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D8.1. Overview of ICT energy consumption

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Abbreviations

ADC	Analog-to-Digital Converter
AMI	Advanced Metering Infrastructure
BS	Base Station
CAGR	Compound Annual Growth Rate
CER	Commission for Energy Regulation
CMD	Channel Mux/Demux
CPE	Customer Premises Equipment
CPU	Central Processing Unit
CRT	Cathode Ray Tube
CWDM	Coarse Wavelength Division Multiplexing
DCeP	Data Center energy Productivity
DCiE	Data Center infrastructure Efficiency
DSL	Digital Subscriber Line
DWDM	Dense Wavelength Division Multiplexing
EDFA	Erbium Doped Fiber Amplifier
EPUB	Energy Per Useful Bit
FTTH	Fiber to the Home
GA	Genetic Algorithm
GMD	Group Multiplexer/Demultiplexer
g-OADM	group Optical Add/Drop Multiplexer
GPUE	Green Power Usage Effectiveness
HDD	Hard Disk Drive
ICT	Information and Communications Technology
IHU	International Hellenic University
IP	Internet Protocol
IT	Information Technology
LCD	Liquid Crystal Display
MAC	Medium Access Control
NCPI	Network Critical Physical Infrastructure
NIC	Network Interface Card

PA	Power Amplifier
PC	Personal Computer
PUE	Power Usage Effectiveness
QoI	Quality of Information
REDD	Reference Energy Disaggregation Data
ROADM	Reconfigurable Optical Add/Drop Multiplexer
ROC	Receiver Operating Characteristic
SNMP	Simple Network Management Protocol
SSD	Solid State Disk
SUT	System Under Test
t-OADM	thin Optical Add/Drop Multiplexer
TREND	Towards Real Energy-efficient Network Design
VNE	Virtual Network Embedding
VoIP	Voice over IP
WSN	Wireless Sensor Network
WSS	Wavelength Selective Switch

1 Introduction

In general, ICT has a green image because it provides solutions to some environmental problems. Well-known solutions are electronic documents (no need to print) and electronic mail (no transportation costs). Teleworking, a system where an employee can work from outside the workplace, is another possible application [1] which has many advantages such as an improved work-life balance, increased productivity, savings of CO2 emissions, space savings and financial benefits [2]. Another example of an ICT-related solution to use energy more efficiently is the use of smart meters. The idea is that energy demand follows energy production and not the other way round [3]. Examples of smart meters are automatic temperature control in buildings and interactive energy management systems in households. The development of smart meters is related with the development of smart grids [2]. This is a power management system provided by ICT [4] that enables varying electricity production methods (such as solar or wind energy) powering the electrical grid. After years of research, it is now being implemented in real-life situations like the Smart Grid in South Korea where the first stage, a smart grid testbed for technical validation, is just being finished [5]. A last example is energy efficient transport planning to lower fuel consumption of traffic companies, called Intelligent Transportation Systems (ITS) [6]. For each of these solutions however, attention should be paid to the rebound effect [1, 3]. Because of decreased costs of a more efficient solution, this solution will probably be used more frequently, leading to the same total cost [3, 4]. All these aspects will be studied in the upcoming JRA8 tasks R8.2, R8.3 and R8.4.

Even though ICT gives some solutions to environmental problems, it also induces some of them. One of these problems is energy consumption of ICT peripherals. It is predicted in [7] that 14% of the worldwide electrical energy in 2020 will be consumed by the ICT sector (corresponding to 8% primary energy). In order to achieve relevant optimizations, progress should be made in different equipment categories (data centers, PCs, network equipment) because all categories have a similar share of the total energy consumption [4]. In this EINS deliverable D8.1, we will give an overview on the carbon footprint of ICT and contribute to establishing comprehensive frameworks and methodologies for measuring and reporting the energy consumption of ICT. This document provides a basis for the other tasks in JRA8.

This deliverable starts with an overview of energy efficiency metrics and benchmarks in section 2. In section 3, the global footprint of ICT in 2007 and 2012 is estimated, as an update of the study performed in [7]. Section 4 presents the energy consumption of six specific use cases, representing the most important domains from the perspective of ICT energy consumption, and highlights the most power consuming parts of these use cases. Promising directions to lower the environmental impact of ICT, for instance through novel network architectures and routing paradigms, are discussed in section 5. Some key findings are summarized in the conclusion section.

2 Energy efficiency metrics and benchmarks

2.1 *Energy efficiency metrics*

To quantitatively evaluate the property of ICT energy consumption, it is inevitable to review different widely applied metrics. However, these metrics have to be carefully differentiated regarding their respective considered input values as well as their range of applicability. For example, some metrics consider performance, while others only focus on power demand. The following metrics are used to compare the overall energy efficiency of ICT systems, like data centers, communication networks and sensor networks.

2.1.1 Power usage effectiveness (PUE)

The PUE is the de facto standard regarding overall data center energy efficiency. It was published in 2007 by the open industry consortium “The Green Grid”. PUE is defined as the ratio of the total facility input power (P_{IN}) over the power delivered to IT (P_{IT}). Data Center infrastructure Efficiency (DCiE) is the inverse of PUE and can be described in a mathematical form as

$$PUE = \frac{1}{DCiE} = \frac{P_{IN}}{P_{IT}}, \qquad 1 < PUE < \infty$$

2.1.2 Green power usage effectiveness (GPUE)

Greenqloud [http://greenqloud.com/] proposes a modified version of the PUE to evaluate data center greenness. In addition to comparing the effective ICT power to total facility power, the GPUE considers the environmental impact of power generation used for the data center. The GPUE is calculated using the following equation:

GPUE=G x PUEx

where G =Σ(%EnergySource x (1 + weight))

weight is a factor depending on the carbon intensity of the power source.

2.1.3 Telco Efficiency (Mbits/kWhrs)

The efficiency of telecommunication equipment is computed according to the metric proposed by the Green Grid Association [http://www.thegreengrid.org/]

$$M_T = \frac{\sum_{i=1}^{k} b_i}{E_{DC}}, \qquad Mbits / KWh$$

In the above equation k is the number of routers in the data center and b_i is the total number of bits coming out from the i^{th} router during the assessment window. E_{DC} is the consumed overall energy during the assessment window. The metric M_T can measure the underutilization of routers or redundant components in the system. As an example, a stream of bits forwarded by a small router would require less energy than the same stream of bits forwarded by a pair of large redundant routers.

The small router would have a higher "bits per kilowatt-hour" metric, implying a more energy efficient system for forwarding the bit stream. The metric can provide important conclusions regarding energy efficiency actions. For example, identify and remove idle servers without affecting the outbound bit stream, provide server consolidation and identify methods to increase bit rates without increasing the power consumption.

2.1.4 Server Efficiency (ops/kWhrs)

The efficiency of the server equipment is modeled as a function of the average central processing unit (CPU) utilization and is correlated to the Specrate and Specpower benchmarks. The CPU utilization for each server in the data center is averaged over an assessment window *T*. The metric is computed according to [http://www.thegreengrid.org/]:

$$M_{<rate,power>} = \frac{T \cdot \sum_{i=1}^{n} \left[U_i \cdot < \frac{B_i}{S_i} > \cdot \left(\frac{CC_i}{CB_i} \right) \right]}{E_{DC}}, \quad \begin{array}{c} Jobs/KWh \\ ssj\_ops/KWh \end{array}$$

In the above formulation, n is the number of servers, U_i is the average CPU utilization over T of server i, B_i is the benchmark Specrate 2006 and S_i is the SPECpower in ssj_ops/sec (server side Java operations per second) at 100% server utilization of server i, CC_i is the nominal clock speed of the CPU of server i, CB_i is the clock speed of the CPU, used to establish B_i. This metric models data centers productivity and the correlation of the actual useful work to the maximum possible work if all servers were running at 100% utilization.

2.1.5 Absolute Energy Efficiency metric (dB)

The Absolute Energy Efficiency Metric proposed in [8] provides a metric (in dB) to express the energy efficiency of any information processing device (whether it is an ICT network system, a data center, a single computer or the human brain) relative to the theoretical minimum energy dissipated to process a bit. It is logarithmic based to deal with the large order of magnitudes of difference with respect to this lower bound, and is defined as:

$$dB\varepsilon = 10 \log_{10} \left(\frac{Power / BitRate}{kT \ln 2} \right)$$

where k is the Boltzmann constant 1.381 x 10-23 J/K

T is the absolute temperature of the medium in Kelvin.

Exemplary values are 115 dBε for a 10 Gb/s transmission system, 125 dBε for a terabit router, and 162 dBε for the UK telecommunications network.

2.1.6 Energy-per-Useful-Bit

In order to compare the energy efficiency of power consumption of sensor networks, Ammer et al. [9] introduce the Energy-per-Useful-Bit (EPUB) of the physical layer of an ad-hoc wireless sensor network as follows:

$$EPUB = \left(\frac{B_D + B_P}{B_D} \right) (P_{TX} + \xi P_{RX}) T$$

where - B_D and B_P are respectively the average number of data and preamble bits in a packet
- T is the bit time in seconds
- P_{TX} is the power of the transmitter in mW
- P_{RX} is the power of the receiver in mW including the analog-to-digital converter (ADC) and synchronization circuitry.
- ξ is a constant determined by the MAC scheme and represents the average proportion of time spent in receive mode (P_{RX}) divided by that spent in transmit mode (P_{TX}) [9]

2.1.7 Other metrics

There are six more metrics that describe the overall efficiency of a data center. The work is described by the Green Grid (www.thegreengrid.org) and incorporates the Data Center energy Productivity (DCeP) metric, DCeP productivity link metric, DCeP sample workload metric, compute units per second trend curve metric, operating system workload efficiency metric.

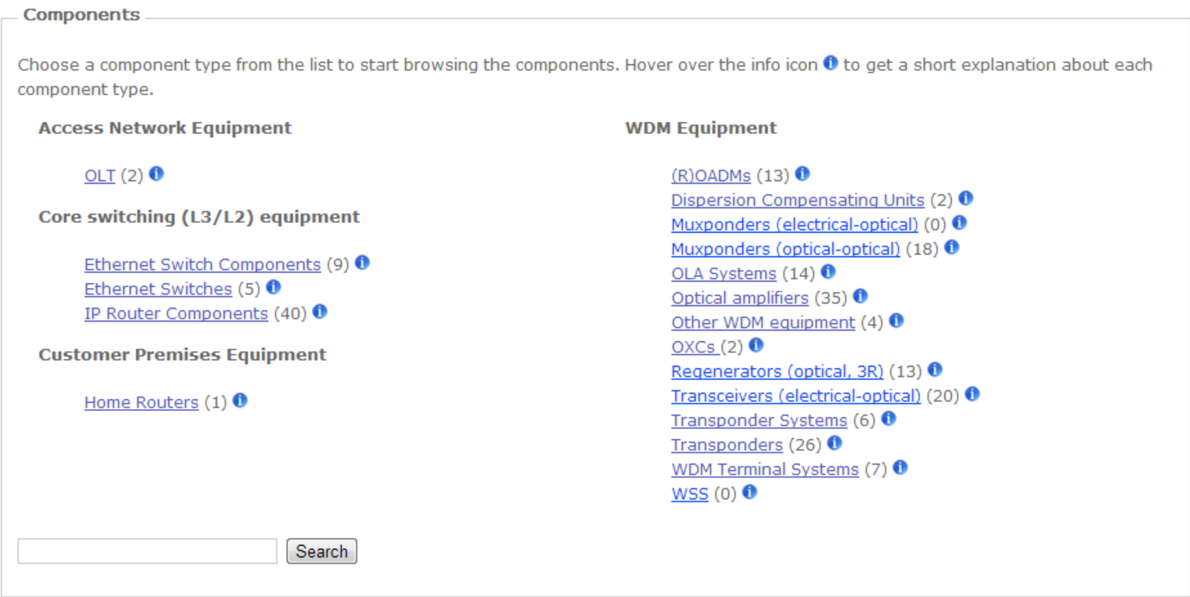
2.2 *Energy efficiency benchmarks*

Energy efficiency benchmarks can be used to compare the power consumption and energy efficiency of different ICT systems. The comparison is done based on an energy efficiency metric that usually evaluates the energy consumption that is needed for a certain piece of equipment (cf. subsection 2.2.1) or to carry out certain operations or more complex tasks (cf. subsections 2.2.2 and 2.2.3).

2.2.1 PowerLib

PowerLib (http://powerlib.intec.ugent.be) is a database of power consumption values for ICT network equipment, and is developed in the framework of the FP7 NoE-TREND (Towards Real Energy efficient Network Design, http://www.fp7-trend.eu). Its main and initial purpose is to collect and provide this data for use in research towards more power-efficient ICT networks. Data on this topic is not readily available, but instead distributed across different data sheets and (academic) publications. By providing a single source, PowerLib wants to facilitate power consumption data collection and referencing. Users can contribute to this database with their own data, preferably by including (links to) sources of the reported values. To do so, users have to register at the website, after which they can request contributing privileges. Search and export functionality is available as well.

The figures below are screenshots from the PowerLib website, and give an idea of the general setup and functionality.



Components

Choose a component type from the list to start browsing the components. Hover over the info icon to get a short explanation about each component type.

Access Network Equipment

- OLT (2)

Core switching (L3/L2) equipment

- Ethernet Switch Components (9)
- Ethernet Switches (5)
- IP Router Components (40)

Customer Premises Equipment

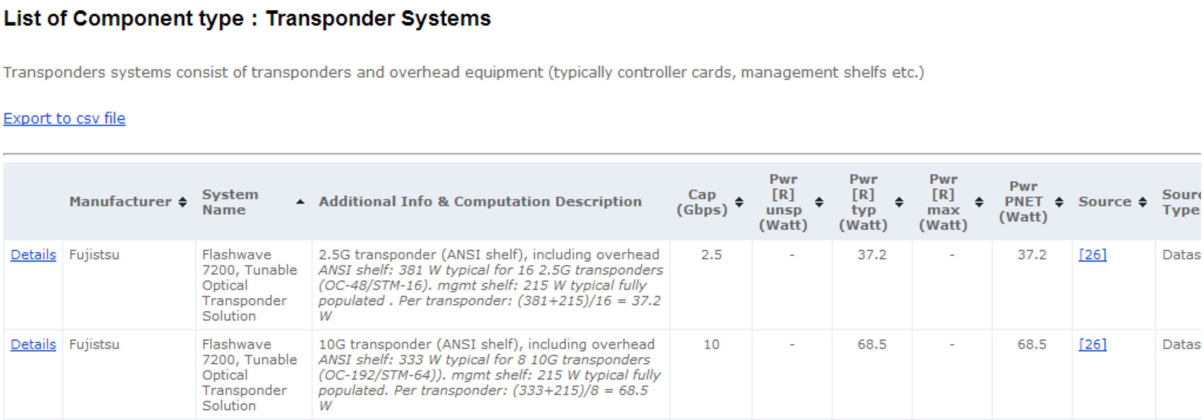
- Home Routers (1)

WDM Equipment

- (R)OADMs (13)
- Dispersion Compensating Units (2)
- Muxponders (electrical-optical) (0)
- Muxponders (optical-optical) (18)
- OLA Systems (14)
- Optical amplifiers (35)
- Other WDM equipment (4)
- OXCs (2)
- Regenerators (optical, 3R) (13)
- Transceivers (electrical-optical) (20)
- Transponder Systems (6)
- Transponders (26)
- WDM Terminal Systems (7)
- WSS (0)

Search

Figure 2-1: PowerLib – components overview



List of Component type : Transponder Systems

Transponders systems consist of transponders and overhead equipment (typically controller cards, management shelfs etc.)

