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Publication Date
2015

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December 1, 2014

The work described in this report was funded by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy, Building Technologies Program under Contract No. DE-AC02-05CH11231.

Acknowledgements

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This report is the product of efforts by many individuals. First and foremost, we are grateful to Janet Flint, Heather Hochrein, Jodi Pincus and all the talented Energy Specialists, Leaders in Field Training, Site Managers and Area Directors at Rising Sun Energy Center for making meter deployment and retrieval a reality. At LBNL, we are extremely grateful to the following staff Research Assistants and students for their dedication in preparing meters, downloading meter data and/or entering data into databases: Thomas Burke, Sophia Dauria, Kelly Elmore, Riley Foster, Danielle Fox, Jie (Jade) Gu, Karlyn Harrod, Evan Kamei, Colin Lawrence-Toombs, Brian McDevitt, Chun Chun Ni, Alex Valenti, Evangelos Vossos, Marley Walker, and Hung-Chia (Dominique) Yang. Moreover, we are grateful to Thomas Burke and Danielle Fox for script development, process documentation and troubleshooting of several metering issues, and to Deborah Ash for the procurement and delivery of meters to LBNL, space and storage logistics, as well as handling of on-going mailing of meters. We thank Mohan Ganeshalingam and Steven Lanzisera for helpful comments that improved this report. Finally we are grateful to Gregory J. Rosenquist and Alex Lekov, project co-leaders of the LBNL Energy Efficiency Standards Group, for providing high-level project support and encouragement.

Abstract

The electricity consumption of miscellaneous electronic loads (MELs) in the home has grown in recent years, and is expected to continue rising. Consumer electronics, in particular, are characterized by swift technological innovation, with varying impacts on energy use. Desktop and laptop computers make up a significant share of MELs' electricity consumption, but their national energy use is difficult to estimate, given uncertainties around shifting user behavior. This report analyzes usage data from 64 computers (45 desktop, 11 laptop, and 8 unknown) collected in 2012 as part of a larger field monitoring effort of 880 households in the San Francisco Bay Area, and compares our results to recent values from the literature. We find that desktop computers are used for an average of 7.3 hours per day (median = 4.2 h/d), while laptops are used for a mean 4.8 hours per day (median = 2.1 h/d). The results for laptops are likely underestimated since they can be charged in other, unmetered outlets. Average unit annual energy consumption (AEC) for desktops is estimated to be 194 kWh/yr (median = 125 kWh/yr), and for laptops 75 kWh/yr (median = 31 kWh/yr). We estimate national annual energy consumption for desktop computers to be 20 TWh. National annual energy use for laptops is estimated to be 11 TWh, markedly higher than previous estimates, likely reflective of laptops drawing more power in On mode in addition to greater market penetration. This result for laptops, however, carries relatively higher uncertainty compared to desktops. Different study methodologies and definitions, changing usage patterns, and uncertainty about how consumers use computers must be considered when interpreting our results with respect to existing analyses. Finally, as energy consumption in On mode is predominant, we outline several energy savings opportunities: improved power management (defaulting to low-power modes after periods of inactivity as well as power scaling), matching the rated power of power supplies to computing needs, and improving the efficiency of individual components.

Keywords: desktop computers, laptop computers, annual energy consumption, field monitoring, power, energy efficiency.

1. Introduction

The electricity consumption of plug loads (also known as miscellaneous electronic loads, or MELs) in the home has steadily increased in recent years (EIA 2013a, IEA 2009) as a result of a proliferation of devices within the home and improving efficiency in other traditional end uses such as space conditioning, lighting, and major household appliances. The share of electricity consumption attributable to consumer electronics is expected to continue growing (IEA 2009). In response to these trends, policymakers and researchers have launched various studies to better understand the energy consumption implications of consumer electronics. It is an area that evolves very quickly due to rapid technological innovation.

Computers (desktop, laptop, and tablet) represent a significant contribution to plug load energy consumption. A recent study estimated total national energy consumption of computers to be approximately 30 terawatt-hours per year (TWh/yr) (Urban et al. 2011). In 2013, 63% of U.S. households owned a desktop computer, 65% owned a laptop or notebook computer, and 39% owned a tablet computer (CEA 2013a). Furthermore, owner households own more than 1 computer on average. The Energy Information Administration (EIA) estimates in its 2013 *Annual Energy Outlook* that approximately

3% of total residential electricity consumption is due to computers and related equipment (EIA 2013a). This estimate, however, depends on assumed power draw and usage pattern data. The power draw of computers in various modes of operation can be measured relatively easily, but average computer usage is more difficult to assess, and is changing quickly with time. The emergence and popularity of tablet computers and smartphones is shifting computing usage away from more traditional machines like laptop and desktop computers.

Several recent studies have examined the usage of computers and related equipment in households, both in the U.S. and in other developed countries (EIA 2013b, Zimmerman et al. 2012, Strack 2012, Urban et al. 2011, Bensch et al. 2010, Enertech 2008, Roth & McKenney 2007, Porter et al. 2006, Chase et al. 2006). The most recent year in which data were collected was 2010, however, and computer technology and consumer behavior trends evolve very rapidly. The emergence of technologies such as tablets, smartphones, and media streaming websites has likely affected computer usage both positively and negatively in recent years. Frequent updates to these computer usage studies are therefore warranted to better understand how computers impact overall energy consumption.

The computer studies mentioned above either relied on field-metered electricity consumption data, or survey questions to infer overall usage. Using an electricity meter to monitor the electricity consumption of computers is the most accurate method of determining computer usage, but it can be very expensive, time intensive, and logistically challenging. Surveys are much easier and cheaper to deploy, especially for large samples, but potentially suffer from social desirability and/or recollection biases (*e.g.*, Pettee et al. 2008).

In this report we present an analysis based on computer usage data collected as part of a larger field data collection study (Greenblatt et al. 2013). By collaborating with an existing organization providing home energy audits, we were able to contain costs and minimize logistical challenges. This study collected data from 880 households in 2012 on a variety of MELs, including 64 computers. This report includes a brief discussion of the data collection methodology in section 2, presents results in section 3, and compares results to previously published estimates of national computer energy use in section 4. Finally, the report is summarized in section 5.

2. Data and Methodology

The data analyzed in this report were collected as part of a MELs field metering study in collaboration with Rising Sun Energy Center[1], a non-profit organization providing workforce development services, residential retrofits, and education on sustainable behaviors and technologies. A total of 1176 electricity meters were deployed in 880 households by a team of Energy Specialists from Rising Sun, in conjunction with their free energy audit program. Meters were installed in fourteen cities in the San Francisco Bay Area between July 2 and August 4, 2012, and left in the field between three to ten weeks. For more details on the overall study design and deployment, see Greenblatt et al. (2013).

[1] http://www.risingsunenergy.org

With respect to computers, data were collected with WattsUp?.Net meters[2] (hereafter "WattsUp"), which recorded full time series electric power data using a 2-minute time interval. A total of 90 WattsUp meters were deployed in the field connected to computers (both desktop and laptop). A small fraction of meters were unrecoverable, and some meters had data quality issues due primarily to multiple power outages (see Greenblatt et al. 2013 for more details). After data processing was complete, records with less than one week of clean data were also excluded from further analysis, as we considered this sampling to be insufficient and unrepresentative. The analysis presented here includes data from 64 WattsUp meters, as listed in Table 1. The monitoring time period of these computers varies from 9 days to over 10 weeks, with an average of approximately 5.6 weeks.

Table 1. Individual computers metered and used in analysis.

Computer Type	WattsUp Meters
Desktop	45
Laptop	11
Unknown	8
All	64

Our sample was restricted to fourteen municipalities in the northern and eastern portions of the San Francisco Bay Area, with the highest participation rates in Richmond (15%), Fremont (13%), Union City (13%), and Pleasanton (12%). Field data collection took place across a range of self-reported income levels, household sizes and age structure, education levels, and racial backgrounds. Since only urban and suburban neighborhoods were represented in our sample, we infer an urban bias, potentially in the direction of higher computer usage.

In order to assess whether our sampling is more widely representative, we can make some broad comparisons with the 2009 Residential Energy Consumption Survey (RECS) administered by the Energy Information Administration (EIA 2013b). RECS is a nationally representative data source that in 2009 surveyed more than 12,000 households, but its questions regarding computer usage lump responses into rather coarse bins for respondents' first- and second-most-used computers. As shown in Figure 1, the regional biases are very small in the data analyzed by Census Division. California on its own, as well as the Pacific Division including California, may display slightly higher self-reported computer usage than the nation as a whole. The RECS data do not allow us to determine whether computer use notably differs between urban and rural areas.

