in some instances. This suggested that either the frequency of measurement, changes in user tasks or a combination may be causing the issue. The rationale being that if the watt metre reports in real time, then the equivalence may only last for one second yet could theoretically be measured by the software for a longer period causing a greater disparity. Before examining the method of measurement used by both sources the impact of user tasks on the watt readings was examined (Fig. 4). Both lowest and highest watt readings were noted during four tasks including logging on (powering on), resting (with applications open), productivity (email, documents, spreadsheets) and video conference calls. The watt meter exhibited as total range of 107% and the software 37% creating a difference of 70% range during the active period. Specifically, the two sources L to H readings ranged across the four tasks as follows:

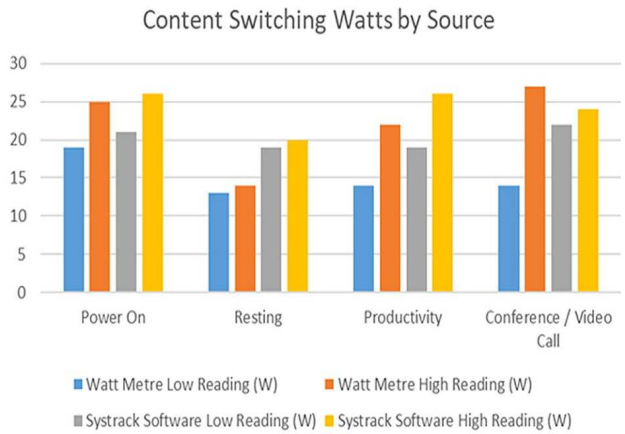


Fig. 4 Task impact of watts required

1. Power on
    a. Watt metre 32%
    b. Software 24%
2. Resting (applications running)
    a. Watt metre 8%
    b. Software 5%
3. Productivity
    a. Watt metre 57%
    b. Software 37%
4. Video conference
    a. Watt metre 93%
    b. Software 9%

The disparity in percentage ranges generated by the watt results clearly indicated that the two sources were using different methods of data capture. As an example, the 84% range disparity attributed to video conferencing is a result of two factors. Firstly, the rapidity of content switching driving the watt requirement changes, as people interact via audio, video and screen presenter ownership. Secondly, the likelihood that only one of the two methods of measurement is able to keep pace. In order to substantiate the hypothesis, the method of watt data capture was examined for both the watt meter and the software.

As expected, the watt meter updated the change in power draw (W) in real time as the user switched tasks, rising and falling as applications, video calls and web pages were opened, utilised and closed or left to rest. Monitored by filming the changes for two hours during a working day, it was noted that the watt metre W value altered on average every three seconds as content interaction or focus changes. Comparatively, the Lakeside software reports measurements every five seconds obtaining power and energy consumption data by querying the hardware bios counters. The data points are then reported as an average power rating in Watts (W) and a total energy consumption figure in kilowatt-hours (kwh) for consecutive ten minute periods during 'OT'. As such, it is true to state the following:

- For a single data capture conducted at 5 s intervals by the software, the watt meter will between 1 or 2 power (W) readings. As such the regularity of data snapshot by the watt meter is feasibly 2:1 compared to the software.
- For each ten-minute average watt measurement reported by the software, the watt meter will have conducted a minimum of 200 calculations compared to the software's 120 readings

Consequently, it is reasonable to state that the software undertakes approximately 40% less W readings per day than the watt metre and this may cause increased margins of error if the components being measured are subject to content switching. As an example, during the 15-h non-interactive period this had no effect as the power requirements did not fluctuate during the 3 s watt metre reading internal and the 5 s software interval. However, during the 9-h active period the rapidity of power fluctuation driven by content switching caused the resulting kWh calculate to increase in disparity by a further 17% when compared to the inactive period. As the 'active OT' period experienced during day 8 represented 37.5% of the 24-h period, the overall disparity was increased by 7% to + 53%, registering energy consumption of 0.478 kWh by the software versus 0.313 kWh. As content switching is random with no day exactly matching another in tasks undertaken or duration it was deemed highly unlikely that examining whether the duration (percentage) of 'OT' would uniformly affect the kWh disparity. As Fig. 5 highlights this was proven to be the case as the lines generated by the OT and kWh disparity do not track one another and instead often cross over with one value exceeding the other.