Export to csv file

	Manufacturer	System Name	Additional Info & Computation Description	Cap (Gbps)	Pwr [R] unsp (Watt)	Pwr [R] typ (Watt)	Pwr [R] max (Watt)	Pwr PNET (Watt)	Source	Sourc Type
Details	Fujistsu	Flashwave 7200, Tunable Optical Transponder Solution	2.5G transponder (ANSI shelf), including overhead *ANSI shelf: 381 W typical for 16 2.5G transponders (OC-48/STM-16). mgmt shelf: 215 W typical fully populated . Per transponder: (381+215)/16 = 37.2 W*	2.5	-	37.2	-	37.2	[26]	Datas
Details	Fujistsu	Flashwave 7200, Tunable Optical Transponder Solution	10G transponder (ANSI shelf), including overhead *ANSI shelf: 333 W typical for 8 10G transponders (OC-192/STM-64)). mgmt shelf: 215 W typical fully populated. Per transponder: (333+215)/8 = 68.5 W*	10	-	68.5	-	68.5	[26]	Datas

Figure 2-2: PowerLib – listing of the transponder component types in the database

Component Info

Type	Transponders
System Name	Double 10GbE Transponder
System Family	
Manufacturer Code	TM_TPD10GbE
Manufacturer	Transmode
Additional Info	-
Computation Description	Max. 40 W in Transponder mode (fully equipped with client and DWDM XFPs). So 20 W for one transponder. (Max 45 W in Regenerator mode with all ports active and using DWDM XPFs.)
Remark	-

Specifications

Capacity	10 Gbps	*Capacity*
Power rated (unspecified)	-	*Power rated, unspecified operation mode*
Power rated (typical)	-	*Power rated, typical operation mode*
Power rated (maximum)	20 Watt	*Power rated, maximum*
Power PNET	15 Watt	*Power value used in PNET paper*

Sources

[31] Datasheet - Transmode - Double 10Ge Transponder

Figure 2-3: PowerLib – detailed power specifications for an example component (transponders)

2.2.2 SPECpower ssj_2008

SPECpower ssj_2008 (http://www.spec.org/power_ssj2008/) evaluates the energy efficiency of computer systems at different load levels. The load on the System Under Test (SUT) is varied between 0% and 100% in 10% steps while the power consumption of the system is measured. During the measurement the number of performed java operations is counted for each load level. The energy efficiency of the SUT is then given in "overall ssj_ops/watt".

2.2.3 JouleSort

JouleSort (http://joulesort.stanford.edu/) is an external sort benchmark that evaluates the energy efficiency of computer systems. The idea behind using external sort — which refers to a class of sorting algorithms that can handle massive amounts of data that do not fit into the main memory but thus must reside in the slower external memory (such as a hard drive) — is to stress all relevant system parts like memory, CPU and I/O. The benchmark measures the energy that was consumed to sort a predefined number of records. The lower the energy needed to sort the records the higher the energy efficiency of the SUT. The metric used by JouleSort is "watt/sorting task".

3 Global footprint of ICT

Currently, there are several methodologies to measure and determine the so-called "footprint" of organizations, services and goods. Some refer only to the amount of CO2 emissions. At first glance, an energy provider that claims to reduce its CO2 emissions seems to have a smaller environmental footprint than an energy provider with higher CO2 emissions. However, this measurement is only limited to CO2 and, for example, does not take into account the amount of nuclear waste that comes with nuclear power generation.

Therefore, the ICT-footprint initiative [http://www.ict-footprint.com], which is initiated by the European Commission DG CONNECT, evaluates and compares several methods of footprinting. It aims to find eventually a global consensus within the ICT industry for a common definition and measurement framework within this respect. Several currently existing methodologies are listed on the website of the ICT footprint initiative: http://www.ict-footprint.eu/methodologies

In order to get a first estimate of the footprint of ICT, we determined the use phase electricity consumption for a number of ICT services. We estimated the worldwide electricity consumption of *communication networks, data centers and personal computers*. We considered the use phase only, the electricity used to manufacture and dispose of equipment was not included. Our results are summarized in Figure 3-1. The collective electricity consumption of communication networks, data centers and personal computers is growing at a rate of 6.6% per year. Together these ICT products and services consumed about 930 TWh in 2012. If this energy was generated as nuclear power, it would require over 100 nuclear reactors (assuming one nuclear reactor produces 1 GW of electricity, like the ones in Tihange, BE). The relative share of these ICT products and services in the total worldwide electricity consumption has increased from about 4% in 2007 to 4.7% in 2012. This does not yet include the electricity consumption of other devices that are often considered as part the footprint of ICT, such as TVs and their set-top boxes, (smart) phones, audio devices etc.

The scopes of the three categories considered and the calculation methods used to obtain the results are elaborated in the following subsections.

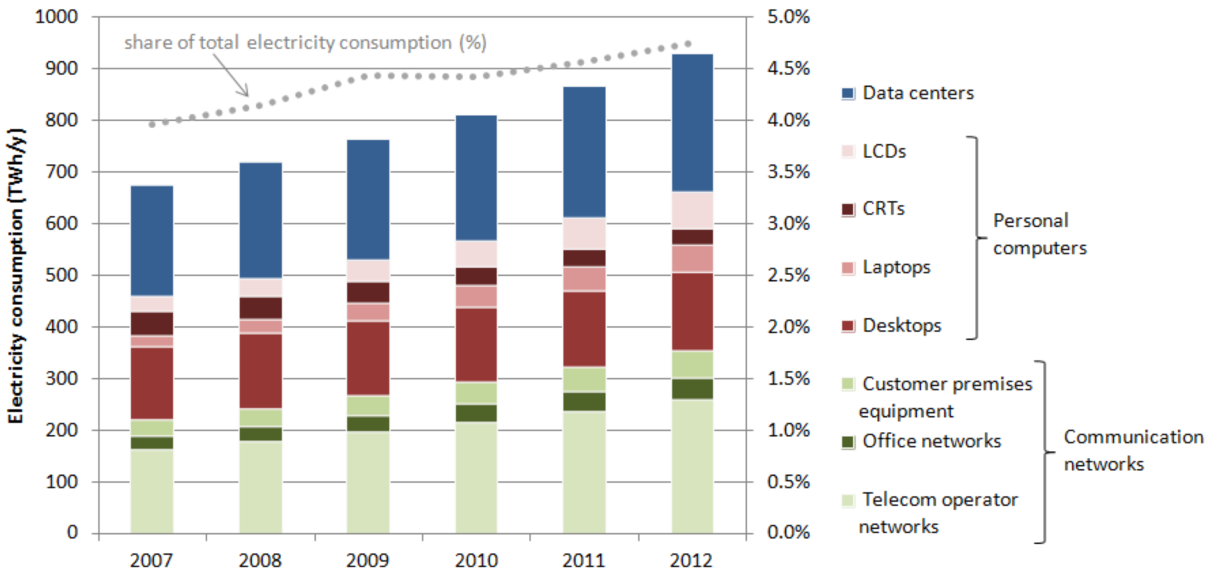


Figure 3-1: Worldwide use phase electricity consumption of communication networks, personal computers and data centers. Their combined share in the total worldwide electricity consumption has grown from about 4% in 2007 to 4.7% in 2012.

3.1 *Communication networks*

We consider three components of communication networks: telecom operator networks, office networks and customer premises equipment. Our calculation method for *telecom operator networks* is similar to the approach used by Malmodin et al. in [10]. We extend their approach by adding a representative sample selection, where we try to match the relative subscription ratios for different services in our sample to the worldwide ratios. We discuss the methodology used for operator networks in detail in section 3.1.1, along with the results of our calculations. In section 3.1.2 we consider the electricity consumption of *office network equipment*. The numbers in this section are mainly based on previous research by Lanzisera et al. [11], but we change the scope to avoid overlap with telecom operator equipment. We also exclude data centers since these will be handled separately in section 3.3. *Customer premises equipment* used to access the network is discussed in section 3.1.3. The equipment considered includes modems and WiFi routers, but excludes end-user equipment such as set-top boxes, TVs and PCs.

3.1.1 Telecom operator networks

Many studies on the electricity consumption in communication networks use a bottom-up approach, where the electricity consumption of individual components of the network is summed to estimate the total consumption (e.g. [12,13]). *The approach we propose is top-down*: we start from the total electricity consumption of a number of telecom providers and based on these numbers we estimate the worldwide electricity consumption in communication networks.

A similar approach was used by Malmodin et al. in [10]. Based on data from a number of telecom operators, they determined the average electricity consumption per mobile subscriber and per fixed subscriber. Multiplying these values with the worldwide subscription numbers and summing the results provided them with an estimate for the worldwide electricity consumption in telecom operator networks.

Unfortunately, it is very *difficult to assign the power consumption of an operator to different services*. Sometimes a distinction between the electricity use of mobile and fixed network equipment is made, but then it is still unclear which part of the fixed network is used to transport data for mobile end-users (this problem was also recognized in [10]). Additionally, we want to make a distinction between fixed broadband and fixed telephony in our study, since we believe the power consumption per user for these services can differ significantly. Attributing the power consumption of the fixed network to broadband and telephone services is even more difficult than for the mobile-fixed case since these two services often share a physical medium.

In order to avoid having to assign the power consumption of the operators to different services, we use a subscription-based *representative sample. The numbers of mobile, fixed broadband and fixed telephone subscriptions in this sample have the same relative ratios as the worldwide subscription numbers. This allows us to extrapolate the power consumption of the sample to a worldwide value using a single scaling factor*, since the percentage of worldwide subscriptions covered is the same for each type of service. Due to the nature of our sample, we are *still taking into account the differences in power consumption for different services.* The drawback of our approach is that we cannot determine the relative contributions of different services to the total network electricity consumption, since we aggregate the electricity consumption for all services.

We select the telecom providers in this study based on their size and on the availability of data. We start by listing some of the world's biggest telecom operators in terms of fixed broadband and mobile customer base. For each of these operators, we try to gather the following information: (a) total annual electricity consumption, (b) breakdown of electricity consumption by activity (offices & retail, data centers, network), (c) number of fixed telephone subscriptions, (d) number of fixed broadband subscriptions and (e) number of mobile subscriptions. Not all of the operators in our initial list disclosed their electricity consumption. Since this information is essential to our calculation we excluded these operators from our sample.

In this section we are only interested in the electricity consumption of operator networks, so we exclude the portion of their electricity consumption that is used in data centers, offices and retail from our calculations (office networks are covered in section 3.1.2, data centers in section 3.3). For some operators, we found the total electricity consumption but were unable to find a breakdown by activity. In these cases we used a value based on the breakdown for other operators. We found that on average, about 13% of electric power is used in offices and retail, 11% is used in data centers and the remaining 76% is used in the network. *Off-grid electricity generation* (e.g. by diesel generators for remote mobile base stations) *is not included in our results.*

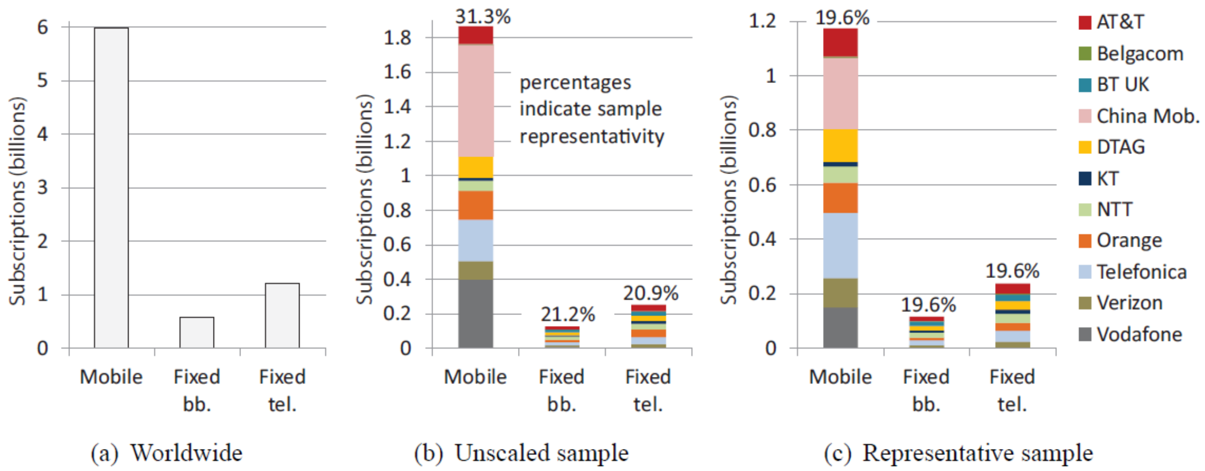


Figure 3-2: Creation of a representative sample of telecom operators for 2011. (a) shows the worldwide number of subscriptions, (b) shows the number of subscriptions in the unscaled sample, (c) shows the number of subscriptions in the representative sample, where each operator is scaled with a weight factor between 0 and 1. The percentages are obtained by dividing the number of subscriptions (per service) in both samples by the worldwide number of subscriptions. In the representative sample, the operator weights are chosen such that the percentages are the same for each type of service (mobile, fixed broadband and fixed telephony).

Table 3-1: Worldwide subscriptions (in millions). Sources: [14,15]. Numbers for 2012 are extrapolations based on values in previous years.

	2007	2008	2009	2010	2011	2012
Mobile subscriptions	3 372	4 034	4 650	5 315	5 975	6 615
Fixed broadband subscriptions	346	409	465	528	590	650
Fixed telephone subscriptions	1 255	1 250	1 249	1 228	1 205	1 182

Once we have determined the network electricity consumption and subscription numbers for each operator, we still need to extrapolate these numbers to an estimate of the worldwide network electricity consumption. As mentioned above, we create a representative sample of operators based on subscription numbers in order to do this. The worldwide subscription numbers for 2011 are given in Figure 3-2(a); the numbers for other years can be found in Table 3-1. Our sample of 11 operators for 2011 is represented in Figure 3-2(b) (electricity consumption values for individual operators are not shown as some of these numbers are confidential). When we compare the numbers of subscriptions in the sample to the worldwide numbers, we see that mobile subscriptions are overrepresented in the sample: 31.3% of worldwide mobile subscriptions are covered, while only 21.2% and 20.9% of fixed broadband and fixed telephone subscriptions are covered respectively.

In order *to create the representative sample* – while keeping the number of subscriptions covered as large as possible – we determine a *weight factor between 0 and 1 for each of the 11 operators, so that when we add the weighted numbers of subscriptions, the following ratios are equal:*

$$\frac{\text{mobile subs in repr. sample}}{\text{worldwide mobile subs}} = \frac{\text{fixed bb. subs in repr. sample}}{\text{worldwide fixed bb. subs}} = \frac{\text{fixed tel. subs in repr. sample}}{\text{worldwide fixed tel. subs}}$$

We solve the optimization problem for five different years, based on the worldwide and operator subscription numbers for 2007-2011, thus creating a representative sample for each of these years. The representative sample for 2011 is depicted in Figure 3-2(c).

Once we have created the representative sample, we *estimate the worldwide network electricity consumption* P_W *by extrapolating the electricity consumption of the representative sample* P_S *as follows:*

$$P_W = \frac{\text{worldwide mobile subs}}{\text{mobile subs in repr. sample}} \times P_S$$

where P_S is the sum of the scaled network electricity consumptions of the operators in the sample (scaled with their respective weight factors). From the first equation it follows that an extrapolation based on the number of broadband or telephone subscriptions would deliver the same result. The calculation of P_W is performed for each year in 2007-2011. For 2012, we estimate the worldwide electricity consumption by extrapolating the values of the previous years. Note that actual data for 2012 was not available at the time this deliverable was written and delivered.