[2] https://www.wattsupmeters.com/secure/products.php?pn=0

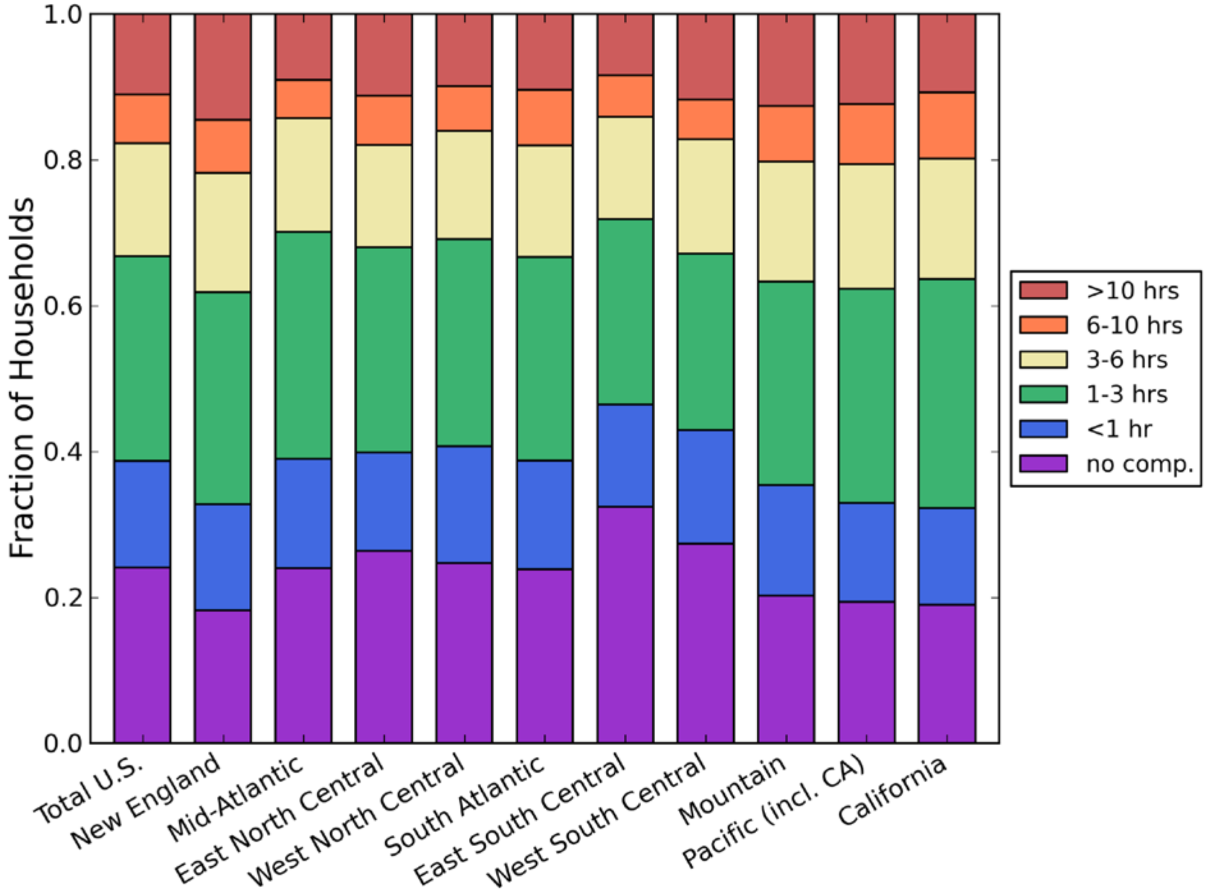

Figure 1. Daily computer usage by Census Division for the most-used computer in a household. Data from 2009 RECS (EIA 2013b).

In contrast to regional bias, RECS data show that household income is tightly correlated with daily computer usage (see Figure 2). However, only 59% of sample households from our larger field-monitoring effort disclosed household income, with 54% of known responses reporting annual income under $60,000 (Greenblatt et al. 2013). At the same time, the San Francisco Bay Area has a high cost of living relative to the rest of the country. With only 64 metered computers, and a large fraction of households who decline to state their income, we cannot conclusively say whether our sample is subject to a systematic income bias. Overall, we suspect that we sampled higher-usage households than did the nationally representative RECS, given our sampling location in an urbanized region of California next to Silicon Valley.

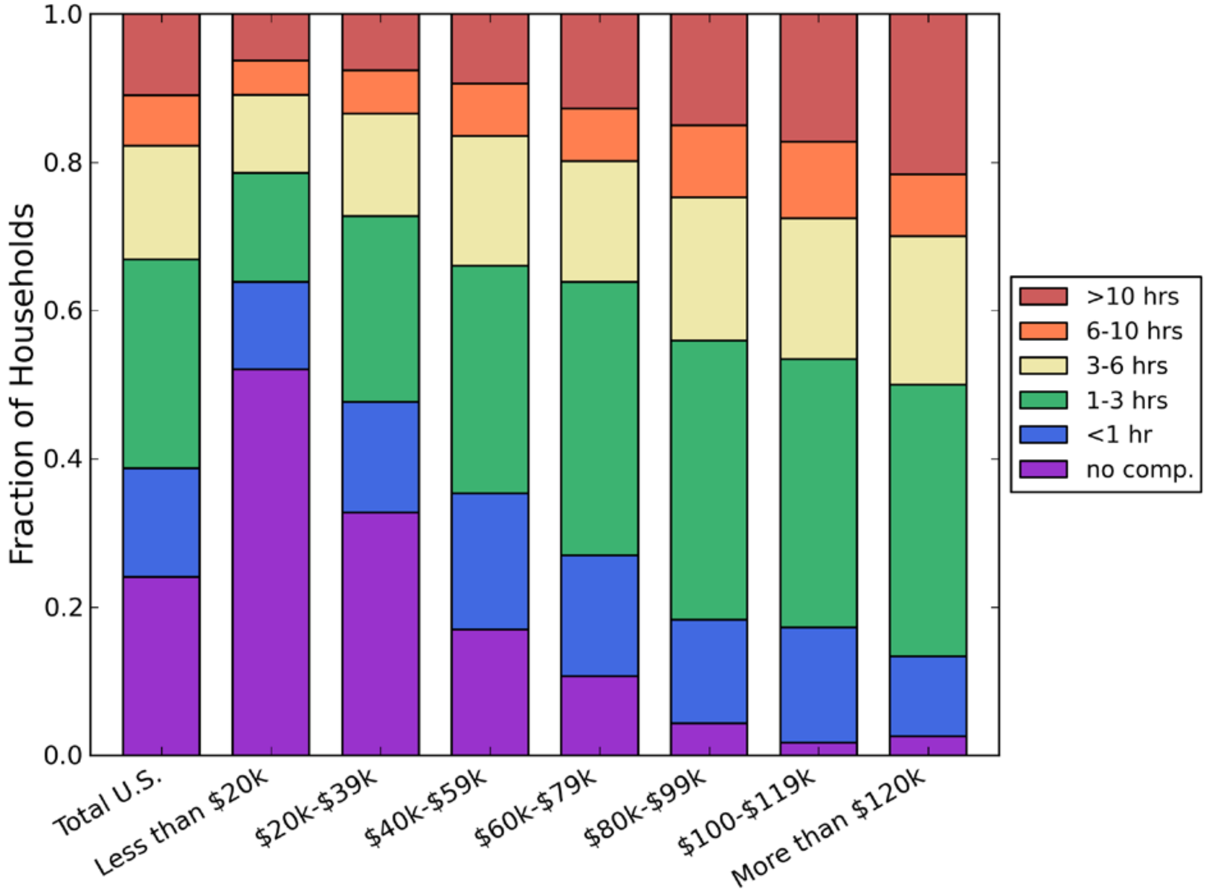

Figure 2. Daily computer usage by household income for the most-used computer in a household. Data from 2009 RECS (EIA 2013b).