As an example, days 23, 27 and 30 all registered 52% OT, yet they have an energy consumption disparity between the software and the watt metre of 49%, 51% and 56% accordingly. In the first two examples the results appear promising that there is a correlation, however the third day questions the validity of the statement. Examining the OT results, notes and calendars for the three days, reveal that days 23 and 27 were spent working on research documents for the majority and therefore similar tasks were undertaken explaining the uniformity of the disparity in both OT and energy consumption. However, day 30 was spent viewing online training videos and participating in conference calls. Consequently, the tasks undertaken were evidently driving up the disparity due to the rapidity of content switching, despite the identical OT. As such, it is fair to state that whilst the active OT certainly influences the overall kWh measurement it is the duration of time spent during this mode undertaking specific tasks that dictate the range of increased over estimation.

To summarise the findings of the accuracy test, it is clear that the software is with substantial error in relation to measuring notebook energy use. Therefore, without compensatory measures being introduced to the calculations to generate concomitant greenhouse gas values for the proposed application, the emissions reporting will also be incorrect.

As the experiment identifies, there are four specific factors that are causing the inaccuracy:

- A 46% uniform over reporting of kWh energy consumption during 'OT'
- An average additional 5% over reporting of kWh energy consumption during 'OT' generated by user content switching outpacing the measurement intervals
- A zero kWh value measured during 'off mode'
- Zero OT recording during 'sleep mode' causing minor associated energy consumption to be excluded

These findings were discussed in depth with the analytics software manufacturer in an attempt to validate the causes suggested by the results. The engineering experts suggested that the uniform over reporting was most likely due to the fact that the software algorithmic tables that are used for component energy consumption had not been updated for several years. They explained that when the analytics software was originally conceived the tables were based upon mechanical hard drives. As the device used in the test had a solid state hard drive which would require less watts to power then this would cause the erroneous but uniform disparity. They accepted that the additional 5% over reporting due to content switching causing a lag in results due to the real time reporting of the watt meter and the software would be an issue during active user time. The zero kWh value measurement during off mode and the zero OT during sleep mode were also accepted as a minor issue that could not be overcome. The positive response was that based upon this research, Lakeside would re-examine their algorithms for component parts and bring them up to date to cope with the introduction of solid state storage and similar modern innovation. Doing so may overcome the main issue of the 48% over reporting although this would require further research.

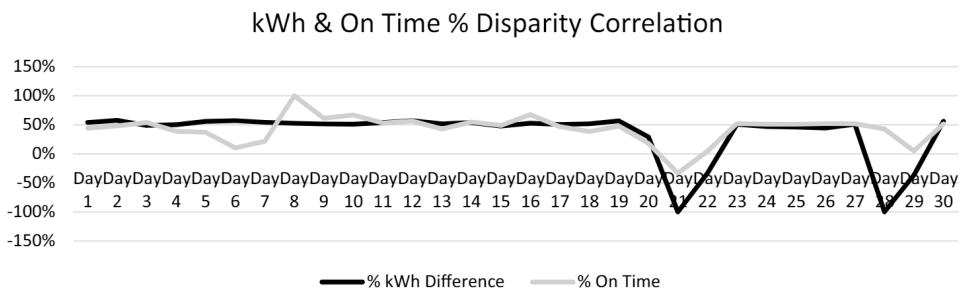


Fig. 5 On time versus kWh disparity

Discussion of results

The objective of the field experiment is to answer the research question, 'can analytics software measure end user computing electricity consumption?' From a practical perspective, the task is feasible as both end user computing device asset and use profile data are captured regardless of existing barriers such as scale and mobility. However, pragmatically, a lack of accuracy related to the electricity consumption results and data omissions generated during the asset profile process indicate that the methodology, is not currently fit for purpose. Specifically, the electricity consumption values were determined by the control measure to be on average + 48% inaccurate. The cause being due to outdated power draw algorithms applied to hard disc drives that have subsequently progressed from mechanical to solid state variants and as such requiring less electricity to operate. Additionally, the node based software failed to capture both the asset profile or use phase data of computer displays due to the software requiring an operating system to interrogate. This aspect is particularly concerning as the anticipated number of displays in operation within the subject environment outnumber mobile and desktop devices by 41%. Considering a watt measured energy consumption value for a modern 24″ Acer B8 monitor is 0.096 kWh per business day (Acer, 2021), the analytics software is omitting a potential 301 kWh per month. Accounting for the + 48% over reporting of electricity consumption generated by the analytics software during the experiment, this equivalent to 36% of the total and therefore can be considered a significant issue. Theoretically, to overcome the problem, the placement of watt metres between each display and the power source is technically feasible as these types of devices are not mobile and can remain connected. Subsequent data could be automatically supplied back to a master server by data loggers and compiled to add to the mobile and desktop computing data. However, undertaking such a task re-introduces the logistics issues that cause companies to avoid the practice in the first instance (Greenblatt et al. 2013) and as such does not represent an advancement of methodology.