In 2007, telecom operator networks consumed almost 160 TWh. By the end of 2012, at an *annual growth rate of 10.2%*, their consumption increased to about 260 TWh per year.

3.1.2 Office networks

The scope of this section is the *electricity used by network equipment in offices, excluding network equipment in data centers*. This includes network equipment in network operator offices but excludes equipment in the telecom network they operate (this was already handled in section 3.1.1).

We do not consider custom enterprise transport networks, such as those between Google or Amazon data centers. There seems to be a growing trend for such companies to roll out their own fiber networks. While it is hard to map these networks, the total power consumption will very likely be negligible, as optical transport networks consume very little compared to other network equipment such as modems, IP routers or base stations. For example, the pan-European Géant network and the US NSFNET network consume each in the order of only a few tens of GWh/y [16]. Nonetheless, with the rise of cloud computing, this might become a relevant component to consider in the future.

We base our estimate on a study by Lanzisera et al. [11], which estimates the USA and worldwide electricity consumption of data network equipment in both residential buildings and offices. Their study focuses on IP-based network equipment only, and does not include the electricity used by power or cooling infrastructure. Their annual electricity consumption estimate is based on an average power consumption per device, and uses values for 2008 with forecasts up to 2012, which we have adopted.

We consider only the equipment relevant in office use (based on a selection of the classification in [11]), *and in addition we add an estimated overhead for cooling.* To estimate this overhead, we start from the approach used for data centers, where the cooling equipment and power provisioning equipment combined typically consume as much as the IT equipment itself. Power provisioning equipment includes uninterruptible power supplies and power conversion devices. The cooling and power provisioning overhead is commonly captured by the so-called Power Usage Effectiveness

(PUE) factor being equal to 2, i.e. the IT power consumption needs to be multiplied by 2 to estimate the total power consumption.

Since the power provisioning in data centers typically makes up about 1/3 to 1/5 of this overhead, but is in general not applicable to office network equipment, the correction factor to account for cooling only is about 1.75. Since not all switches are installed in cooled locations, we have accounted only half of the cooling factor, which gives an overhead factor of 1.375 for switches.

The results are shown in Table 3-2. The worldwide office network equipment is estimated to consume 42 TWh in 2012.

Table 3-2: Office networks: cooling overhead factors and worldwide electricity use per type of equipment (electricity use estimates are adaptations of the values in [11]).

	Cooling overhead	Electricity use, 2007 (TWh)	Electricity use, 2012 (TWh)
switching - 10/100	1.38	12.7	10.7
switching - 10/100/1000	1.38	5.4	17.5
routers - small & medium	1.75	3.5	4.2
enterprise WLAN	1.00	1.0	2.3
security - small and medium	1.75	5.3	7.7
Total		27.8	42.4

3.1.3 Customer premises equipment

In this section, we consider the electricity consumption of *residential network access equipment.* In order to access the network, every internet subscriber requires a *modem*. Most users also have a *WiFi router* installed, *often with integrated wired switching and routing capabilities*. The modem and WiFi router may also come in a single box. We estimate the worldwide power consumption by multiplying average power consumption values of these residential devices per access technology category with the number of subscriptions per category.

We already know the worldwide number of fixed broadband subscriptions for 2007-2012 from Table 3-1. We distribute these subscriptions among different broadband access technologies using percentages from [17,18]. Based on the percentage of broadband subscriptions (of total internet) in [19] we derive the number of narrowband subscriptions. The *subscription numbers per access technology* for 2007 and 2012 are given in Table 3-3. Values for 2012 are extrapolations based on data from previous years, as actual data for 2012 was not available at the time this deliverable was written.

Table 3-3: Customer premises equipment: average power consumption per user, numbers of subscriptions and worldwide annual electricity use.

	Power per user (W)	Subscribers, 2007 (million)	Electricity use, 2007 (TWh)	Subscribers, 2012 (million)	Electricity use, 2012 (TWh)
Cable	9.5	74	6.2	123	10.2
DSL	7.1	228	14.2	388	24.1
FTTH	13.0	38	4.3	115	13.1
Other broadband	8.3	6	0.4	24	1.8
Narrowband (dial-up)	2.5	283	6.3	142	3.1
Total		629	31.4	792	52.4

The *power per user* values for *cable*, *digital subscriber line (DSL)* and *fiber to the home (FTTH)* were adopted from a study by Lanzisera et al. [11]. In their study, the authors assume that few users use a modem without a WiFi router and that this number is comparable to those with multiple WiFi routers (or WiFi repeaters). This assertion is confirmed by data in [20] on the installed base of home network equipment: in 2010, there were 46.4 million modem-only devices and 46.2 million wireless routers installed in USA households.

For end-users accessing the Internet through *other broadband* technologies such as satellite and fixed wireless access, we assumed the power consumption is comparable to that of the more common broadband technologies. The end result is not very sensitive to this value due to the small user base.

For *narrowband* users we assumed the average power consumption of a dial-up modem from [21]. This value is significantly lower due to the limited time in which the device is active, compared to always-on broadband modems.

The results are included in Table 3-3. The power consumption by customer premises equipment was 31.4 TWh in 2007 and reached 52.4 TWh in 2012. This corresponds to an *annual growth rate of 10.8%*.

3.2 *Personal computers*

We base our estimates for the number of personal computers on statistics from the UN [14,22]. These numbers *include desktops and laptops, but exclude terminals connected to the mainframe and devices such as smart-phones or tablets that have only some, but not all, of the functions of a PC* (e.g. they may lack a full-sized keyboard, a large screen, ...) [23]. *Our end result also includes the energy consumption of (external) monitors connected to these personal computers.*

The worldwide energy consumption is calculated by multiplying average energy consumption values per device by numbers of devices. We distinguish between household and office desktops and laptops, and CRT (cathode ray tube) and LCD (liquid crystal display) displays.

3.2.1 Number of PCs

Based on the *average number of PCs per 100 inhabitants* for each country (*UN data*, [22]) and population data for these countries [14] (we used the "Medium variant" of UN population prospects), we estimate the worldwide number of PCs. There are some gaps in the data for the number of PCs per 100 inhabitants. For some countries the data is only missing for one or two years. We fill in these blanks by making a linear interpolation of the previous and the next year for which data is available. For other countries there is little or no data available, so we can't interpolate data from other years. We assume the number of PCs per 100 inhabitants in these countries equals the average value for the region they belong to. Based on these assumptions, we estimate the *total number of PCs in use per region and worldwide for 2000-2006*. From 2007 onwards, there is not enough data available in the UN database to make a reliable estimate.

However, *annual PC sales numbers* are available for 1991-2010 [24]. If we know the lifetime distribution of PCs, we can use these sales data to determine the number of PCs in use in 2007-2010. We model the lifetime distribution of personal computers as a curve that is initially flat, followed by an exponential decay. This curve is determined by two parameters: the threshold and the decay constant. Based on the number of personal computers in use in 2000-2006 and the sales data for 1991-2006, we estimate the threshold of the lifetime curve is at 2.5 years, after which 26% of the PCs still in use are discarded each year. This corresponds to an average lifetime of 5.9 years. Combining this lifetime model with historical sales data (and an exponential extrapolation of this sales data to predict sales in 2011-2012) provides us with an estimate for the *number of PCs in use in 2007-2012*.

Based on these calculations we estimate *over 1 billion personal computers were in use in 2007 and by the end of 2012, increased to just over 1.8 billion.*

3.2.2 Laptops and desktops, household and office computers

Laptops typically consume less energy than desktops. We therefore need an estimate of the number of laptops and desktops that are in use. This can be derived indirectly from the *annual sales data for laptops and desktops* [24,25] and the lifetime model of personal computers we determined in the previous section. The share of laptops has been significantly increased in the past five years, from about 32% of installed base of personal computers in 2007 to 54% in 2012.

A distinction is made between *computers that are used in an office environment and computers that are used in households*, since the *usage patterns in these environments differ*. In [20], a study on the electricity consumption of consumer electronics in households, the number of desktops and laptops in USA households are given. Combining these numbers with the total installed base of laptops and desktops in the USA (obtained in the calculations in the previous paragraph) allows us to estimate the distribution of computers per type (laptop/desktop) and environment (household/office). *We assume the worldwide distribution is similar to that in the USA.*

3.2.3 External monitors

The screens integrated in laptops are taken into account in the power consumption of laptops, but we still need to consider external displays, attached to most desktops and some laptops. Unfortunately we could not find any worldwide estimates for the number of computer monitors that are currently in use. In [20], survey results indicate that *96% of desktops and 26% of laptops in USA households were* *connected to an external display in 2010. We assume these percentages apply to all laptops and desktops worldwide* to obtain the number of external computer monitors in use in 2010. We can't simply apply these percentages for other years, since the number of displays per device has increased over the years. *To estimate the growth rate for the number of monitors, we also use data from the USA study*, where the number of computer monitors in households in 2005, 2006 and 2010 are given. Based on these numbers we expect the number of monitors to increase by 12.06% annually. We apply this growth rate to the 2010 value we obtained above to estimate the number of monitors for 2006-2012.

We make a distinction between CRT and LCD monitors, since the latter are typically more energy efficient. We did not find historic trends for the percentage of CRT displays in use in all regions, but we are able to derive the penetration curve of CRTs in the USA installed base from values for 2006-2010 in [20] and the fact that the first LCD monitors were commercially available around 1999 [26]. We then use the difference in transition time from CRT to LCD TVs (in sales data) as an indication for how many years we should offset the USA curve in time for other regions. For example, Indian LCD TV shipments surpassed those of CRT TVs in 2012, while the USA and Europe saw their LCD TV shipments exceed those of CRTs in 2007. This means that we shifted the curve for the number of CRT monitors in India 5 years into the future. Combining these curves with the installed base of computers per region provides us with a weighted average for the percentage of CRT and LCD monitors in use worldwide.

3.2.4 Power consumption per device

To the best of our knowledge, *there are no worldwide values available for the average power consumption of desktops and laptops*. One of the main challenges when determining the average power consumption of these devices is that even though the numbers for power consumption in active, sleep and off mode are known, we have no recent information on how many hours computers are left on and in sleep mode during the day. Though there are no worldwide averages available, we did find *average values for the USA* [20], so we *based our estimates on these numbers. Based on a study on the carbon footprint of ICT in Australia* [27] *and* the previously mentioned study on the energy consumption of *consumer electronics in USA homes* [20] we obtained an *average annual energy consumption value for CRTs and LCDs.*

It must be noted that values found in literature for the power consumption of PCs show a large spread. For example, according to [28], an average laptop in Europe consumed 116 kWh/y in 2007 and an average laptop in Switzerland consumed 47.5 kWh/y in 2008, while in [20] the average energy consumption of a laptop in the USA is estimated at 72 kWh/y. It is clear that further research in this area could greatly increase the reliability of our estimates.

3.2.5 Results

The final results of our calculations are given in Table 3-4. The total energy consumption by personal computers and their displays is currently around 300 TWh per year. The *annual growth rate of this total electricity consumption is 5.3%*. This growth rate is significantly lower than for device numbers (which is around 11-12% for monitors and computers), mainly due to the growing popularity of laptops and LCD monitors, which are more energy efficient than desktops and CRT monitors.

Table 3-4: Personal computers and computer monitors: average power consumption per device (taking into account active and inactive times) and worldwide electricity use per type of equipment.

	Power/device, 2007 (W)	Power/device, 2012 (W)	Electricity use, 2007 (TWh)	Electricity use, 2012 (TWh)
Office desktops	17.0	15.7	51.4	46.2
Household desktops	26.4	24.3	91.2	105.9
Office laptops	5.2	4.4	4.1	8.3
Household laptops	7.9	6.7	17.7	45.2
CRT monitors	20.0	20.0	46.6	31.9
LCD monitors	8.0	8.0	27.9	69.6
Total			238.9	307.1

3.3 *Data Centers*

To estimate the total electricity used by data centers worldwide in 2012, we base ourselves on the latest study by Koomey on this topic [29]. *Koomey provides an estimation of data center power consumption for 2010. In general, we extended these trends to 2012.* However, there are two main differences: (a) we include orphaned servers (which were estimated in [29] to potentially be a large percentage of the servers in the field, but not included in any of his final results), and (b) we analyzed data from spec.org [30] that shows a potential decrease of electricity use per server for the period 2008-2012.

The data center power consumption is calculated as follows. To get the worldwide power consumption of *servers* we multiply, for each of three server classes, the average power per server by the number of servers worldwide. We then add the electricity used by *storage equipment* (tapes and hard disks), *communication equipment* (such as network switches) and *infrastructure equipment* (such as cooling and power provisioning losses) by applying three overhead factors.

3.3.1 Electricity use per server

We consider Koomey's (i.e., IDC's) three cost-based classes of servers: volume servers (< $25 000 per unit), mid-range servers (between $25 000 and $500 000 per unit) and high-end servers (> $500 000 per unit).

To get recent data on the electricity use per server, we analyzed the server power consumption (at 50% average target load) for all servers up to 1000 W in the spec.org power database [30] between January 2008 and December 2012. We created a volume and mid-range cluster by separating the servers at 350 W (based on the power per server in 2005). The volume servers cluster shows a -3% CAGR (compound annual growth rate) in power per server in the period 2008-2012, and the mid-range servers cluster shows a 0% CAGR (i.e. no change) for the same period, the high-end cluster is not captured at all by the sample.

We chose not to apply these CAGR values in our calculations since the spec.org sample is probably biased towards more energy-efficient servers, and it is unclear whether it is representative for the actual server distribution worldwide. However, these trends do suggest that the increase in power per server from 2000-2005 reported in [29] hasn't continued. Therefore we *assume the same power per server values as reported for the year 2005 in [29]*.

3.3.2 Worldwide number of servers

For the worldwide number of servers in 2012, we assume that the 2005 to 2010 server growth trends reported in [29] continue to 2012. These trends showed a slower growth of volume servers (5.9% p.a.) and a faster growth of high-end servers (13.1%).

We assume continued trends based on Gartner reporting a 7% increase of server shipments in 2011 [31], with Gartner's shipment data roughly corresponding to the 2010 shipments in [29]. If yearly decommission rates (as a percentage of the installed base) have not changed, this would translate to an overall 7% installed base growth, which corresponds roughly to the 5.9% p.a. growth rate of volume servers between 2005 and 2010.

The number of servers worldwide is adjusted upwards with a factor 1.25 to account for orphaned servers, i.e., about 20% of the servers in data centers are using electricity but no longer delivering computing services. We derived this factor from [29], where orphaned servers are estimated to account for 10-30% of all servers (based on anecdotal evidence).

3.3.3 Overhead power consumption

The *storage* and *communication equipment* power consumption is added as a fixed percentage of the server power consumption, i.e. 24% and 15% respectively. The *infrastructure overhead* (PUE) is a factor ≥1 we apply to the previous end results. For 2012, we assumed a 5% improvement on the 2010 upper bound value of 1.92 in [29], given the increased focus on energy-efficiency, which results in a PUE = 1.82.

3.3.4 Results

Data centers worldwide are estimated to have consumed 268 TWh in 2012. If we perform the same analysis for the year 2007 – with a PUE scaled linearly between 2 (the value for 2005) and 1.82 (the value for 2012), and assuming the same trends for the installed base – we find 216 TWh.

Table 3-5: Data centers: worldwide power consumption in 2012. We adapted data from [29] by including orphaned servers and adjusting the power per device trend for 2005-2010 downwards.