In order to perform a detailed usage analysis, the time series data were labeled as belonging to one of three mode categories: Off, Standby, and On. The Off mode category is associated with a power reading of 0.0 W, and typically occurs when the computer is either unplugged (*e.g.*, in the case of laptops), or with a power draw so low it registers as 0.0 W. The Standby mode category (which, in reality, is a collection of individual and distinct functional modes) is when a computer is not being actively used. This mode may include the standard "sleep" function on many computers. Additionally, when a computer is turned off by the user, but the residual power draw is non-zero (*e.g.*, due to power supplies), it will be labeled as Standby in our analysis. Finally, the On mode category is when a computer is actively being used. This category includes when the computer is idle (*e.g.*, turned on but not currently processing any logical instructions and not receiving any data input).

Figure 3 displays the cumulative distributions of individual WattsUp power measurements for all computers metered in our study. The separation between Standby and On was chosen to be 8 W for all devices. This clearly separates clusters of data for all computer types (gaps in clusters of data manifest themselves as horizontal lines in a cumulative distribution).

In addition to the computers, several monitors connected to computers were also metered. Of the 64 computers with WattsUp meter data, 10 have coincident monitor WattsUp data which pass the same data quality checks as for computers. These 10 pairs of computers and monitors were analyzed to determine whether one device was being left on while the other was turned off. The separation between Standby and On for monitors was also chosen to be 8 W, based on the cumulative distribution of power measurements.

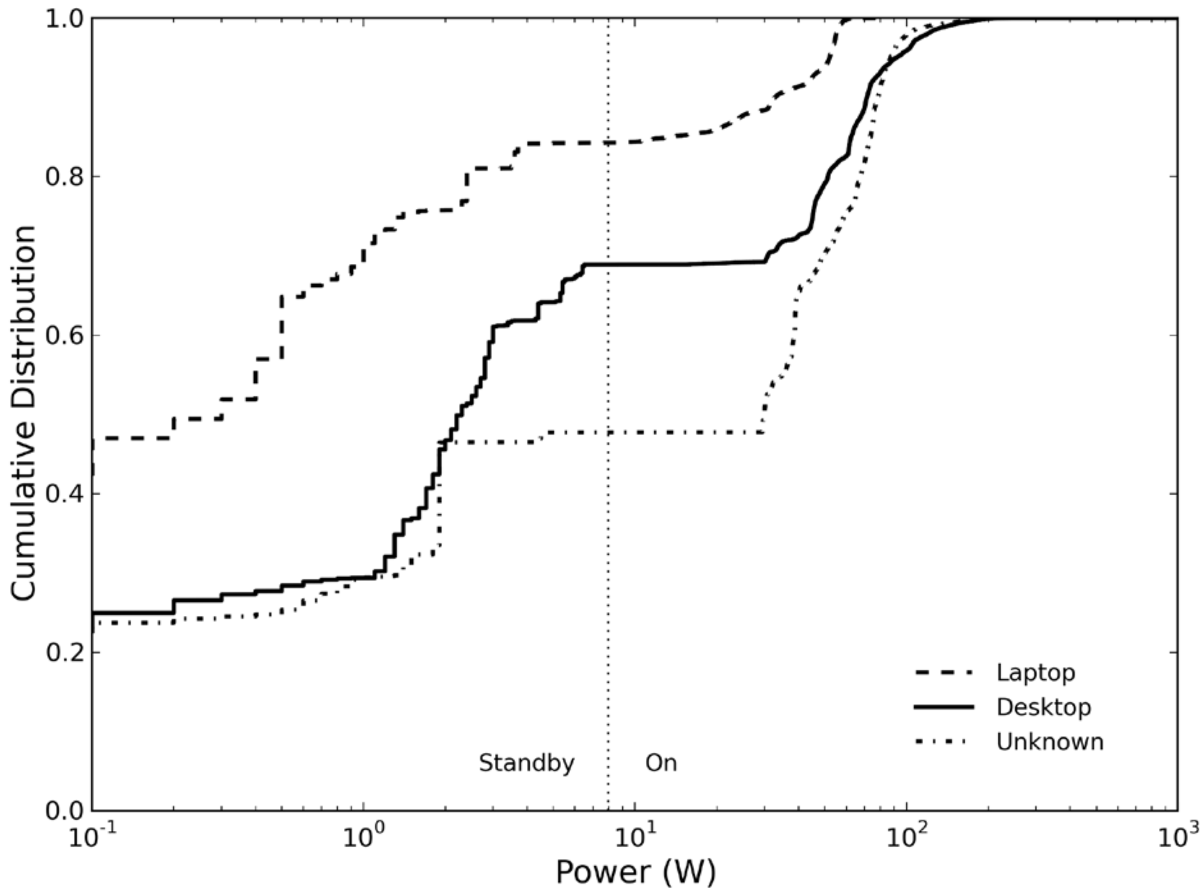

Figure 3. Cumulative distributions of power measurements for all computer types. The horizontal axis is on a logarithmic scale. Measurements are labeled as belonging to one of three mode categories: Off, Standby, or On. Off mode is for measurements of 0.0 W. Standby mode includes all measures greater than 0 W but less than 8 W for all computers. On mode includes measurements greater than 8 W for all computers.

3. Results

Table 2 lists the average and median power measurements in Standby and On mode for all computer types. We also include the range of literature values for computer Standby and On mode power. Our results are generally consistent with other report values, with the possible exception of laptop On mode power. This might be due to the newer generation of laptop computers sampled in our study, which likely have greater functionality and capability than older laptops. Errors are estimated using the bootstrap resampling method, due to the smaller sample size and somewhat exponential distribution. With this method, a sample of data (of equal size as the original) is reconstructed many times (of order 10,000 times) by randomly sampling from the original distribution of data. A given data point can be sampled more than once in a reconstructed sample (known as sampling with replacement). The value of interest (*e.g.*, average usage) is calculated for each reconstructed sample. The variance in the distribution of that value over all samples is then assumed to estimate the error in that value from the original data set.

Table 2. Average and median power in Standby and On modes for all computer types. Literature values are from Zimmerman et al. (2012), Urban et al. (2011), Bensch et al. (2010), Roth & McKenney (2007), Porter et al. (2006), and Chase et al. (2006). Errors represent the 95% confidence interval estimated using the bootstrap resampling method with 10,000 reconstructed samples.

Console Type	Standby Power (W)			On Power (W)		
	Average	Median	Literature	Average	Median	Literature
Desktop	$2.0^{+0.6}_{-0.4}$	1.9	2.4 - 5.7	$66.1^{+7.6}_{-7.6}$	65.8	60 - 75
Laptop	$1.7^{+1.5}_{-0.9}$	1.0	0.7 - 2.6	$32.0^{+7.0}_{-5.2}$	32.5	19 - 32.3
Unknown	$2.1^{+1.7}_{-1.1}$	1.4	-	$53.1^{+12.0}_{-10.4}$	51.0	-
All	$2.0^{+0.5}_{-0.4}$	1.7	-	$58.5^{+6.5}_{-6.3}$	56.7	-

Figure 4 shows the distribution of computers by the fraction of time the computer is in On mode, as opposed to Standby or Off. Approximately 50% of all computers are in On mode for 4 to 5 hours per day or less, while a few individual computers are left on nearly 24 hours per day. We do not have any data on whether these computers are being actively used when they are in On mode (*e.g.*, using occupancy sensors). A computer left idling is considered in On mode, so there is likely a good fraction of time that could otherwise be spent in Standby or Off mode (especially for those computers on all day). Laptop computers in general have a lower fraction of time spent in On mode because they are mobile devices that can be unplugged. The usage results are with respect to the electric outlet, not the user, and represent the fraction of time to recharge the laptop battery using that outlet. As part of the initial meter installation procedure we encouraged users to always charge laptops using the metered outlet. We could not verify with any certainty if this was the case, however. Therefore, the results for laptops are potentially underestimated because of the laptop computer's ability to be plugged in elsewhere (and therefore not metered). Table 3 lists the average and median usage for all computer types.

The minority of computers left in On mode nearly all day significantly affect the average usage as compared to the median. The average fraction of time spent in either Off, Standby, or On modes is also shown in Figure 5. Note that there are very large variations about these averages for individual computers, with some computers on nearly 24 hours per day.