In isolation, the barriers of mobility and scale (Greenblatt et al. 2013) are overcome as numerous devices subject to use in multiple locations, such as notebooks, are measured in real time regardless of location and quantity. It is reasonable therefore to suggest that, as 86% of global end user computing devices are now mobile (Gartner 2021), the analytics software removes the logistics issues associated with watt metres that is causing a shortage of available end user computing use phase electricity consumption field data (Karpagam and Yung 2017; Belkhir and Elmeligi 2017). However, setting aside the electricity consumption measurement error, omissions related to the captured location data prove an issue with regards to the production of scope 2 greenhouse gas quantification. Specifically, 21% of devices were not identified by location due to possible IP masking. As location data is essential to the application of appropriate electricity consumption (kWh) to greenhouse gas ($kgCO_2e$) conversion factors (DoBEIS 2021), the calculation of scope 2 concomitant emissions will also suffer invalidity due to a lack of specificity.

One aspect of the process does however arguably offer a possibility to expand research appreciation of use profile data. This is delivered by the analytics software 'OT' measurements that proved almost 100% accurate during the experiment. Theoretically, determining the duration of human–computer interaction at scale could prove valuable. The rationale being that creating granular profiles for users by specific business types and job roles, could enhance end user computing annual scope 2 greenhouse gas reporting. As an example, a determined average number of active computing hours applied to accounting tools such as the JISC (2019) tool could improve the accuracy of estimation by moving away from pre-determine 'time' use profile data applied as a standard to all business types. Although, as per the objective of the experiment, attaining accurate use phase electricity consumption values that include human interaction will still be required to account for the increased power draw created by use.

Conclusion

Whilst the asset data relating to end user computing devices can be improved by supplementary actions discussed in the results, the current omission of peripheral device profiling and electricity consumption errors of 48% cause the proposed methodology to be currently inappropriate to produce meaningful kWh and concomitant scope 2 emissions data. As such, it is reasonable to conclude that the proposed data capture process partially overcomes scale and mobility issues at the cost of inclusion and accuracy. As end user computing device energy consumption measurement is undertaken for several purposes, including device selection and scope 2 reporting, certain aspects of the discovered capabilities may prove useful. As an example, if an organisation wishes to use analytics to support a sustainable device procurement programme, then the method may be of worth. The rationale being that whilst inaccurate to an average of 48% in relation to electricity consumption, the software does have the ability to uniformly identify differing energy use results across multiple devices. As such a stacked ranking of energy efficient devices could be compiled and fed back to procurement teams as supplementary information

to current benchmark results such as the Energy Star typical energy consumption value. However, in comparison, if the analytics method is to be used to generate use phase data for either product carbon footprint reporting or mandatory emissions reporting, then it would prove inappropriate due to the omission of monitors and the excess reporting of power draw averages. Contrarily, if the method is to be used within mobile only environments, then it is reasonable to suggest an improvement in accessible field data has been achieved. The rationale being that as associated research substantiates (Sutton-Parker 2020) that use phase electricity consumption values determined by the Energy Star benchmarks create an error range of −48% to + 107%, then reducing this to a near constant + 48% via analytics software is arguably a step in the right direction.

Limitations and recommendations

It is recognised that the control user was conducted on one notebook and a wider experiment with increased numbers of devices, brands and operating systems is suggested in order to further improve the comparative results. The rationale being that where mechanical hard drives exist in legacy equipment the software may prove more accurate. It is also noted that the analytics use profile data proved highly accurate and as such generates patterns of working hours for the subject organisation. This creates a feasible recommendation to advance the process of end user computing energy consumption that accounts for the active operational mode. Firstly, if specific models of devices within an organisation can be measured by an accurate watt meter for a number of business days, then patterns of electricity consumption by both vertical and role based use could be formed. Applying this as an hourly electricity consumption value to the analytics use profile by user would then arguably form an accurate value for the energy consumption and concomitant emissions. As such, it is recommended that in conjunction with improvements to algorithms undertaken by the software vendor, further research to triangulate measured energy consumption with OT should be explored.

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Declarations

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