Server class	Volume	Mid-range	High-end
Power per server	222 W	607 W	8 106 W
Installed base (inc. orphaned servers)	44.301 M	1.110 M	0.187 M
Number of servers (incl. orphaned servers)	Installed base × 1.25		
Storage power consumption	24% of total server power consumption		
Communication power consumption	15% of total server power consumption		
Infrastructure power consumption	PUE = 1.82		
Total power consumption	219 TWh	15 TWh	34 TWh

4 Specific use cases

In the previous section, an overview of the global ICT footprint is given, by using a high-level approach. In this section, some use cases are described to present the energy consumption from a more specific point of view. In this way, the most power consuming parts of these use cases are highlighted, which allows us to define some interesting energy saving techniques in the next section.

Six use cases are handled, and they represent the most important domains from the perspective of ICT energy consumption. The first three cases describe specific examples of the three domains we studied in our global ICT footprint study, i.e. (local) telecom network, PCs, and data centers. The latter three cases handle some important ICT environments, i.e. offices, universities and residential users.

4.1 *Energy footprint of a national DWDM network*

As telecom network, we consider an optical network from an anonymized small operator that is using dense wavelength division multiplexing (DWDM) technology.

4.1.1 WDM network nodes

The DWDM network under consideration consists of three types of network nodes, namely group optical add/drop multiplexer/demultiplexer (g-OADM) nodes, thin optical add/drop multiplexer/demultiplexer (t-OADM) nodes and the reconfigurable optical add/drop multiplexer/demultiplexer (ROADM) nodes. Connections start or terminate at an (R)OADM. For (R)OADM nodes that are traversed along the computed path, but are not meant to be the destination of the request, the connections are optically passed through the (R)OADM node without any optical-electronic-optical conversion. Optical bypassing ensures that connections not intended for the intermediate (R)OADM node are handled by the optical layer and not passed on to the lower layers, leading to lower core router capacity usage. However, this can only occur at wavelength granularity. Conversion to an electronic signal will only be done at the intended destination (R)OADM node.

4.1.1.1 Group Optical Add/Drop Multiplexer/Demultiplexer Node

g-OADM nodes, via manual configuration allow to add/drop wavelengths of a predefined wavelength group at the source or destination nodes. A g-OADM node may consist of Erbium Doped Fiber Amplifier (EDFA) modules and Group Multiplexer/Demultiplexer (GMD) modules. GMD modules support up to nine Channel Mux/Demux (CMD) filters, capable of offering between 36 to 72 10Gbps wavelengths with 50GHz spacing between them. These 72 wavelengths are grouped into nine bands of eight wavelengths. Each group is supported by a CMD filter. Two types of CMD filters are used, namely the CMD4 filter with four wavelength ports or the sCMD8 filter with eight wavelength ports. For a group of eight wavelengths dropped from the GMD module, the CMD4 filter can only utilize four of the wavelengths while the sCMD8 filter can utilize all eight wavelengths. Both types of CMD can coexist on the same line.

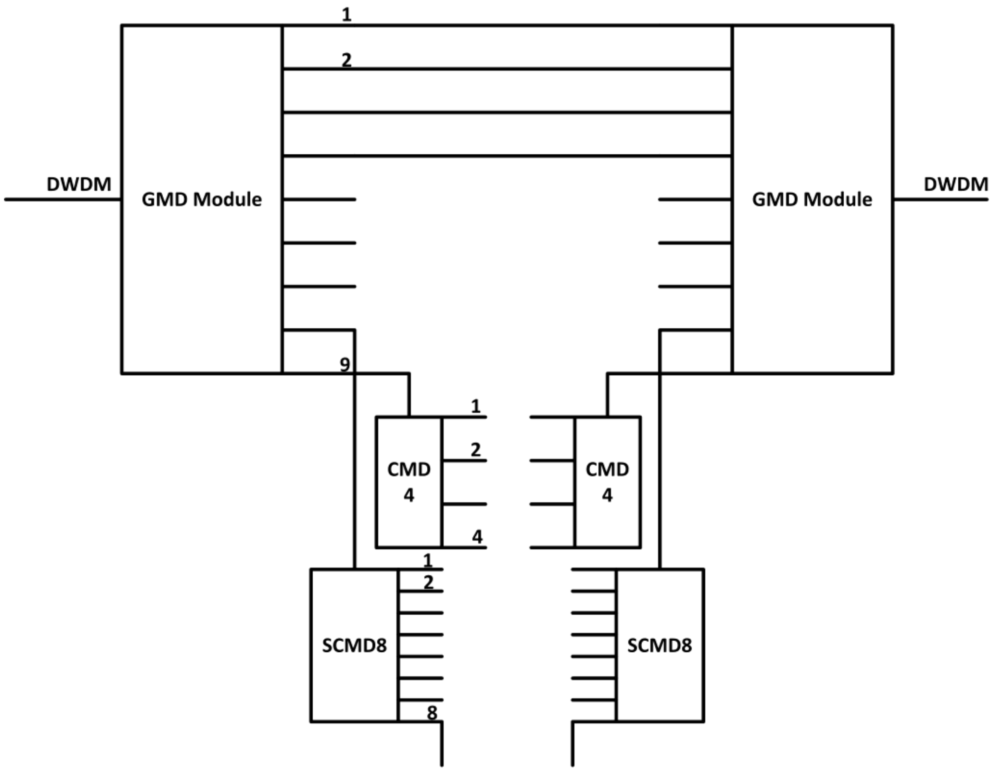


Figure 4-1: Group Optical Add/Drop Multiplexer/Demultiplexer Node

4.1.1.2 Thin Optical Add/Drop Multiplexer/Demultiplexer Node

Unlike g-OADM, a t-OADM node has no need of GMD modules to multiplex/demultiplex connection requests. The t-OADM manages connection multiplexing/demultiplexing directly by using cascaded sCMD8 filters. Up to three sCMD8 can be put in series, yielding maximum 24 wavelengths capacity at the t-OADM. Although the full capacity is lower than with a g-OADM, the t-OADM is much cheaper and smaller than the g-OADM. A t-OADM is used mostly for small network sites with low connection requests.

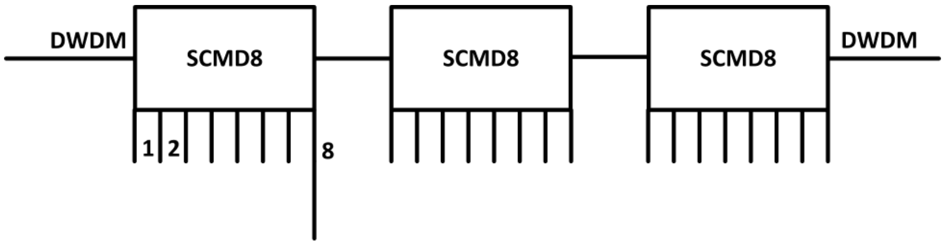


Figure 4-2: Thin Optical Add/Drop Multiplexer/Demultiplexer Node

4.1.1.3 Reconfigurable Optical Add/Drop Multiplexer/Demultiplexer Node

ROADM nodes operate with the same purpose as OADM nodes. However, ROADM nodes allow faster automated adding/dropping of wavelengths with minimal user intervention at the cost of more expensive equipment. While GMD modules in OADM nodes can only drop groups of eight wavelengths at a time, the Wavelength Selective Switch (WSS) module in ROADM nodes can even drop wavelengths at a single wavelength granularity. A 50GHz WSS module with either CMD44 or sCMD8 filters allows termination or rerouting of any wavelength to any port while connecting up to five nodes at a ROADM node. Three ports of the splitter can be connected to series of three sCMD8s, with total 72 wavelength capacity or by using only one port with connection to two CMD44, supporting 88 wavelength capacity. However, the price of a CMD44 is higher than that of a sCMD8.

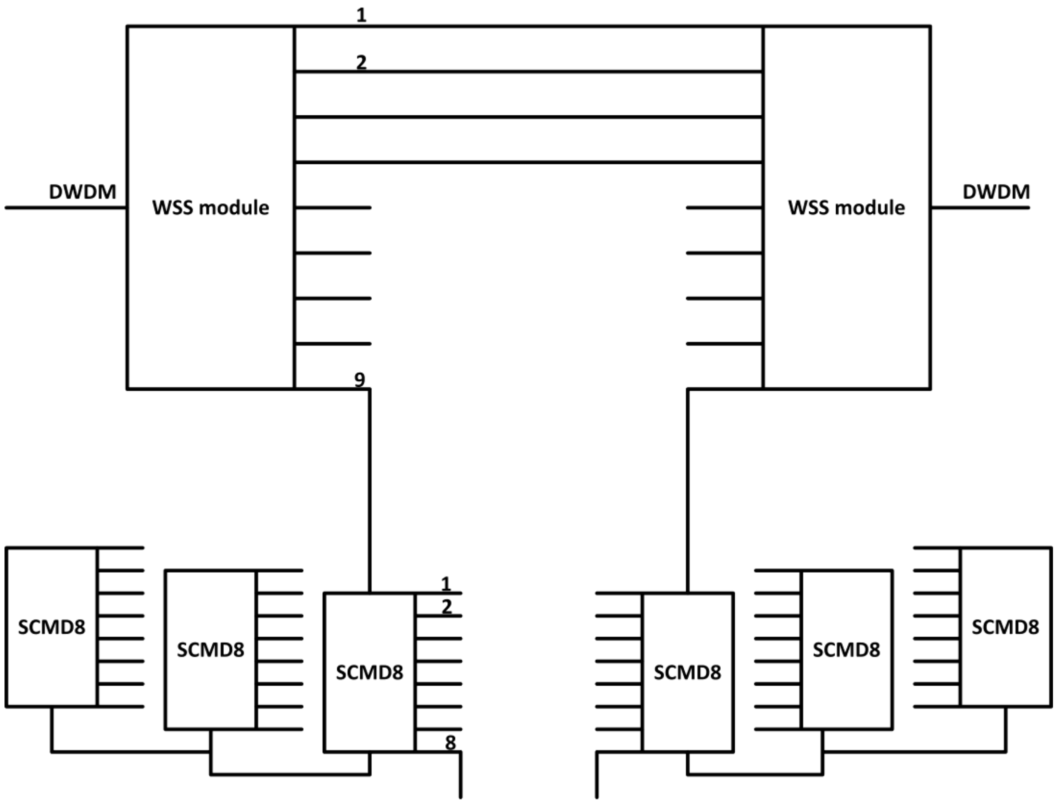


Figure 4-3: Reconfigurable Optical Add/Drop Multiplexer/Demultiplexer Node

4.1.2 WDM Network Services

Lightpaths generally have no more than 0.01% packet loss, lower than 10ms maximum round-trip time and negligible jitter. One could differentiate in the requested level of availability by deploying protection schemes [32] (e.g., 99.5% for a single lightpath, 99.9% for a protected lightpath, and 99.95% for a redundant lightpath). A protected lightpath is made possible by computing two link-disjoint dedicated paths with the primary path transmitting the actual data, while the backup path is activated within 60ms in case of unavailability of the primary path. A redundant protection scheme computes two link-disjoint dedicated paths where both of them are used for transmitting data.

One could also differentiate in terms of speed, e.g. a direct high-speed DWDM service or a slower Coarse WDM (CWDM) service.

4.1.2.1 DWDM Service

DWDM connections are multiplexed/de-multiplexed at the optical cross-connect from core L1/L2 switches. At the core switches, multiple streams from slots of tributary, line, transponder or photonic interfaces are multiplexed into lambdas. Dispersion is electronically compensated at the multi-protocol linecards.

Core switches have a finite number of available slots. Some slots are reserved for the switching matrix module(s), and the others can be inserted with any combination of GE circuit packs, 2.5GE circuit packs or 10GE circuit packs, depending on the switching capacity of the switching matrix module(s) used.

4.1.2.2 CWDM Service

For lower speed connections (below 1Gbps) CWDM rings could be used, providing Ethernet service for up to 120km distance. Several linecards can be supported and transmission can scale up to 1Gbps for a linecard. The transmission can be either protected or unprotected. CWDM with wavelengths between 1270 to 1611 nm offers less sophisticated and cheaper transceiver design at the cost of increased channel spacing. Every CWDM node has an ITU-T CWDM OADM coupler to drop traffic.

4.1.3 Energy Consumption per Equipment

In our DWDM network under study, five types of equipment contributed to more than 97% of the energy consumption, namely the optical cross-connects (which configure lambdas into optical fibers and amplify signals), the core switches (which map Ethernet or several other interface signals into lambdas), the customer premise equipment (for automated variable bandwidth allocation for up to 1Gbps), and the metro switches (which enable virtual private networking in a ring structure). The core switches accounted for nearly half of the network power consumption.

The average energy consumption per equipment type (obtained via measurements) is shown in Table 4-1 (where the total energy is computed using a PUE of 2):

Table 4-1: Average energy consumption per equipment type in a WDM network

Network Element	Energy (Wh)	#Used	Total Energy (Wh)
Core switch	614	95	116660
Customer premise equipment	61	382	46604
Optical cross-connect	91	135	24570
Metro switch type 1	259	25	12950
Metro switch type 2	862	20	34480

Based on the numbers in the table, the energy consumption of the network is 235,264 Wh or 2.0609 GWh yearly (corresponding to 0.0002% of the total energy consumption of telecom networks in 2012).

4.1.4 Energy Consumption per Equipment Modules

The energy consumption per equipment mentioned in the previous section reflects the average consumption. Realistically, the energy consumption of equipment differs according to their usage in the network. A core switch with only three circuit packs would not use as much energy as a core switch with twelve circuit packs. Hence, we have further analyzed the network's energy consumption at module granularity. We thereby only focus on the core switches and optical cross-connects, since they consume most energy. The following energy consumption is used (power numbers without * were obtained from the specs, while power numbers with * are assumed):

Table 4-2: Energy consumption per equipment module in a WDM network

Network Element	Network Module	#Max Module per Element	Energy (Wh)
Core switch	Monitoring and cooling	1	21.2
	Switching matrix (80Gbps)	2	44
	Switching matrix (160Gbps)	2	45
	Circuit Pack (10*GE)	4/12	43
	Circuit Pack (4*GE L2SS)	6	81
	Circuit Pack (4*GE)	12	35
Optical Cross-Connect	Monitoring and cooling	1	15*
	Amplifier	1	34
	Cross-connect (WSS)	1	100*
	Cross-connect (GMD)	1	50*
	Channel filter (CMD4)	9	5*
	Channel filter (sCMD8)	3/9	15*
	Channel filter (CMD44)	2	50*

Based on these numbers, the energy consumption of the core switches varied from 523 to 849 Wh, while the energy consumption of optical cross-connects varied from 67 to 284 Wh. The variation in energy consumption is caused by the module configuration of the network equipment, which depends on the traffic inbound/outbound at the corresponding network equipment.

When only considering the energy consumption of the network, i.e. without the customer equipment, and using a PUE of 1, the total energy consumption of the optical cross-connects and core switches in the DWDM network accumulates to 6.5014 kWh.

4.2 *Energy footprint of PCs*

The following section will describe qualitative considerations regarding the power consumption of different components that are commonly found in most computers today.

4.2.1 Central processing unit (CPU)

CPUs are the major consumers of dynamic power in computers, i.e. power demand between idle and fully utilized states varies significantly. As CPU load is highly volatile, sophisticated power saving mechanisms have been developed over many years. The first of these mechanisms were so called C-states, which are sleep states of the CPU. In case a CPU is idle, certain parts of it may be switched off to decrease power consumption, however to bring the processor back to fully active state, a certain delay is introduced. This delay will depend on the ‘deepness’ of the sleep state. C-states do only apply in case of complete idleness of the CPU.

Additionally, in scenarios where the CPU is partially loaded, power saving is enabled by P-states. P-states are an implementation of dynamic voltage and frequency scaling for CPUs. This allows the CPU to operate at different clock speeds and operating voltages depending on the current load. When running the CPU at lower clock speeds, it is possible to reduce the operating voltage. This is a feasible approach for saving power, as the power of a CMOS circuit is calculated via the following formula:

$$P = CfV^2$$

where C is the capacitance of the circuit, f the frequency and V the voltage. P-state switching can happen multiple times per second, so the impact on performance is very little.