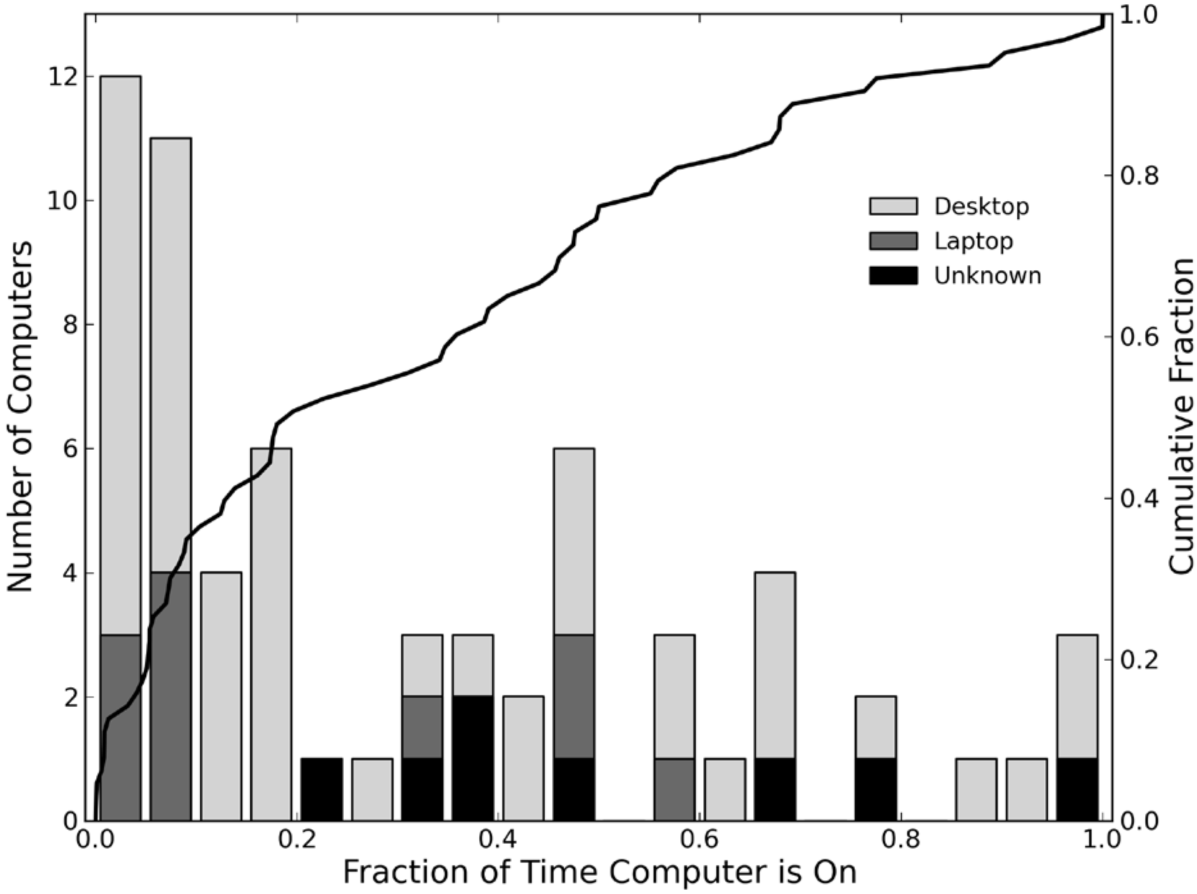

Figure 4. Distribution of individual computers by the total fraction of time in On mode. Results are shown separately for each computer type (left vertical axis). The histogram bins are evenly distributed from 0 to 1, and are 0.05 wide. The first histogram bin includes values of 0. Also shown is the continuous cumulative distribution of all computers together (solid line, right vertical axis).

Table 3. Average and median usage for computers, in hours per day. Errors represent the 95% confidence interval estimated using the bootstrap resampling method with 10,000 reconstructed samples.

Computer Type	Average Usage (hr/day)	Median Usage (hr/day)
Desktop	$7.3^{+2.3}_{-1.9}$	4.2
Laptop	$4.8^{+3.5}_{-2.5}$	2.1
Unknown	$12.6^{+5.0}_{-3.4}$	10.2
All	$7.6^{+1.8}_{-1.6}$	4.5

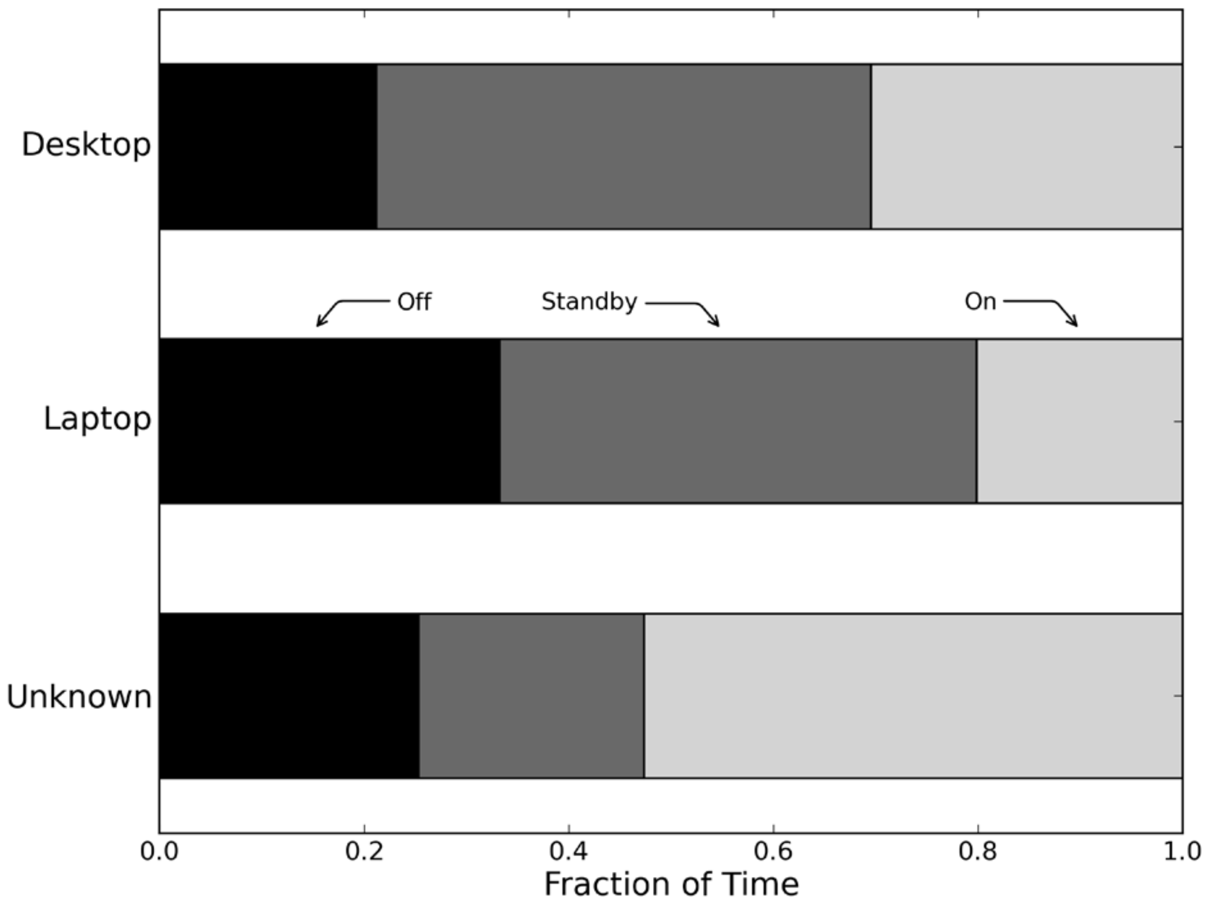

Figure 5. Average fraction of time spent in either Off, Standby, or On modes, for each computer type.