Another trend in CPU architecture is the move from single, high frequency cores towards slower multi-core CPUs. This allows for using a lower supply voltage, which in turn lowers power demand. However, the performance depends heavily on the multi-threading capability of the software.

4.2.2 Hard disk drives (HDD) and solid state disks (SSD)

Current non-volatile storage in computer systems mostly relies on hard disk drives (HDDs) – rotating disks on which data is recorded magnetically. Data density on these HDDs has increased significantly over the past years, reaching several terabytes per drive. However, from an energy efficiency point of view, these drives perform quite poorly: Even in idle mode, the platters of the HDD are kept spinning at high speeds (in server environments often 10,000 to 15,000 rpm) which consumes power and generates heat. To decrease power consumption, the rpm may be reduced; however this directly decreases HDD performance. On the other hand, the HDD may be spun down while idle, which introduced a significant wakeup delay due to the limited acceleration of the platters.

A new concept of data storage are solid state disks (SSDs). These hardware components offer several advantages over current HDDs, as they do not have any moving parts. SSDs offer a much higher performance than HDDs, as no seeking delays apply. Also, energy efficiency of SSDs is much higher as nearly no power is used in idle mode (< 1W). However, the price of SSD storage is much higher than traditional HDDs (around a factor of 10).

4.2.3 Network Interface Cards (NIC)

NICs are available in almost any computer today, at least when connected to a network. In case a computer hosts services available on the network (LAN or WAN), it has to be ‘always on’, i.e. be ready to answer requests at any time. This holds true even for service clients, which have to confirm their availability via ‘keep-alive’ messages. These ‘soft-state’ concepts are a foundation of the current Internet, however, the necessity for constant availability interferes with sleep states and other power saving modes.

One suggested method to overcome this is the concept of network presence proxying. To make a client appear online and ready to receive messages, the network presence is delegated to another device in the network (e.g. the router). It is then possible to shut down the delegating device.

Another point worth addressing concerning energy efficiency is the speed of Ethernet connections. Current home equipment has speeds of 1Gbps, server equipment even more. Most times, this speed is not needed, e.g. Internet traffic or just keep-alive messages. As (multi)gigabit connections require a significantly higher amount of power than 10 or 100 megabit connections, an automatic decrease of line speed would be worthwhile. However, current auto negotiation protocols for connection speed selection are not suited for this concept, as they cause an interruption of the connection.

4.3 *Energy footprint of a data center*

Regarding sustainable Internet, one of the most critical parameters to observe is data centers. Data centers are responsible for great energy inefficiencies and energy waste. At the International Hellenic University (IHU), the energy consumption of data centers is studied within the Smart IHU project (http://rad.ihu.edu.gr).

4.3.1 Monitoring

The Smart IHU project aims to deploy smart meters and actuators to monitor in real time the energy consumption of the building but also to provide automation and energy management (http://rad.ihu.edu.gr/smartihu/). The Advanced Metering Infrastructure (AMI) is based on a wireless sensor network that operates over heterogeneous protocols. Within the platform, data center energy demands are captured by commodity clamp sensors (operating at RF 434 MHz unlicensed band) deployed in the three phase installation of the building. In addition, the power needs from the servers of the data center are monitored with plug sensors operating at 2.4GHz (mesh zigbee platform). Traffic, CPU and UPS load are captured through SNMP requests (TCP/IP). Finally environmental parameters such as humidity, temperature and luminance in the data center room are monitored through a ZigBee sensor network.

4.3.2 Energy Efficiency Metrics of Smart International Hellenic University (IHU) platform

In order to investigate and propose directions to optimize energy consumption in a data center it is important to quantize its performance. This can be achieved by using a standard metric to measure the inefficiencies. Data center's energy efficiency can be broadly defined as the amount of useful computation divided by the total energy used during the process. There are two types of energy efficiency metrics. The first describes the efficiency of the NCPI (network critical physical infrastructure) equipment and the second models the useful work to the power consumption. The used metrics are those presented in sections 2.1 and 2.2.

4.3.3 Results

In the next figures some snapshots are shown from the online web analytics for PUE, telco efficiency (Mbits/kWhr) and server efficiency (Ops/kWhr).

Figure 4-4: Snapshot of the PUE from the smart IHU portal (http://smart.ihu.edu.gr/)

Figure 4-5: Snapshot of the telco efficiency (Mbits/kWhr) from the smart IHU portal (http://smart.ihu.edu.gr/)

Figure 4-6: Snapshot of the server efficiency (Ops/kWhr) from the smart IHU portal (http://smart.ihu.edu.gr/)

4.4 *ICT engagement in modern offices*

At Lancaster University, the staff base of the university campus is utilized as a test bed for a large scale monitoring deployment to represent modern office environments. This activity is done as part of the CURRENT project (http://current.lancs.ac.uk), which aims to engage users to raise awareness of the impact of their energy use and to gain their support in participating to be a part of the project, monitoring how these users interact with the ICT equipment which surrounds us in our day-to-day working lives, and finally to encourage the users to reduce their carbon footprint by applying various social techniques to help raise understanding and promote sustainable green energy practices.

It can be generally assumed that when the computer of an office worker is left unattended and idle, it is consuming a large portion of its total power profile, without fulfilling any useful purpose; and is therefore wasting energy. To determine when users leave their computers unattended, monitoring software has been developed which listens to various operating system events (such as screen saver activation and deactivation, power on/off and hibernation, network login etc.) and logs this information to a central database for both real-time and offline processing.

To alleviate the task of deploying this software manually on a large scale, the existing IT infrastructure of the Lancaster campus is utilized to deploy, perform upgrades and manage this software remotely. User accounts are automatically added into a Microsoft Active Directory Organizational Unit. When the user reboots their machine the software is automatically pushed to their computer and the software begins the logging process of how users interact with their computers. This process is depicted in Figure 4-7.

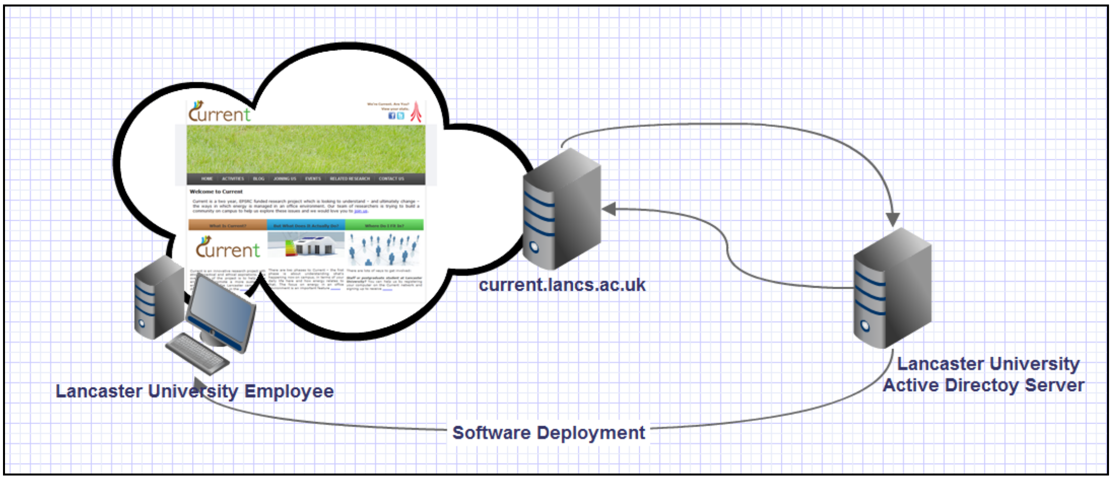


Figure 4-7: Software deployment process for the CURRENT monitoring process.

Over a period of 3 months it has been determined that office computers are on average left unattended and switched on 28% of the time, switched on and in use for 18%, and turned off/hibernating/sleeping 54% across all the monitored participants. Given that the average energy consumption of a laptop computer is around 37W and 64W for a desktop computer or Apple MAC in an idle state, the average total wasted energy just from leaving a computer switched on when not in use per year could be on average 110KW per computer, equating to a cost of around £15 and contributing to around 100Kg of waste carbon footprint increase per computer per year. For an organization with the staff base comparable to that of the University of Lancaster (around 2000 full time staff) this would result in a net cost of around £30,000 and 200,000Kg of carbon production annually, just through staff leaving their computers turned on whilst not using them.

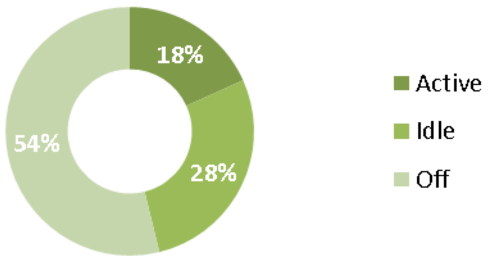


Figure 4-8: Computer usage statistics for campus network.

The next phases for the CURRENT project aim to determine how much energy is wasted for other devices which now often surround us within modern office environments. An extensive survey of what devices are found in modern offices has been performed and is awaiting publication. Selected groups of users will have the IT equipment found within their offices equipped with wireless, hardware energy monitors, as well as monitoring light and heating usage. These wireless monitoring devices will stream data in real-time, helping to determine and quantify where energy is further wasted.

4.5 *Energy Footprint of Universities*

This section describes three initiatives to monitor the energy footprint of a European university: Delft University of Technology (the Netherlands), Lancaster University (UK) and International Hellenic University (Greece). At Delft University of Technology the energy of the university is monitored since 2005, at Lancaster University a first indication is given for the energy waste due to inactive users, and at International Hellenic University, the energy of a (smart) university building is monitored.

4.5.1 Delft University of Technology (TUDelft)

Delft University of Technology has created an energy monitor (see http://www.energymonitor.tudelft.nl) that displays the energy consumption of the university from 2005 onwards, as reproduced in Table 4-3:

Table 4-3: Energy consumption of TUDelft in the period 2005-2011

	Natural gas		Electricity		Thermal power		Total prime energy	CO2 emission
	m3	MWh prime	MWh	MWh prime	MWh	MWh prime	MWh prime	ton
2011	1.569.561	13.799	56.191	142.717	41.493	48.580	205.096	45.690
2010	2.033.671	17.879	57.919	145.573	54.606	66.617	230.070	50.792
2009	1.858.992	16.344	57.982	143.772	45.443	55.604	215.719	47.751
2008	1.993.171	17.523	54.954	137.636	42.408	53.531	208.690	46.123
2007	1.832.914	16.114	55.818	134.632	40.874	50.684	201.431	45.277
2006	1.985.862	17.459	53.057	129.193	49.838	57.440	204.092	45.154
2005	2.087.550	18.353	51.807	125.491	51.292	58.542	202.385	44.054

Prime energy, in addition to the energy consumption, also includes the amount of energy used in transporting the energy.

4.5.2 Lancaster University

As part of the CURRENT project (http://current.lancs.ac.uk) of Lancaster University, efforts have been made to determine how users of office networks interact with ICT which now surrounds us in our everyday life. The project uses the University as its test bed to represent a modern office environment. Members of the University faculty are encouraged to participate and sign up to be part of the monitoring process. Once signed up, software is used to monitor for system level calls on their desktop and laptop computers to determine when there are periods of inactivity between the user and computer, and therefore, identify when energy is potentially being wasted. Preliminary results indicate that on average, across all participants so far and considering laptop and desktop computers, it has been found that these cross-sections of computers are turned off (including sleeping states) for approximately 54%, actively used 18% and powered on but left idle 28% of the time.

4.5.3 International Hellenic University (IHU)

A web based and desktop application for energy analytics, monitoring and energy management of ICT infrastructure and smart appliances in a university building is presented in the Smart IHU (Smart International Hellenic University) project (http://rad.ihu.edu.gr). To achieve this target, smart meters/actuators and sensor nodes that operate over heterogeneous communication platforms (RF 434MHz, Zigbee, Wi-Fi, ZWave) are deployed. Each node is responsible to capture critical parameters such as energy consumption, light, luminance, CO_2 levels and transmit information to the central agent. In order to capture ICT related info such as CPU and router traffic, Simple Network Management Protocol (SNMP) requests run in the data center and the PC lab of the university. Finally, to quantify the energy efficiency important metrics as indicated by the Green Grid Association are reported.

One of the research goals of the Smart IHU project is also to develop middleware, based on web services, for the integration of the Wi-Fi, Zigbee, RF 433MHz and ZWave standards that are used. The project incorporates the following research directions:

1. Deployment of Wireless Sensor/Actuator Networks (WSN) for remote monitoring and Management. Wireless platforms of ZigBee, Wi-Fi and ZWave are mainly considered.
2. Integration of the wireless platforms using Semantic Web Services.
3. Application of the WSNs for Energy Analytics, Energy Efficiency and Management, Optimization and Automation.
4. On line data presentation for e-Learning.
5. Green Data center- Monitoring the energy efficiency of the data center of the International Hellenic University.

6. Smart Grid- Support of Smart Building/Smart Grid technologies and algorithms for demand response.
7. Development of sophisticated algorithms. Decision Support Systems (DSS), Ontologies, AI Planning

CERTH is developing its own hardware and software platform and will report the activities in a future deliverable of EINS JRA8.

4.6 *Residential Market*

This section presents three different datasets for the energy consumption of residential houses: REDD (Reference Energy Disaggregation Data), UMASS, and Irish CER (Commission for Energy Regulation) dataset. Following data is available:

- REDD: data of six residential houses over a period of two months
- UMASS: data of three real homes and electricity usage of 400 houses
- Irish CER: data of 5,000 Irish houses over two years

4.6.1 REDD dataset

The REDD dataset (Reference Energy Disaggregation Data, http://redd.csail.mit.edu/) consists of two main types of home electricity data:

- high-frequency current/voltage waveform data of the two power mains (as well as the voltage signal for a single phase) every 1 second, and
- lower-frequency power data including the mains and individual, labeled circuits in the house.

The data reflects to 6 residential houses for a period close to 2 months, but continuous for an upper period of 2 weeks. On the REDD dataset, we found that 10 appliances account for 90% of the total power consumed over 2 weeks.

Top Appliance usage over 2 weeks	
Refrigerator	18.42%
Lighting-1	14.42%
Kitchen_outlets	10.26%
Washer_dryer	9.29%
Microwave	8.28%
Dishwaser	7.96%
Kitchen_outlets-2	7.08%
Lighting -2	6.65%
Oven-1	4.88%
Lighting-3	4.60%
12 bathroom_gfi	2.38%
4 oven	1.82%
15 kitchen_outlets	1.66%
10 washer_dryer --	1.29%
16 kitchen_outlets	0.92%
13 electric_heat	0.05%
14 stove	0.04%
19 washer_dryer	0.01%

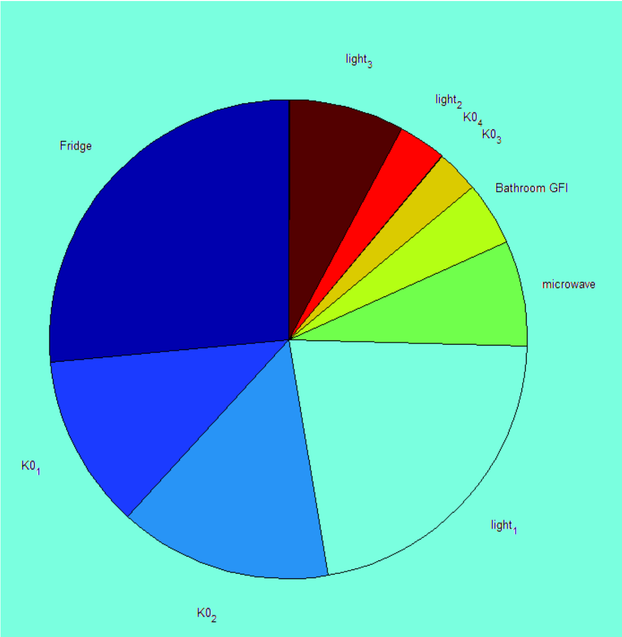


Figure 4-9: Mean energy consumption composition

4.6.2 UMASS dataset

The UMASS dataset (http://traces.cs.umass.edu/index.php/Smart/Smart) consists of a wide variety of data in three real homes, including electrical (usage and generation), environmental (e.g., temperature and humidity), and operational (e.g., wall switch events). They have also gathered electricity usage data every minute from 400+ anonymous homes. The composition of the data set per house is described below:

- **Home A**
    - Electrical data from circuits

    - Electrical data from individual energy meters
    - Electrical data from dimmable and non-dimmable switches
    - Voltage and frequency data on both electrical phases
    - Environmental data (indoor and outdoor)
    - Furnace on/off data
    - Door open/close data
    - Motion detector data
- **Home B**
    - Aggregate electrical data
    - Environmental data
- **Home C**
    - Aggregate electrical data
    - Environmental data
    - Generation data (solar, wind, and battery voltage)
- **Microgrid dataset**
    - Electrical data over a single 24-hour period from 443 unique homes

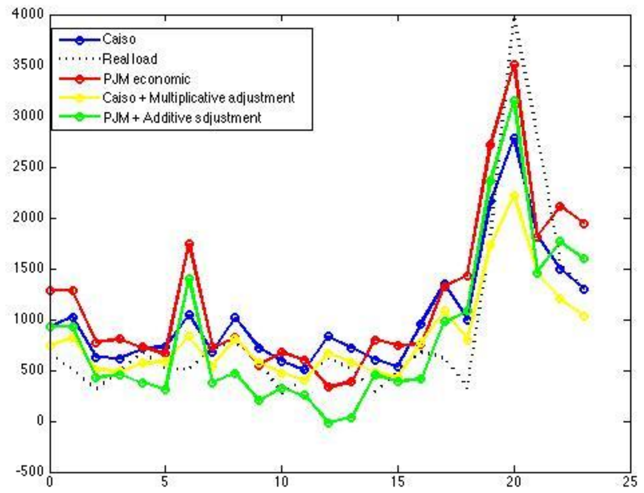


Figure 4-10: Baseline calculation for house B of UMASS dataset using various methods against real data.

4.6.3 Irish Commission for Energy Regulation (CER) dataset

The CER initiated the Smart Metering Project in 2007 with the purpose of undertaking trials to assess the performance of Smart Meters, their impact on consumers' energy consumption and the economic case for a wider national rollout. The Smart Metering Electricity Customer Behaviour Trials (CBTs) took place during 2009 and 2010 with over 5,000 Irish homes and businesses participating. The purpose of the trials was to assess the impact on consumer's electricity consumption in order to inform the cost-benefit analysis for a national rollout.

Electric Ireland residential and business customers, and Bord Gáis Energy business customers, who participated in the trials had an electricity smart meter installed in their homes/premises and agreed to take part in research to help establish how smart metering can help shape energy usage behaviour across a variety of demographics, lifestyles and home sizes. The data is publicly available from http://www.ucd.ie/issda/data/commissionforenergyregulation/, provided that a certain data request form is signed by the interested parties.

5 Energy Efficiency Options

A few promising directions to lower the environmental impact of ICT, for instance through novel network architectures and routing paradigms, were already discussed in EINS deliverable D13.1 "Survey on Internet Science Research". In this section, special attention is given to energy efficiency options for communication networks and wireless sensor networks, and a few network monitoring tools are presented that can be used for energy efficiency.

5.1 *Energy Efficiency in Communication Networks*

In the past, the communications industry has mainly focused on maximizing network throughput and minimizing latency, often neglecting power consumption in its network design. In recent years however, energy efficient networking has received more attention due to a number of reasons. Increasing energy prices have made electricity bills a significant cost factor for large telecom operators. Additionally, global warming is making the need to evolve towards a more sustainable society evident. To that end, political initiatives are beginning to put requirements on manufacturers and operators to lower the carbon footprint of communication networks (e.g. the Broadband Equipment Code of Conduct by the European Commission [33]).

Various international research projects have set green goals for 2020 [34]. For example, GreenTouch (http://www.greentouch.org, partners include China Mobile, Samsung) aims to reduce energy per bit by a factor of 1000 from current levels for both wired and wireless communication networks. In order to integrate the activities of different European networking actors, including manufacturers, operators and research centers, the FP7-TREND Network of Excellence (http://www.fp7-trend.eu/) was established, to design energy-efficient, scalable and sustainable future networks. Other important FP7 projects in the domain of energy efficient communication networks are: FP7-ECONET (http://www.econet-project.eu), exploiting dynamic adaptive technologies for wired network devices that allow saving energy when a device is not used), and FP7-EARTH (https://www.ict-earth.eu), investigating the energy efficiency of mobile communication systems).

A number of strategies have been proposed to improve the energy efficiency of communication networks, as also detailed in following research papers [35, 36]. In the next subsections, we focus on two promising options: the use of sleep modes and network virtualization.

5.1.1 Sleep mode operations

When considering sleep modes, the main research question focuses on the functionality of each component in the system and the requirement of this component to be active at a certain point in time. In order to get an estimate of the potential savings by sleep mode introduction in a communication network, the layout of the network needs to be analyzed as well as the consequences of temporarily switching off components. Also other parameters like wake-up times and flexibility require consideration.

Sleep mode operation is especially promising in the access network. Due to fewer users sharing the same equipment compared to core networks, there is high underutilization of electronic processing. This allows exploitation of dynamic power management and sleep modes, in both wired and wireless networks. Completely switching off network elements as well as switching off only specific components can be considered.

In wired access networks, the Customer Premises Equipment (CPE) is one of the biggest power consumers. Sleep modes in CPEs can lead to significant energy savings, considering most CPEs do not transmit or receive traffic for long times (e.g. a CPE that is switched on 24/24 and 7/7, while it is only used 1 to 3 hours per day, can be powered down 90% of the time). Additionally, both for the CPE as well as other access network elements, power shedding of functional blocks (e.g. specific user network interfaces) that are not in use for shorter time frames is possible. Different research papers are discussing these sleep mode aspects in detail, see [37, 38]. Recent standards [39] have defined sleep cycles on XG-PON (10 Gbit/s capable Passive Optical Network) over a time scale of tens of milliseconds. Another example is the Energy Efficient Ethernet standard that reduces the power consumption of the Ethernet interfaces [40], and similar techniques can be applied to other interfaces.

In wireless access networks, it is commonly accepted that reducing the power consumption of the BS is key as the overall energy efficiency of a BS is low [41, 42]. An additional degree of freedom exists for minimizing power consumption by transferring traffic from a BS powered down to another BS which may overlap in coverage. Hence, several opportunities for sleep mode operation, especially at the BS, can be analyzed. Examples are switching off of entire cell sites, discontinuous operation of power amplifiers (PAs) and carrier aggregation on multiple PAs allowing power shedding of the PAs. As illustrated in the examples above, for sleep mode operation, a lot of research is already ongoing and several solutions are being proposed and investigated, like e.g. [43, 44, 45]. When considering these solutions, possible rebound effects (putting one element in sleep can lead to a power increase of another element) and end-user performance need to be taken into account.

Sleep modes can also be applied in the core network. Traffic aggregation can be applied to maximize energy savings [46, 47]. By forcing traffic in periods of low load to follow specific routes, few routes with high loads will contain all traffic, while most other routes will be idle. Network elements of these idle routes can be temporarily switched off. When putting routes to sleep, the impact on algorithms used in the MAC layer and network layer needs to be taken into account. Additionally, the internet topology needs to be modified so that it allows route adaptation and hardware needs to be designed to allow software-enabled sleep. Traffic aggregation may also lead to energy savings when the energy consumption of network equipment also depends on the amount of traffic being processed, as for instance demonstrated in [48].

5.1.2 Network virtualization

Network virtualization has been discussed as a solution to the perceived ossification of the current Internet [49, 50]. Several variants of network virtualization have been investigated [51] and it is already widely used in current Future Internet testbeds [52, 53, 54]. Rising energy costs lead to an increased focus on energy-efficiency of ICT equipment. Network virtualization can be used to tackle this problem through consolidation of virtualized network resources. To achieve this goal it is, however, necessary to decide how the virtual network resources should be mapped onto physical hardware. This is complicated by the fact that virtual resources will have performance requirements (e.g. a virtual link can demand a certain bandwidth), whereas physical resources are performance-limited (e.g. a physical link can only provide a certain bandwidth). Finding an optimal mapping of virtual resources onto physical resources under a number of constraints is known as the Virtual Network Embedding (VNE) problem. Regarding energy and power consumption as key goals, an energy-efficient VNE algorithm has to first minimize the amount of physical hardware that is in active use and second distribute the virtual resource such that energy-efficient equipment is prioritized.

5.2 *Energy Efficiency in Sensor Networks*

The usefulness of wireless sensor networks (WSNs) is too a large degree depending on its live time with a given amount of energy in form of batteries, because in many cases it would be very cumbersome and expensive to exchange batteries. In order to prolong this live time, sensor networks have from the beginning to be designed energy efficient, which means to trade live time against timeliness, accuracy, and quality of collected data. The following sub-sections give a brief overview on the main strategies to address this tradeoff and how to model energy consumption in WSNs.

5.2.1 Sustainable Sensor Data Collection

Efficient sensor data collection has been extensively studied. Sensor networks are usually intended to last for long periods of time, such as months or even years. In sensor networks, due to the limited energy available on a sensor board, if a sensor remains active continuously, its energy will be depleted quickly leading to its death. To prolong the network lifetime, sensors alternate between being active and sleeping. There are several sensor selection algorithms to achieve this while still achieving the goal of deployment. The decision as to which sensor should be activated takes into account a variety of factors depending on the algorithm such as desired accuracy, required coverage, or the type of information required. Sensors are selected to do one or multiple missions. These missions can be general and related to the function of the network, such as monitoring the whole field by ensuring complete coverage. At a given time, the system might be required to do multiple missions, i.e. monitoring multiple events. So, in sustainable sensor data collection there are two conflicting goals: (1) to collect information of high accuracy and (2) to lower the cost of operation. This trade-off is usually modeled using the notions of utility and cost.

The schemes based on the purpose of selection can be classified into the following classes [55]:

1. Coverage schemes: include selection schemes that are used to ensure sensing coverage of the location or targets of interest. If the static sensor nodes are densely deployed, such that there there is redundancy in coverage, then only a subset of sensors need to be active in order to achieve full coverage while the rest can enter sleep mode. This conserves energy and hence prolongs the network lifetime. Selection schemes are used to decide which sensors are to be turned on and for how long. Perillo and Heinzelman [56] divide the sensor nodes into sets, such that each set is capable of providing complete coverage of the field and only one set is active at a time. In their paper, Cardei and Du [57] divide the sensors in the field into a maximum number of disjoint sets, such that every set completely covers all the targets and only one set is active at a time in a round-robin order. In Shih et al., [58], full coverage with minimal sensors is obtained by identifying the redundant sensors and turning them off. Identification of redundant sensors is done using Voronoi diagrams. Lu et al. [59] take a different approach in which they aim to provide k-coverage, which means that every point in the field is covered by at least k sensors. The paper by Yan et al. [60] provides a “self-scheduling” scheme, in which time of operation is the only parameter in the selection process. The sensors are time-synchronized, and each sensor generates a random

reference time which is exchanged with its neighbors. Each sensor then establishes its sleep-awake cycle by observing the reference time of its neighbors.

2. Single mission assignment schemes: include schemes that select sensors for a single specific mission. In a sensor network which must perform a specific mission repeatedly over time, sensors need to be selected such that the mission is accomplished in the most efficient manner. The objective of such selection schemes is to select the sensor nodes that are most useful for the mission. This notion of "usefulness" is quantified using a "utility" value. Byers and Nasser [61] developed a model for such applications in which the global objectives are defined based on utility functions and a cost model for energy consumption due to sensing and data delivery. In their algorithm, a set of sensors has a total utility function that depends on the number of individual sensors and their placement. The authors use an objective function that maximizes the utility of a sensor network over its lifetime subject to the energy consumption. In a recent work by Bian et al. [62], a generic framework in which the application can specify the utility values of the sensors is presented. The goal here is to select a sequence of sensors sets such that the total utility is maximized, while not exceeding the available energy. Alternatively, the framework can be used to look for the most cost-effective sensor set, maximizing the product of utility and sensor lifetime.

3. Multiple mission assignment schemes: include schemes that select sensors so that multiple specific missions are collectively accomplished. These multiple missions may belong to one big operation, or may belong to multiple operations that the sensor network is responsible for. Ai and Abouzeid [63] provide a greedy heuristic to cover the maximum number of targets with the minimum number of active sensors. The sensors here are directional and covering each target can be viewed as a different mission. Mullen et al. [64] model the system as a market and explore the advantages of incorporating e-commerce concepts to sensor management. The two main components in this model are the mission manager and sensor manager, which are implemented using genetic algorithms (GA). The mission manager allocates budget to the application (consumer), based on the different missions involved in the application and their requirements. Using these budget values, the consumer places bids to the sensor manager. Based on these bids, the sensor manager allocates sensors to the missions. Ostwald et al. [65] use multi-modal sensors and assume that multiple missions may arrive simultaneously. The possible sensor configurations, i.e. which sensor operates in which mode, and the mission utility value for each mission are translated into a bid. The winner is determined using a modified combinatorial auction algorithm. Bisdikian [66] looked at sensor sampling models and their effects on the quality of information. If video sensors were considered, a video sensor that is the closest to an event might not be the best candidate for selection because its view of the event might be obscured by smoke. Also, although it is embedded in some of the information-gain schemes, the issue of conditional utilities needs to be studied in more detail. By conditional utilities, it is meant how the selection of one sensor would affect the utility of another sensor.

A utility-based sensor selection framework is proposed in [62] in which the applications can specify the utility of each set of sensors in a WSN. Submodular and supermodular utility function classes are considered. The goal is to select a sequence of sets to maximize the total utility while not exceeding the available energy. In [67], the problem of sensor selection, where a set of sensors is selected according to the maximum a posteriori or the maximum likelihood rules, is formulated as optimizations of submodular functions over uniform matroids. A heuristic approach based on convex optimization is proposed in [68] for the sensor selection problem with the objective of minimizing the estimation error. In our scenario, the network model is different and the objective is to maximize the net benefit. As we allow multiple applications, which potentially have different valuation functions, we cannot identify up front in which function category our utility function falls.

Simultaneous placement and scheduling of sensors is considered in [69], where an algorithm is proposed to efficiently and simultaneously decide where to place sensors and when to activate them using the submodularity of the utility function. Two distributed sensor scheduling approaches are proposed in [70, 71]. These works are based on the assumption that the utility function is submodular.