We calculate the estimated annual energy consumption (AEC) of all individual computers, assuming that the usage observed during the metering period is representative of the yearly average. We acknowledge the uncertainty in projecting annual usage based on an average of 6 weeks of data per device, although we note that previous work on commercial plug-load metering suggests that 6 weeks provides a reasonable level of confidence (Lanzisera et al. 2013). A much longer metering period only marginally improves annual energy estimate confidence intervals. Furthermore, we do not expect computer usage to vary significantly throughout the year. The full metering period covers late summer to autumn, likely encompassing any minor seasonal effect (*e.g.*, school not in session during the summer). Therefore, we can simply extend the aggregate energy measured over the metering period to 365 days. Figure 6 shows the distributions of AEC for each computer type, and also includes the cumulative distribution of all computers for comparison. Table 4 lists the average and median AEC for each computer type. The median AEC for all computers is 126 kWh/yr, although the top 20% of computers consume more than 300 kWh/yr. Unsurprisingly, the AEC of laptops is considerably less than for desktop computers, although the AEC of laptops is in all likelihood underestimated. Laptops are mobile devices that can be charged via other outlets in the home (without using the WattsUp meter), or even outside the home. As a result, the AEC calculation probably excludes some fraction of total energy consumption. The highest AEC in our sample was 563 kWh/yr, for a desktop computer that was on over 88% of the time.

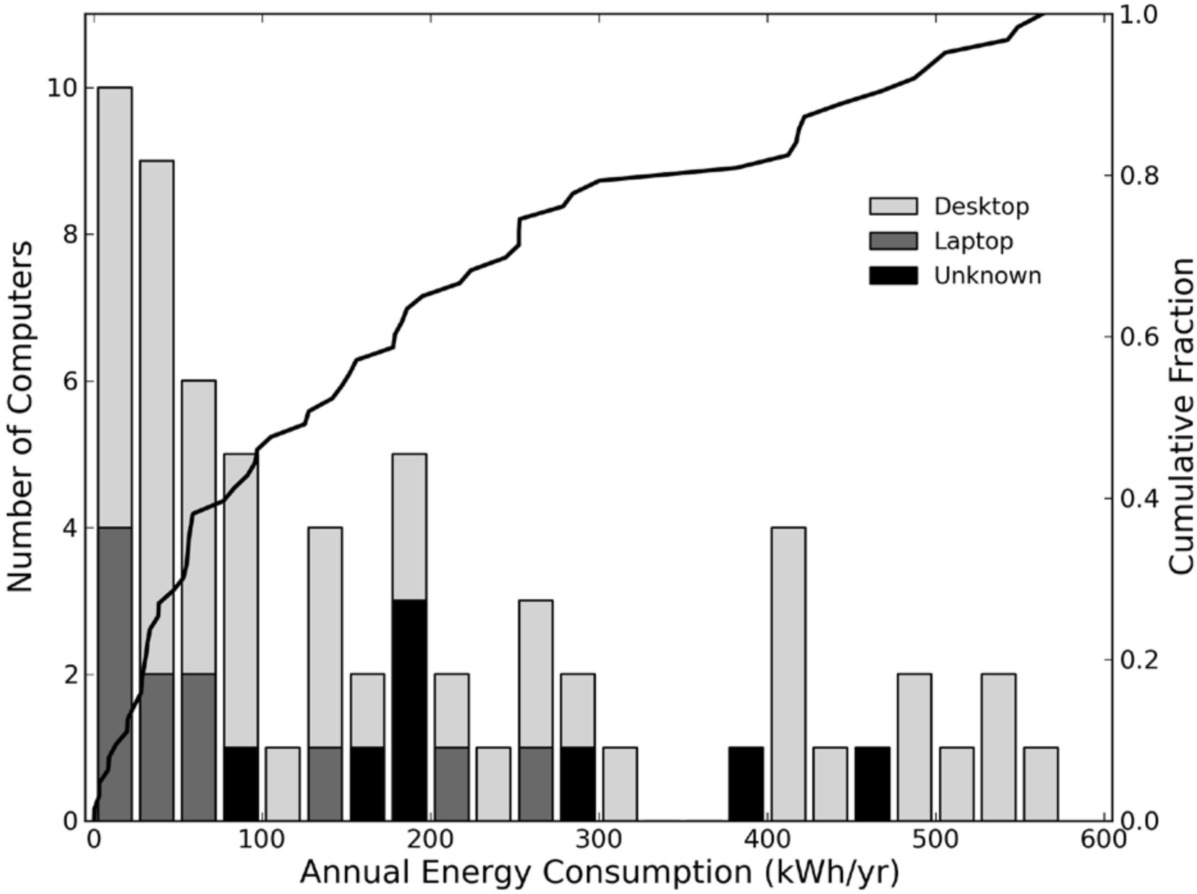

Figure 6. Distribution of individual computers by the estimated annual energy consumption. Results are shown separately for each computer type (left vertical axis). The histogram bins are evenly distributed between 0 and 600 kWh/yr, and are 25 kWh/yr wide. Also shown is the continuous cumulative distribution of all computer types together (right vertical axis).

Table 4. Average and median estimated annual energy consumption for all computers. Errors represent the 95% confidence interval estimated using the bootstrap resampling method with 10,000 reconstructed samples.

Computer Type	Average AEC (kWh/yr)	Median AEC (kWh/yr)
Desktop	194^{+57}_{-49}	125
Laptop	75^{+63}_{-39}	31
Unknown	242^{+95}_{-70}	191
All	179^{+44}_{-38}	126

Lastly, Figure 7 shows the ratio of monitor On time to computer On time, for the 10 computers with coincident monitor usage data. Ratios greater than 1 indicate that the monitor is left in On mode after the computer is put in Standby or Off mode. Only 2 monitors exhibit a ratio greater than 1, for 2 computers with very low usage. The other monitors exhibit ratios between 0.6 and 1, suggesting that on average a significant fraction of computer On time is associated with a blank monitor. This presumably occurs when the user has stepped away from the computer for an extended period of time, triggering the monitor's power management.

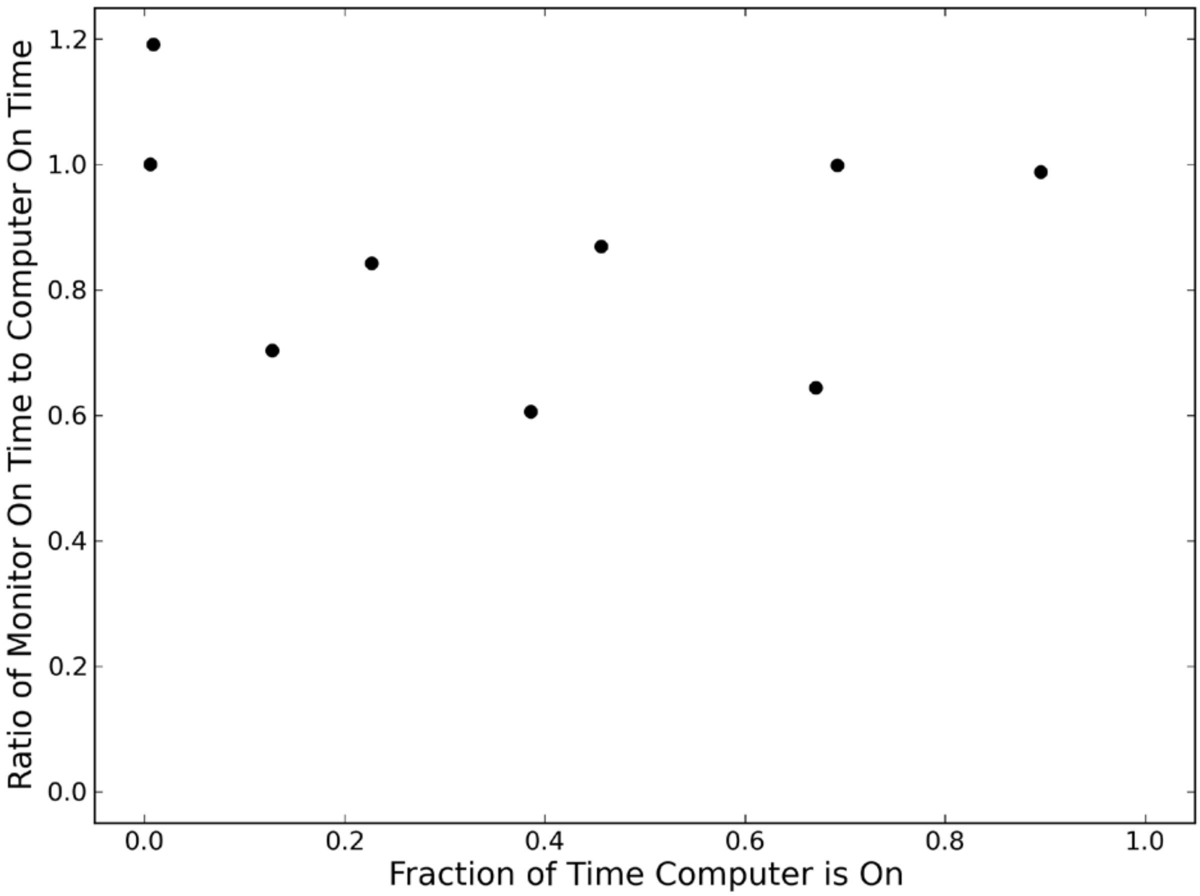

Figure 7. Fraction of time the monitor was on when the computer was also on, as a function of the fraction of time the computer was on during the day. There are 10 computers in the data set with concurrent monitor WattsUp data. One data point is much greater than 1 for a computer with very low usage, and is not included in the figure.

4. Discussion

National Energy Consumption

Under the assumption that our metering results are representative of nationwide usage, we can estimate total national energy consumption due to computers. We find an average AEC for desktops of 194 kWh/yr (from a sample of 45) and 75 kWh/yr for laptops (from a sample of 11), with greater uncertainty for laptops likely as a result of the smaller sample size, as well as the difficulty of determining duty cycles when the laptop is not plugged in (*i.e.,* away from the WattsUp meter). The installed base in 2013 of desktop computers in the U.S. is estimated to be 105 million units, while that of laptops, notebooks, and netbooks is 147 million units (CEA 2013a). Assuming that all of these computers are usable, we estimate national energy consumption is $20.4^{+6.0}_{-5.1}$ TWh for desktops and $11.0^{+9.3}_{-5.7}$ TWh for laptops in 2013. As a comparison, EIA's *Annual Energy Outlook* estimates that in 2012 the U.S. residential sector consumed 1375 TWh of electricity, 38 TWh (2.8%) of which was due to desktop and laptop computers, monitors, and networking equipment (EIA 2013a). Our results appear to be consistent with EIA, especially since their category includes additional equipment resulting in higher energy consumption. Another comparison can be made to the most recent EIA Residential Energy Consumption Survey (RECS) for which data are available (EIA 2013b).The 2009 RECS collected interview data from 12,083 nationally representative households; the results are summarized in Table 5. CEA's stock estimates for desktops make up 42% of the installed base of computers, while laptops make up 58%. It is difficult to directly compare this breakdown of desktops vs. laptops with RECS, given that they ask participants about their most- and second most-used computers if they used more than one computer, instead of how many of each type are used. Laptops have also increased in market share relative to desktops in recent years, while more computers overall are present in homes today than in 2009. Moreover, RECS queried about the number of computers *used* in a home, not the number *owned*, which may partially explain the discrepancies in installed base. The average daily usage from our study is $7.3^{+2.3}_{-1.9}$ hours for desktops and $4.8^{+3.5}_{-2.5}$ for laptops. While at first blush this appears quite a bit higher than RECS, the latter data are self-reported, and it is likely that respondents think only about times when they are actively using their computers, instead of the total time spent in On mode. Additionally, it's possible that computer usage has increased from 2009 to 2012.

Table 5: Data regarding computer usage from the 2009 Residential Energy Consumption Survey (EIA 2013b).

	Most-Used Computer	Second Most-Used Computer
Desktops %	56%	40%
Notebooks %	44%	60%
Hours Used Per Day:		
<1	19%	35%
1-3	37%	34%
3-6	20%	14%
6-10	9%	6%
>10	14%	11%
Units in Stock	148.4 million	

A review of prior studies of computer usage and electricity consumption has established a range of estimates for typical duty cycles, unit energy use, and national energy use; these findings are summarized in Table 6 and Table 7. All of these studies were performed in the U.S. except for Zimmerman et al. (2012) and Enertech (2008), which are from Europe. Methodologically, the majority of the studies summarized in Table 6 and Table 7 analyzed field-metering data to determine computer energy usage. Zimmerman et al. (2012) monitored the energy consumption of electric appliances in 225 U.K. households for one month, and 26 households for an entire year; 106 desktops and 168 laptops were metered. Note in Table 7 the relatively low amount of time spent in both active and standby modes for laptop computers, with 85% of the time spent in off mode. This discrepancy is likely due to the difficulty of determining usage for portable computers when they are disconnected from the mains (and the meter). Bensch et al. (2010) metered 42 desktops and 17 laptops for almost one month in 50 Minnesota households after conducting a thousand-household phone survey and a 260-household detailed appliance survey via mail. Metering results and in-home interviews led them to identify computer power management as the single most important energy-saving opportunity in metered homes. Microsoft (2008) determined the time computers spent in each ACPI (Advanced Configuration and Power Interface) power state for 37,388 desktops and 35,195 laptops over a two-month period in early 2008, while Enertech (2008) metered 451 desktops and 139 laptops in 400 Swedish households, largely for one month. Porter et al. (2006) collected field measurements from 75 Californian homes over one week, covering 43 desktops and 7 laptops.

More recently, the Northwest Energy Efficiency Alliance's (NEEA) Residential Building Stock Assessment Metering Study collected metered data in 101 Pacific Northwest homes between April 2012 and March 2013. Every five minutes, WattsUp meters logged the power draw of consumer electronics, including computers, in order to yield results for usage profiles, load shapes, and annual energy consumption. We cannot make direct comparisons with our field-metering data, as the NEEA study did not split sample computers into desktops and laptops, and it is unclear how many of each type of computer were metered. However, the study methodology reads: "The surveyors conducted a census of computers by room. They counted only computers that were plugged in or in some way directly in use. Thus, laptops that were not immediately obvious were not included" (Ecotope 2014). From this, we infer that at least some of the metered computers were indeed laptops. On average, desktop computers were reported to use 330 (±44) kWh/year (n=49), and spent 11 (±1) hours/day in high-power mode, 11 (±1) hours/day in low-power mode, and 2 (±0.8) hours/day in off mode. In any case, the NEEA mean AEC of 330 kWh is roughly consistent with recent estimates from the literature and our study, though their higher figure is driven primarily by longer daily usage.

Other studies, namely Urban et al. (2014), Dewart et al. (2013), Urban et al. (2011), Roth & McKenney (2007), and Chase et al. (2006), were primarily survey-based. Several developed energy use estimates using a range of sources in addition to usage surveys, such as data from prior literature, expert interviews, and targeted laboratory power draw measurements. Survey methods, however, are susceptible to certain potential biases, such as recollection bias for low-intensity activities, a social desirability bias (wanting to appear more energy conscious), and calculation mistakes respondents may make when estimating their total or average computer usage. These biases are similar to those for reporting television viewing, for example (Pettee et al. 2008). As Roth & McKenney (2007) acknowledge, "consumers may have a reasonable idea of how much they have actively used various [consumer electronic] devices recently, they likely are not as aware of the time that the products spend in idle instead of off mode". We therefore consider it likely that usage estimates from these studies lead to under-reporting of time spent in standby mode, and potentially active mode as well.

In comparison to these previous studies, our findings are largely consistent when it comes to active mode power draw and unit energy consumption. We see that the average active power draw for desktops has decreased slightly since 2005, even though computer functionality and capability have increased over that time. We suspect that the increased capabilities of central processing units (CPUs) and graphics processing units (GPUs) have come at greater efficiency from better design and electronics, to limit the amount of energy that more powerful computer components would otherwise give off as heat, and therefore keep internal cooling requirements reasonable. The ENERGY STAR specifications for computers may also have played a role here, as they incentivize manufacturers to improve efficiency in order to qualify their products.

With respect to laptops, our estimate for mean power draw is higher than that of any other study. The survey-based papers—Urban et al. (2014) and (2011), Roth & McKenney (2007), and Chase et al. (2006)—may underestimate laptop power draw, since real-world use with different applications and peripherals can require more power than a search of the literature, laboratory test, or ENERGY STAR specifications might suggest. Dewart et al. (2013) in particular suggest a 30% real-world adjustment factor to the latter. We also expect that laptops are drawing more power than before given that they are getting more powerful, with many consumers now relying on them as their primary computer, while tablets and smartphones have replaced less computationally intensive tasks on laptops.