5.2.2 Leverage sampling rates

In sensor network, there is a trade-off between energy consumption and quality of information (QoI) from the sensors. Therefore, it is critically important to select for every sensing task a set of sensors that minimizes the cost, yet satisfies the user specified QoI in a timely and efficient manner. The QoI is a function of not just a chosen sensor but also the number of collected samples. The impact of sampling rate has been studied in term of timeliness, accuracy, confidence and precision on transient event detection, context detection and activity recognition. For example, in Bisdikian [66] the author has analyzed the impact of sampling rates on the quality attributes as timeliness and confidence to transient event detection. Continuing Bisdikian's work, Zadehi et al. [72] suggested the use of specialized QoI model to capture the accuracy of detecting transient events with inputs as sampling rates. Unlike the previous approaches, which individually capture the accuracy of event detection, Roy et al. [73] focus on the optimal selection of sensors and their tolerance ranges or precisions of data value for context detection. The precision values determine with the specific accuracy of context detection how frequently samples will be sent to the sink. In recent study, based on empirical knowledge that QoI of activity recognition can be formulated as a function of sampling rates, Viet et al. [74] propose a model to control the accuracy by adapting the number of samples collected from sensors. Given the need to collect information from sensors with the specific user required accuracy, they propose to reduce the energy use at sensors by reducing the numbers of samples collected at each sensor, or sending a reduced number of samples to the sink.

5.2.3 Energy consumption modeling

Energy efficient operation is critical in WSNs. Accurate prediction of sensor network lifetime requires an accurate energy consumption model. Andrew et al. [75] proposed the modeling of short-range transceivers that takes into account energy dissipation during start-up, receive, and transmit mode of a micro sensor. Using this model they conclude that the battery life can be improved significantly by increasing data rate or reducing star-up time. In other research, Ammer et al. [9] propose the Energy per Useful Bit (EPUB) metric for evaluating and comparing sensor network physical layers (see section 2.1.6). EPUB includes the energy consumption of both the transmitter and receiver, and amortized the energy consumption during the synchronization preamble over the number of data bits in the packet. Unlike the previous approaches, which consider the model of only a single node, Qin Wang et al. [76] propose power consumption models for a WSN device, and for a multi-hop network, which include the radio parameters and efficiency of power amplifier. One of recent issues is how to build the model of energy consumption for a mobile phone. The challenges include the complexity of modern mobile phones, many context sensitive applications continuously running in the background and applications operating in varying conditions. Since every device and application has its own profile for energy consumption, it is a demand to build profiles for the device and application. Several works have built profiles for mobile phone devices as in [77, 78]. Notably, Zhang et al. [79] propose an automated online power model construction technique that uses built-in battery voltage sensors and knowledge of battery discharge behavior to monitor power consumption while controlling the power management and activity states of each component such as CPU, LCD, as well as GPS, Wi-Fi, audio, cellular interfaces.

5.3 *Use of network monitoring information for energy-efficiency*

Many authors have shown that there is a significant percentage of hosts which are left switched on in office buildings at night and weekend, whose energy consumption is significant (as also indicated in section 4.4). For example, the authors in [80] estimated the energy savings of shutting computers down during night-time and weekends at 17 TWh/year and 7 TWh/year, respectively. This motivates the development of techniques that can detect switched-on hosts in a simple and scalable way.

In this light, we have provided traffic analysis techniques that enable the detection of switched-on machines in a network by monitoring hosts' network activity [81]. Note that it is expected that almost every host connected to the Internet generates traffic because of automatic software updates (e.g., operating systems and antiviruses), background email, and voice-over-IP (VoIP) clients, among other reasons. Once a set of switched-on machines are identified, the network managers could suggest users to switch off their computers at night.

Three challenges have been addressed in this approach. First, we note that firewalls are present in almost all medium-large size networks. We have found that firewalls may respond to externally originated connections on behalf of an internal host (using the host's IP address), even when such host is switched off. We note that unwanted externally originated connections due to malicious traffic (attacks and port scans) are very common in the current Internet. In addition, we have found that local software firewalls running on end-hosts may block active probes. Second, flow-level measurements often suffer from packet sampling, which reduces their precision. Finally, it is possible that a host generates no traffic even though it is switched on.

The proposal is to automatically detect switched-on hosts analyzing activity through network monitoring using both packet-level and flow-level traffic monitors. To evaluate the accuracy of the proposed techniques, we use measurements from two different scenarios: the Spanish Academic Network (RedIRIS, http://www.rediris.es) and a selected campus within RedIRIS, the Public University of Navarra (UPNA) campus. The traffic collection in RedIRIS is at the flow record level (Netflow) whereas packet level analysis is performed in the UPNA campus network. Figure 5-1 shows the experimental setup.

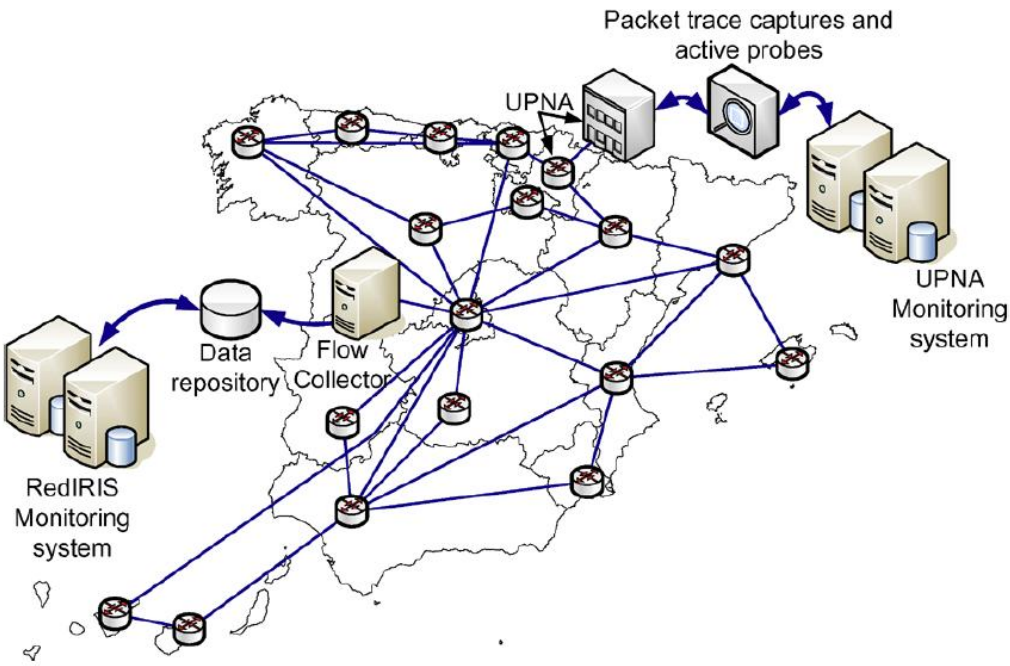


Figure 5-1: Experimental setup for network monitoring.

Figure 5-2 shows the Receiver Operating Characteristic (ROC) of the different approaches to detect switched-on computers. On the one hand, active probing techniques such as ARPing have a great accuracy but are intrusive in the network. Sampled Netflow approaches are the simplest in terms of implementation complexity, but have a poor performance in terms of true positives. Packet-level approaches are almost as good as active probing techniques but require the collection of all packets traversing the link. Finally, the use of non-sampled Netflow appears as a promising solution in terms of complexity and accuracy. More details can be found in [80].

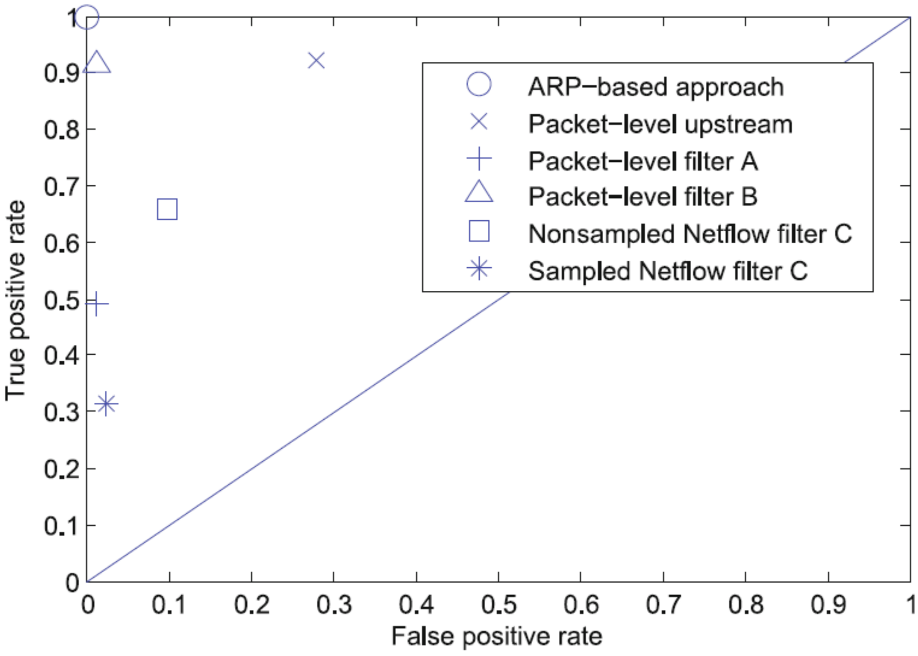


Figure 5-2: ROC of the different approaches to detect switched-on PCs

6 Conclusions

This EINS deliverable D8.1 gives an overview of task R8.1 “Assessment and reduction strategies for ICT energy consumption” and it provides a basis for the other tasks in JRA8. Task R8.1 aims to give an overview on the carbon footprint of the Internet and to contribute to establishing comprehensive frameworks and methodologies for measuring and reporting the energy consumption of ICT.

An important contribution of the deliverable is a global ICT footprint study, conducted for 2007 and 2012. We determined the use phase electricity consumption for a number of ICT services: communication networks, data centers and personal computers. The collective electricity consumption of communication networks, data centers and personal computers is growing at a rate of 6.6% per year. Together these ICT products and services consumed about 670 TWh in 2007, and about 930 TWh in 2012. The relative share of these ICT products and services in the total worldwide electricity consumption has increased from about 4% in 2007 to 4.7% in 2012. This even does not yet include the electricity consumption of other devices that are often considered as part of the ICT footprint, such as TVs and their set-top boxes, (smart) phones, audio devices etc. The above figures indicate that it is important to optimize the energy consumption of ICT in the coming years to create a sustainable ICT environment.

Next to the global footprint study, some specific use cases are elaborated in a next section, dealing with telecom networks, personal computers, data centers, offices, universities and residential users. This section indicates the most power consuming parts of the handled use cases, and clearly shows that there is room for optimization. The energy consumption of a small anonymized telecom operator is considered and the different equipment types contributing to its total energy consumption are listed, giving a good indication of the most consuming parts of the network. For this specific operator, a yearly consumption of 2.06 GWh is calculated. For PCs, the most recent evolution of CPUs, hard disks and network interface cards are presented, indicating the increasing effort for producing less energy consuming equipment (although some of the equipment is nowadays not yet commonly used due to its high prices). Regarding sustainable ICT, one of the most critical parts to observe is data centers, as they are responsible for great energy inefficiencies and energy waste. However, we see an increasing effort to make data centers much more energy efficient. One specific data center platform is monitored and its performance is quantized, which is important in order to investigate and propose directions to optimize its energy consumption. This can be achieved by using some standard metrics to measure the inefficiencies, and we used the following metrics: power usage effectiveness (PUE), telco efficiency (Mbits/kWhr) and server efficiency (Ops/kWhr). More conclusions will be generated in the next JRA8 activities.

For office networks, special attention is given to the energy wastage because of unattended and idle computers, consuming a large portion of power without fulfilling any useful purpose. It has been determined that office computers are on average left unattended and switched on 28% of the time, corresponding to a total wasted energy of 110 kW per computer on average. In a next phase, it is the aim to determine how much energy is wasted for other devices which often surround us within modern office environments. A university is a specific example of an office environment, and the power consumption of three universities is considered: Delft University of Technology (the Netherlands), Lancaster University (UK) and International Hellenic University (Greece). At TUDelft, the energy of the university is monitored since 2005, at Lancaster University a first indication is given for the energy wastage due to inactive users and at International Hellenic University, the energy of a (smart) university building is monitored. Finally, the energy consumption of residential users is considered and three relevant data sets are referred to: REDD (Reference Energy Disaggregation Data, with data of six residential houses), UMASS (with detailed data of three houses and electricity usage of 400 houses), and Irish CER (Commission for Energy Regulation, with data of 5,000 houses). A lot of the available data will be used as benchmarking data in the other JRA8 tasks. An important collaborative work that is planned in the framework of JRA8 deals with real-time monitoring of residential power consumption and using social networks for creating a changing customer behavior. Having real data sets at hand is an important tool for the further evaluation.

While the specific use cases proved that there is room for optimization, the last section of this deliverable discusses a few promising directions to lower the environmental impact of ICT, for instance through novel network architectures and routing paradigms. Special attention is given to communication networks, wireless sensor networks and network monitoring tools for energy efficiency. For communication networks, two promising options are the usage of sleep modes and the introduction of network virtualization. Also the results from various initiatives worldwide are scanned and summarized (e.g. GreenTouch initiative and running FP7 instruments). In sensor networks, sensors alternate between being active and sleeping and there are several sensor selection algorithms to achieve this while still achieving the goal of deployment. In sustainable sensor data collection there are two conflicting goals: (1) to collect information of high accuracy and (2) to lower the cost of operation. This trade-off is usually modeled using the notions of utility and cost. Monitoring tools are very important as a significant percentage of hosts are left switched on in office buildings at night and weekend, whose energy consumption is significant. Therefore, it is important to automatically detect switched-on hosts by analyzing activity through network monitoring.

Based on the initial findings in D8.1 and the specific interests of the different JRA8 partners, we are defining several topics to collaborate from Y2 onwards. Current topics of interest are dealing with residential users (including real-time power monitoring and studying the related user behavior, e.g. by using social networks), office networks & data centers (and the usage of smart grids to tune the energy consumption to the energy production, especially by reducing peak loads), telecom networks (and specific energy consumption models and energy efficiency strategies), etc. While D8.1 is explicitly presenting an overview of ICT energy consumption, the upcoming JRA8 studies should also be extended in scope towards sustainability in a broader context than that of energy consumption.

7 References

1. P. Fernando and A. Okuda, “Green ICT : A Cool Factor in the Wake of Multiple Meltdowns,” ESCAP Technical Paper, 2009.
2. S. Ruth, “Reducing ICT-related Carbon Emissions: An Exemplar for Global Energy Policy,” IETE Technical Review, vol. 28, no. 3, pp. 207–212, 2011.
3. F. Mattern, T. Staake, and M. Weiss, “ICT for green: how computers can help us to conserve energy,” in Proceedings of the 1st International Conference on Energy-Efficient Computing and Networking, ser. e-Energy ’10. New York, NY, USA: ACM, 2010, pp. 1–10.
4. W. Vereecken, W. Van Heddeghem, D. Colle, M. Pickavet, and P. Demeester, “Overall ICT footprint and green communication technologies,” in Communications, Control and Signal Processing (ISCCSP), 2010 4th International Symposium on, March 2010, pp. 1 –6.
5. J. Kim and H.-I. Park, “A National Vision,” IEEE power and energy magazine, pp. 40–50, February 2011.
6. G. Koutitas and P. Demestichas, “A Review of Energy Efficiency in Telecommunication Networks,” Telfor Journal, vol. 2, no. 1, pp. 2–7, 2010.
7. M. Pickavet, W. Vereecken, S. Demeyer, P. Audenaert, B. Vermeulen, C. Develder, D. Colle, B. Dhoedt, and P. Demeester, “Worldwide energy needs for ICT: the rise of power-aware networking,” 2nd International Symposium on Advanced Networks and Telecommunication Systems, ANTS 2008, December 2008, pp. 1–3.
8. M. Parker and S. Walker, “Roadmapping ICT: An Absolute Energy Efficiency Metric,” Journal of Optical Communications and Networking, vol. 3, no. 8, pp. A49–A58, 2011.
9. J. Ammer and J. Rabacy, “The Energy-per-Useful-Bit Metric for Evaluating and Optimizing Sensor Network Physical Layers,” in 2006 3rd Annual IEEE Communications Society on Sensor and Ad Hoc Communications and Networks, 2006. SECON ’06, 2006, vol. 2, pp. 695 –700.
10. J. Malmodin, A. Moberg, D. Lundén, G. Finnveden, and N. Lövehagen, “Greenhouse Gas Emissions and Operational Electricity Use in the ICT and Entertainment & Media Sectors,” J. Ind. Ecol. **14**, 770 –790 (2010).
11. S. Lanzisera, B. Nordman, and R. Brown, “Data network equipment energy use and savings potential in buildings,” Energy Efficiency **5**, 149 –162 (2012).
12. D. Kilper, G. Atkinson, S. Korotky, S. Goyal, P. Vetter, D. Suvakovic, and O. Blume, “Power trends in communication networks,” IEEE J. Sel. Topics Quantum Electron. **17**, 275 –284 (2011).
13. J. Baliga, R. Ayre, K. Hinton, and R. Tucker, “Energy consumption in wired and wireless access networks,” IEEE Commun. Mag. **49**, 70 –77 (2011).
14. “World population prospects: the 2010 revision,” UN Population Division (2011). http://data.un.org/Data.aspx?q=population&d=PopDiv&f=variableID%3a12
15. “Global ICT developments, 2001-2011,” ITU World Telecommunication / ICT Indicators database (2011). http://www.itu.int/ITU-D/ict/statistics
16. W. Van Heddeghem, F. Idzikowski, W. Vereecken, D. Colle, M. Pickavet, and P. Demeester, “Power consumption modeling in optical multilayer networks,” Photonic Netw Commun **24**, 86–102 (2012).