When examining usage trends since 2005, we find that both desktops and laptops have been potentially used less often in the past several years, although our results are not statistically significant due to the sample size. The increased availability and maturation of tablet computers, smartphones, and smart TVs has shifted more casual media consumption away from computers toward these other technologies. This effect was highlighted in a recent Nielsen report showing that the mean time spent using the internet on a computer has decreased since 2012, while correspondingly increasing on other digital devices (Nielsen 2014). We acknowledge, however, the potential underestimate of laptop usage in our sample due to the portable nature of the computers. It is impossible to quantify this effect, if present. The laptop usage reported by Zimmerman et al. (2012) is surely affected by this issue.

Table 6: Recent energy use estimates for desktop computers (without monitors). Values in italics are derived from data in reference.

Study	Average Usage[a] (h/d)	Average Usage (h/yr)	Average Active Power Draw[a] (W)	Average Annual Unit Energy Consumption[b] (kWh/yr)	National Annual Energy Consumption (TWh/yr)	Average Standby Usage (h/yr)	Average Standby Power Draw (W)	Average Standby Energy Consumption (kWh/yr)	Units in Stock (millions)	Applicable Year
This study	$7.3^{+2.3}_{-1.9}$	2670^{+840}_{-690}	$66.1^{+7.6}_{-7.6}$	194^{+57}_{-49}	20^{+6}_{-5}		$2.0^{+0.6}_{-0.4}$		105	2012
Urban et al. (2014)	7.7	2789	*62*[c]	186	16	2088	3.4	7.0	88[d]	2013
Zimmerman et al. (2012)	4.5	1649	67.2	166	-	3407	5.7	-	-	2010-2011
Urban et al. (2011)	9.4	3420	60	220	22	2150	4	9	101	2010
Bensch et al. (2010)	11.2	4088	68.9	262.3	-	-	2.4	*9.7*[e]	-	2009
Microsoft (2008)	9.8	3574	-	-	-	-	-	-	-	2008
Roth & McKenney (2007)	8.2	2990	75	237	21	330	4	1	90	2006
Porter et al. (2006)	8.4	3066	70	255.2	-	5694[f]	5.6	31.3	-	2006
Chase et al. (2006)	9.2	3372	75	264	-	319	4	1	-	2005

[a] In active/active-idle mode (not in standby, and not off)
[b] Across all modes: active/active-idle, standby, and off
[c] Weighted average of active, short idle, and long idle modes
[d] Plugged-in installed base used in the month prior to survey
[e] Active mode represented 96.3% of energy consumed, so calculated standby consumption by multiplying 3.7% by AEC (262.3 kWh)
[f] Figures for standby usage, power draw, and unit energy consumption include both standby and "low-power" mode

Table 7: Recent energy use estimates for laptop computers. Values in italics are derived from data in reference.

Study	Average Usage[g] (h/d)	Average Usage (h/yr)	Average Active Power Draw[g](W)	Average Annual Unit Energy Consumption[h] (kWh/yr)	National Annual Energy Consumption (TWh/yr)	Average Standby Usage (h/yr)	Average Standby Power Draw (W)	Average Unit Standby Energy Consumption (kWh/yr)	Units in Stock (millions)	Applicable Year
This study	$4.8^{+3.5}_{-2.5}$	1750^{+1280}_{-910}	$32.0^{+7.0}_{-5.2}$	75^{+63}_{-39}	11^{+9}_{-6}		$1.7^{+1.5}_{-0.9}$		147	2012
Urban et al. (2014)	6.3	2058	*27*[i]	53	4.9	2202	1.6	3.5	93[j]	2013
Dewart et al. (2013)	-	-	-	*27*[k]	-	-	-	-	-	2012
Zimmerman et al. (2012)	2.3	832	32.3	29	-	554	1.6	-	-	2010-2011
Urban et al. (2011)	9.4	2915	19	62	8.3	2210	2	4	132	2010
Bensch et al. (2010)	10.4	3796	29.7	113	-	-	0.7	*3.3*[l]	-	2009
Microsoft (2008)		2330	-	-	-	-	-	-	-	2008
Enertech (2008)	-	-	-	35	-	-	2.6	-	-	2005-2008
Roth & McKenney (2007)	6.5	2368	25	72	2.8	935	2	2	39	2006
Porter et al. (2006)	8.2	2978	22	82.9	-	5081[m]	1.4	7	-	2006
Chase et al. (2006)	8.1	*2968*[n]	*21*	74	-	437	2	13	-	2005

[g] In active/active-idle mode (not in standby, and not off)
[h] Across all modes: active/active-idle, standby, and off
[i] Weighted average of active-charging, active, short idle, and long idle modes
[j] Plugged-in installed base used in the month prior to survey.

[k] Derived from figures for 2013 California stock (22.9 million units) and 2013 statewide energy use (623 GWh/yr). Estimated duty cycle for notebooks aligns with ENERGY STAR V. 6.0 specifications. Statewide energy use includes real-world adjustment factor of 30% for notebooks.
[l] Active mode represented 97.1% of energy consumed, so calculated standby consumption by multiplying 2.9% by AEC (113 kWh)
[m] Figures for standby usage, power draw, and unit energy consumption include both standby and “low-power” mode; time in “no power” mode was 8%
[n] Includes time spent in “standby mode”, defined in Chase et al. (2006) as “the state in which the machine is on, but neither producing useful work nor in sleep mode.” With an average power draw of 14 W for notebooks, we collapse this definition of standby into our active/active-idle mode, and calculate a weighted average for active power draw.

Definitional differences for power modes across existing studies also muddle the consensus for the metrics related to standby mode in Table 6 and Table 7. Papers variously refer to "standby," "sleep," "hibernation," or "low power", all with slightly different and conflicting definitions. Examining Porter et al. (2006) in contrast to our findings highlights the difficulties presented by different approaches to defining mode categories. They observe that their sampled desktops did not spend any time in "no power" mode, resulting in a considerably higher number of annual hours spent in standby. It is likely that desktop computers at that time had a non-zero power draw even when turned off, yielding this result. Presumably, however, users did regularly shut down their computers. In an effort to be consistent in reporting results, we collapse the "standby" and "low power" modes found in Porter et al. into the larger standby category in the tables above. Our study does not include a separate definition for an analogous "low power" mode because we do not see any evidence for it in our cumulative distribution data. This is likely due to our newer computer sample. Technological innovation in recent years means that computers draw less power when switched off or put to sleep, such that all of these separate modes fall below our 8 W threshold. Power meter sensitivity is also a factor. It is possible that computers with a lower non-zero power draw may be measured at zero watts, while older computers draw measurable power (*e.g.*, 1 W), which in our analysis is lumped into standby mode. However, while caution is advisable in interpreting standby mode metrics, these definitional differences do not significantly impact unit energy consumption or AEC, as the active mode is by far the dominant component of total computer energy consumption.

Our small sample size, geographic restriction, and no correction for demographics might suggest that our findings are not necessarily representative of the energy consumption associated with computers nationwide. If anything, we are potentially sampling higher-usage households as a result of our urban/suburban and higher-income sample in the San Francisco Bay Area. We also acknowledge that social desirability and self-selection bias may play a role in our study, given that participants were recruited via an energy audit program and were aware that their energy consumption was being monitored. Nevertheless, we expect this bias, if it exists, to be very small and unlikely to persist over the full length of the monitoring period due to the automated nature of the data collection process. When we consider our results along with many other recent studies from a variety of difference sources using different methodologies, our results are comparable. We are confident that our findings reasonably approximate per-unit and national computer energy consumption, and potentially indicate a decline in average usage and national energy consumption in recent years.

Energy Savings Opportunities

One motive for our study was to explore how computer user behavior is changing along with rapidly evolving technology and usage patterns. Opportunities to save energy, however, remain similar to those mentioned in the literature. While computer performance does vary, the electricity consumption for computers with similar form factors and functionalities ranges widely, indicating opportunities to increase efficiency. As active mode energy use continues to be predominant, it also represents the biggest opportunity for energy savings. To this end, many studies, such as Dewart et al. (2013), Urban et al. (2011), and Bensch et al. (2010), have pointed to the necessity of better power management, which can be achieved either by switching computers to a lower-power state after a certain period of inactivity, or through power scaling.

Bensch et al. (2010) consider power management to be “the single most important opportunity” to save energy that they identified, as their power metering and occupancy sensor data showed that almost three quarters of desktop electricity consumption occurred when no one was in front of the computer. Although our study does not include occupancy sensor data, we do see that computer active mode usage was generally higher than monitor active mode usage. Given that monitors typically have decent power management settings enabled by default, this supports Bensch et al.’s assertion that power management is a big savings opportunity. If we assume, however, that monitor active mode usage is a good indicator of when users are actually in front of the computer, then our results suggest potential electricity savings are much less than three quarters of total consumption. Perhaps this is an indication of the progress made in getting power management enabled by default in computers between Bensch et al.’s study (data collection took place between December 2008 and October 2009) and our study.

Power scaling, on the other hand, is a technique that lowers power demand when performance is less of a concern, for example in processors, integrated displays, communication busses, and hard drives. Dynamic voltage scaling refers to decreasing the CPU voltage at times of less-intense usage, while dynamic frequency scaling lowers the speed (clock rate) of the CPU; these options are often used in conjunction with one another. Some processors can also selectively cut electrical current to parts of their circuitry that are not in use (power gating). These techniques can also be applied to GPUs, especially during periods of activity not requiring intensive graphics processing.

Another way to reduce computer energy consumption lies in enhancing power supply efficiency. Power supply units (PSUs) convert AC electric mains power to low-voltage DC power for computers’ internal components. Conversion efficiency at 20% load, reflective of typical operating conditions, ranges from 75-85% for tested 300 W PSUs (Wanless et al. 2013). 80 PLUS[3] is a voluntary certification program launched by Ecos Consulting and the Electric Power Research Institute that promotes energy-efficient PSUs by requiring qualifying products to be at least 80% efficient at 20%, 50%, and 100% of maximum rated power. Since at low loads PSU efficiency drops markedly, another energy savings opportunity is to match PSU capacity with the computer’s power needs, rather than defaulting to PSUs with a higher rated output than necessary.

Future energy savings will also be achieved as other individual components become more efficient. The power demand of central processing units (CPUs) is significantly variable depending on capacity and the application(s) being run, and typically ranges from <5 W to 70 W in idle mode. Reducing power demand can be achieved through a number of actions: smaller transistors can operate on lower voltages, and new materials can be used to reduce the subsequent voltage leakage; clock gating, or disabling parts of the circuitry when they are not being used, reduces switching power demand to zero. However, many of these opportunities have already been implemented for CPUs, and new energy-saving paths may only materialize through implementing low-energy mobile and embedded processors in desktops and

[3] http://www.plugloadsolutions.com/80PlusPowerSupplies.aspx

notebooks. Next, hard disk drives (HDDs), traditionally rapidly rotating disks onto which data are recorded, are increasingly being supplanted by solid state drives (SSDs), which have non-volatile memory (usually flash) and no moving parts. Traditional HDDs can use less power with smaller disk sizes and by decreasing spinning speed, though “spinning down” the hard drive during idle mode can negatively affect product usability as access time increases. SSDs require significantly less power in idle mode than do HDDs, but currently carry a high, though falling, cost, and have limited storage capacity. The power required by graphics processing units (GPUs) also varies appreciably depending on functionality and product efficiency. Discrete GPUs, usually found on a separate card with dedicated graphics memory, are often the largest power consumer of a computer system, especially on high-performance or gaming machines with multiple GPUs. Delforge and Wold (2012) find that discrete graphics cards were present in one third to one half of desktops on the market in 2010, and that they can consume between 20 and 60 percent of total PC energy use. As graphics performance is limited by power draw and heat dissipation, manufacturers have an incentive to increase performance per watt, whether through re-engineering (*e.g.,* AMD’s ZeroCore Power and Nvidia’s Kepler technologies) or by powering down discrete GPUs when not in use.

By identifying, and in some cases deriving, percentage savings estimates from the literature, we can apply these to our results in order to generate back-of-the-envelope national energy savings estimates. Chase et al. (2006) estimated desktop energy savings of 32% with smaller form factors and improved power management, and identify laptop energy savings of 54% through a 25% increase in standby efficiency and enabling power management in nine out of ten laptops. Ecova (2008) developed and tested a prototype desktop computer with a blend of efficient laptop and desktop technologies, as well as off-the-shelf components such as a right-sized 80 PLUS PSU and a hybrid hard drive. This prototype cost only $40 more than the unit retail price, and consumed less than 30% of the electricity used by ENERGY STAR certified desktops, a 70% savings. More recently, Zimmerman et al. (2012) found that overall computer electricity consumption can be cut in half by replacing their sampled desktop PCs with laptops, and sampled laptops with those that require only 30 W in ON mode and 0.5 W in standby. Dewart et al. (2013) explored the potential of component electricity savings in depth; comparing their scenarios with and without a California Energy Commission efficiency standard yields energy savings of 64% for desktops and 34% for desktops. Finally, Wanless et al. (2013) determined that desktop electricity consumption can be reduced cost-effectively by 30%.

Given the range of electricity savings estimates above, we present three scenarios for desktops: savings of 30%, 50%, and 70%. As laptops’ form factor inherently drives more efficient design and makes 70% savings less achievable, we consider only two scenarios for laptops: 30% and 50% savings. We further use our results for unit AEC, national AEC, and units in stock. Assuming all installed units are instantly swapped with more efficient models, desktops would consume 6, 10, and 14 TWh/yr less nationwide, depending on the scenario, while laptops would consume 3.3 and 5.5 TWh/yr less. Alternatively, we can use projected shipment estimates of 12.24 million desktops and 29.08 million laptops in 2013 (CEA 2013b). Assuming the same scenarios as above, energy savings for desktops would be 0.7, 1.2, and 1.7 TWh/yr for newly shipped products. The savings for laptops would be 0.7 and 1.1 TWh/yr, depending on the scenario.

5. Summary

Uncertainties around user behavior have made it difficult to accurately assess the national energy consumption of desktop and laptop computers. In particular, computer usage patterns are changing quickly with time as the rising market share of tablet computers and smartphones shifts computing away from more traditional platforms. Most computer energy use occurs when computers are in active mode, in which they are often left idle. Computer capability and functionality is also exponentially increasing, potentially driving up electrical power demand. However, the swift pace of technological innovation in this field yields improvements in both functionality and efficiency. Remarkably, studies from the past eight years estimate nearly constant national annual energy consumption for desktops around 20 TWh, with a wider range for laptops of 3-11 TWh annually.

As part of a larger field-metering study of households in the San Francisco Bay Area, we obtained full time series power data from 64 individual computers (45 desktops, 11 laptops, and 8 of unknown type). From our data, we conclude the following:

1. Approximately 50% of all computers are in On mode for 4 to 5 hours per day or less, while a few individual computers are left on nearly 24 hours per day. The minority of computers left in On mode nearly all day significantly increase the mean usage as compared to the median. On mode includes when the computer is idle.
2. Average usage for desktop computers was 7.3 hours per day, while for laptop computers it was 4.8 hours per day. Computers of unknown type were used on average 12.6 hours per day (likely desktops). The median usage was only 4.2, 2.1, and 10.2 hours per day for desktops, laptops, and computers of unknown type, respectively. These results are generally lower than in most other studies, probably indicative of casual media consumption shifting away from personal computers towards tables, smartphones, and smart TVs. The results for laptops are likely underestimated because of the laptop computer's ability to be plugged in elsewhere, and thus not metered.
3. National energy use for desktops is estimated to be 20 TWh annually in 2012. This is on par with recent estimates in the literature. Although computer usage is potentially declining, there are many more computers than several years ago. National energy use for laptops is approximately 11 TWh annually in 2012, markedly up from previous estimates. This likely reflects a higher power draw for laptops in On mode, as well as more laptops in homes compared to several years ago. Note that increased functionality and efficiency are opposing trends in terms of energy consumption.
4. The average unit energy use for desktops is estimated to be 194 kWh/yr, with a median of 125 kWh/yr. Average unit energy use for laptops was found to be 75 kWh/yr, with a median of 31 kWh/yr. A desktop that was on over 88% of the time represented the highest AEC in our sample of 563 kWh/yr – similar to that of a standard-size refrigerator in homes in 2012.
5. Different methodological and definitional approaches, changing usage patterns, and uncertainty about how and how long consumers use computers result in a range of estimates for average usage, unit energy consumption, and standby energy use between various studies. These differences must be considered when interpreting our results with respect to existing studies.

6. Energy savings opportunities include improved power management (defaulting to low-power modes after inactivity as well as power scaling), matching the rated power of power supplies to computing needs, and improving the efficiency of individual components.

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