17. “World broadband statistics: Q4 2007,” Point-Topic (2008).
18. “World broadband statistics: Q4 2011,” Point-Topic (2012).
19. “The little data book on information and communication technology,” The World Bank / ITU (2007-2012).
20. B. Urban, V. Tiefenbeck, and K. Roth, “Energy consumption of consumer electronics in U.S. homes in 2010.” Fraunhofer Center for Sustainable Energy Systems (2011).
21. C. Cremer, W. Eichhammer, M. Friedewald, P. Georgieff, S. Rieth-Hoerst, B. Schlomann, P. Zoche, B. Aebischer, and A. Huser, “Energy consumption of information and communication technology (ICT) in Germany up to2010: summary of the final report to the German federal ministry of economics and labour,” (2003).
22. “Millennium development goals indicators,” UN Statistics Division (2010). http://mdgs.un.org/unsd/mdg/Data.aspx
23. “Definitions of world telecommunication/ICT indicators,” ITU (2010). http://www.itu.int/ITU-D/ict/material/TelecomICT_Indicators_Definition_March2010_for_web.pdf
24. Asymco, “A brief history of personal computer vendors,” http://www.asymco.com/hire-me/historic-computer-shipments/ (2011).
25. M. Murphy and M. Meeker, “KPCB top mobile internet trends,” http://www.slideshare.net/kleinerperkins/kpcb-top-10-mobile-trends-feb-2011 (2011).
26. F.-K. Wang and K.-K. Chang, “Modified diffusion model with multiple products using a hybrid GA approach,” Expert Systems with Applications **36**, 12613 – 12620 (2009).
27. “Carbon and computers in Australia - the energy consumption and carbon footprint of ICT usage in Australia in 2010,” ACS (2010).
28. A. Andrae and O. Andersen, “Life cycle assessments of consumer electronics - are they consistent?” The International Journal of Life Cycle Assessment **15**, 827–836 (2010).
29. J. Koomey, “Growth in data center electricity use 2005 to 2010,” http://www.analyticspress.com/datacenters.html (2011).
30. spec.org, “SPECpower ssj2008 benchmark,” http://www.spec.org/benchmarks.html Data used up to June 28, 2012.
31. “Gartner says worldwide server revenue grew 7.9 percent and shipments increased 7 percent in 2011,” (2011). Press release available at: http://www.gartner.com/it/page.jsp?id=1935717
32. F.A. Kuipers, “An Overview of Algorithms for Network Survivability,” ISRN Communications and Networking, vol. 2012, Article ID 932456, 19 pages, 2012.
33. “Code of Conduct on Energy Consumption of Broadband Equipment (Version 3),” European Commission - Institute for the Energy - Renewable Energy Unit (2008).
34. Y. Chen, S. Zhang, S. Xu and G. Y. Li, “Fundamental trade-offs on green wireless networks,” Communications Magazine, IEEE, vol. 49, no. 6, p. 30–37 (Jun. 2011).
35. W. Vereecken, W. Van Heddeghem, M. Deruyck, B. Puype, B. Lannoo, W. Joseph, D. Colle, L. Martens, and P. Demeester, “Power consumption in telecommunication networks: overview and reduction strategies”, Communications Magazine, IEEE, 49(6):62 –69 (June 2011).

36. R. Bolla, R. Bruschi, F. Davoli, and F. Cucchietti, Energy Efficiency in the Future Internet: A Survey of Existing Approaches and Trends in Energy-Aware Fixed Network Infrastructures. Communications Surveys Tutorials, IEEE, vol. 13, no. 2, p. 223–244 (2011)
37. P. Vetter, L. Lefevre, L. Gasca, K. Kanonakis, L. Kazovsky, B. Lannoo, A. Lee, C. Monney, X. Qiu, F. Saliou, and A. Wonfor, “Research Roadmap for Green Wireline Access”, Workshop on Green Communications and Networking, IEEE ICC’12 (2012).
38. R. Bolla, F. Davoli, R. Bruschi, K. Christensen, F. Cucchietti, and S. Singh, “The potential impact of green technologies in next-generation wireline networks: Is there room for energy saving optimization?”, Communications Magazine, IEEE, vol. 49, no. 8, p. 80–86 (Aug. 2011).
39. ITU-T G.987 10-Gigabit-capable passive optical network XG-PON.
40. IEEE 802.3az Amendment 5: MAC Parameters, PHY layers, and management parameters.
41. C. Han, T. Harrold, S. Armour, I. Krikidis, S. Videv, P. Grant, H. Haas, J. Thompson, I. Ku, C.-X. Wang, T. A. Le, M. Nakhai, J. Zhang, and L. Hanzo, “Green radio: radio techniques to enable energy-efficient wireless networks,” Communications Magazine, IEEE, vol. 49, no. 6, pp. 46 –54, June 2011.
42. M. Deruyck, E. Tanghe, W. Joseph, and L. Martens, “Modelling and optimization of power consumption in wireless access networks”, Elsevier Comput. Commun, vol. 34, no. 17, pp. 2036–2046 (2011).
43. L. Correia, D. Zeller, O. Blume, D. Ferling, Y. Jading, I. Gódor, G. Auer, and L. Van der Perre, “Challenges and enabling technologies for energy aware mobile radio networks”, IEEE Commun. Mag. Vol. 48, no. 11, pp. 66–72 (2010).
44. E. Oh, B. Krishnamachari, X. Liu, and Z. Niu, “Toward dynamic energy-efficient operation of cellular network infrastructure”, IEEE Commun. Mag, Vol. 49, no. 6, pp. 56–61 (2011).
45. Z. Niu, Y. Wu, J. Gong, and Z Yang, “Cell zooming for cost-efficient Green cellular networks”, IEEE Commun. Mag, Vol. 48, no. 11, pp. 74–79 (2011).
46. M. Gupta and S. Singh, “Greening of the internet,” In Proceedings of the 2003 conference on Applications, technologies, architectures, and protocols for computer communications (SIGCOMM '03), 19–26 (2003).
47. B. Puype, W. Vereecken, D. Colle, M. Pickavet, and P. Demeester, “Multilayer traffic engineering for energy efficiency”, Photonic Network Communications, Vol. 21, No. 2, April 2011, pp. 127-140.
48. S. Yang and F.A. Kuipers, Energy-Aware Path Selection for Scheduled Lightpaths in IP-over-WDM Networks, Proc. of the 18th Annual Symposium on Communications and Vehicular Technology (IEEE SCVT 2011), Ghent, Belgium, November 22-23, 2011.
49. T. Anderson, L. Peterson, S. Shenker, and J. Turner, “Overcoming the internet impasse through virtualization,” Computer, vol. 38, pp. 34–41, April 2005.
[Online]. Available: http://portal.acm.org/citation.cfm?id=1058219.1058273
50. N. Feamster, L. Gao, and J. Rexford, “How to lease the internet in your spare time,” ACM SIGCOMM Computer Communication Review, vol. 37, pp. 61–64, 2007.
51. N. M. K. Chowdhury and R. Boutaba, “A survey of network virtualization,” Computer Networks, vol. 54, no. 5, pp. 862 – 876, 2010.

[Online]. Available: http://www.sciencedirect.com/science/article/B6VRG-4XKBYY4-4/2/91ac30e6e1c4d24c53d95798a6148f03

52. A. Bavier, N. Feamster, M. Huang, L. Peterson, and J. Rexford, "In vini veritas: realistic and controlled network experimentation," SIGCOMM Comput. Commun. Rev., vol. 36, pp. 3–14, August 2006. [Online]. Available: http://doi.acm.org/10.1145/1151659.1159916
53. "GENI - Global Environment for Networking Innovations." [Online]. Available: http://www.geni.net
54. D. Schwerdel, D. Günther, R. Henjes, B. Reuther, and P. Müller, "German-lab experimental facility," in Future Internet - FIS 2010, ser. Lecture Notes in Computer Science, A. Berre, A. Gmez-Prez, K. Tutschku, and D. Fensel, Eds., vol. 6369. Springer Berlin / Heidelberg, 2010, pp. 1–10, [Online]. Available: http://dx.doi.org/10.1007/978-3-642-15877-3_1
55. H. Rowaihy, S. Eswaran, M. Johnson, D. Verma, A. Bar-noy, T. Brown, "A survey of sensor selection schemes in wireless sensor networks", In SPIE Defense and Security Symposium Conference on Unattended Ground, Sea, and Air Sensor Technologies and Applications IX, 2007.
56. M. Perillo and W. Heinzelman, "Optimal sensor management under energy and reliability constraints," in Proceedings of the IEEE Conference on Wireless Communications and Networking, March 2003.
57. M. Cardei and D.-Z. Du, "Improving Wireless Sensor Network Lifetime through Power Aware Organization", ACM Wireless Networks, Vol. 11, No. 3, pp. 333-340, May 2005.
58. K. Shih, Y. Chen, C. Chiang, and B. Liu, "A distributed active sensor selection scheme for wireless sensor networks," in Proceedings of the IEEE Symposium on Computers and Communications, June 2006.
59. J. Lu, L. Bao, and T. Suda, "Coverage-aware sensor engagement in dense sensor networks," in Proceedings of the International Conference on Embedded and Ubiquitous Computing - EUC 2005, Dec. 2005.
60. T. Yan, T. He, and J. Stankovic, "Differentiated surveillance for sensor networks," in Proceedings of 1st International Conference on Embedded networked sensor systems, 2003.
61. J. Byers and G. Nasser, "Utility-based decision-making in wireless sensor networks," in Proceedings of the IEEE Workshop on Mobile and Ad Hoc Networking and Computing, 2000.
62. F. Bian, D. Kempe, and R. Govindan, "Utility-based sensor selection," in Proceedings of the IEEE Conference on Information Processing in Sensor Network (IPSN 2006), April 2006.
63. J. Ai and A. Abouzeid, "Coverage by directional sensors in randomly deployed wireless sensor networks," Journal of Combinatorial Optimization , Feb. 2006.
64. T. Mullen, V. Avasarala, and D. L. Hall, "Customer-driven sensor management," IEEE Intelligent Systems 21, pp. 41–49, March/April 2006.
65. J. Ostwald, V. Lesser, and S. Abdallah, "Combinatorial auctions for resource allocation in a distributed sensor network," in Proceedings of the IEEE Real-Time Systems Symposium, December 2005.
66. C. Bisdikian, "On sensor sampling and quality of information: A starting point," in 3rd IEEE Int'l Workshop on Sensor Networks and Systems for Pervasive Computing (PerSeNS 2007), a PerCom'07 Workshop, (White Plains, NY), March 19-23, 2007, pp. 279–284.

67. M. Shamaiah, S. Banerjee, and H. Vikalo. Greedy sensor selection: Leveraging submodularity. In CDC, 2010.
68. S. Joshi and S. Boyd. Sensor selection via convex optimization. Trans. Sig. Proc., 57(2), Feb. 2009.
69. A. Krause, R. Rajagopal, A. Gupta, and C. Guestrin. Simultaneous optimization of sensor placements and balanced schedules. IEEE Trans. Automat. Contr., 56(10):2390-2405, 2011.
70. M. Huber, A. Kuwertz, F. Sawo, and U. Hanebeck. Distributed greedy sensor scheduling for model-based reconstruction of space-time continuous physical phenomena. In Proc. FUSION, 2009.
71. D. Golovin, M. Faulkner, and A. Krause. Online distributed sensor selection. In Proc. IPSN, 2010.
72. S. Zahedi, M. B. Srivastava, and C. Bisdikian, “A computational framework for quality of information analysis for detection-oriented sensor networks,” in Military Communications Conference, 2008. MILCOM 2008. IEEE, 2008, pp. 1–7.
73. N. Roy, A. Misra, C. Julien, S. K. Das, and J. Biswas, “An energy-efficient quality adaptive framework for multi-modal sensor context recognition,” in 2011 IEEE International Conference on Pervasive Computing and Communications (PerCom), 2011, pp. 63 –73.
74. N. H. Viet, E. Munthe-Kaas, and T. Plagemann, “Quality and Energy Aware Data Acquisition for Activity and Locomotion Recognition,” in 2013 IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops), 2013.
75. A. Y. Wang and C. G. Sodini, “A simple energy model for wireless microsensor transceivers,” in IEEE Global Telecommunications Conference, 2004. GLOBECOM ’04, 2004, vol. 5, pp. 3205 – 3209 Vol.5.
76. Q. Wang and W. Yang, “Energy Consumption Model for Power Management in Wireless Sensor Networks,” in 4th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks, 2007. SECON ’07, 2007, pp. 142 –151.
77. J. Flinn and M. Satyanarayanan, “PowerScope: A Tool for Profiling the Energy Usage of Mobile Applications,” Proceedings of the Second IEEE Workshop on Mobile Computer Systems and Applications (WMCSA ’99), 1999, p. 2.
78. A. Rice and S. Hay, “Decomposing power measurements for mobile devices,” 2010 IEEE International Conference on Pervasive Computing and Communications (PerCom), 2010, pp. 70–78.
79. L. Zhang, B. Tiwana, Z. Qian, Z. Wang, R. P. Dick, Z. M. Mao, and L. Yang, “Accurate online power estimation and automatic battery behavior based power model generation for smartphones,” in Proceedings of the eighth IEEE/ACM/IFIP international conference on Hardware/software codesign and system synthesis, New York, NY, USA, 2010, pp. 105–114.
80. K. Kawamoto, J.G. Koomey, B. Nordman, R.E. Brown, M.A. Piette, M. Ting, A.K. Meier, “Electricity used by office equipment and network equipment in the U.S.”, LBNL-45917 Report, Environmental Energy Technologies Division, Ernest Orlando Lawrence Berkeley National Laboratory University of California, Berkeley, USA, February 2001.

81. J. L. García-Dorado, E. Magaña, P. Reviriego, M. Izal, D. Morató, J. A. Maestro, J. Aracil and J. E. López de Vergara, "Network monitoring for energy efficiency in large-scale networks: the case of the Spanish Academic Network", The Journal of Supercomputing, Volume 62, no. 3 (2012), pp. 1284-1304.