IoT 2024

Energy & Sustainability

Sebastian Büttrich – update 202403

Agenda: Energy

- IoT and Energy – two main aspects
- Context: Sustainability
- **1/ IoT as consumer in larger ICT context**
- **2/ IoT Life Cycle Analysis – a case**
- **3/ Practical aspects on device level**

IoT and Energy / Two angles

IoT and Energy – **two angles:**

1/ IoT (and digitalization in general) is **seen as an integral part of the green transition and of reaching CO2 neutrality**

2/ IoT relies heavily on **infrastructure, data centers, networks ss well as batteries, circuits, MCUs - and thus itself is a significant consumer**

The big picture: IoT in larger ICT context

Sustainability is a fashionable term that deserves some scrutiny.

(Of course entirely impossible within the scope of a side note to one small lecture ...)

Sustainability as a concept

Sustainability is a fashionable term that deserves some scrutiny.

(Of course entirely impossible within the scope of a side note to one small lecture ...)

The concept of sustainability, or *Nachhaltigkeit* in German, can be traced back to Hans Carl von Carlowitz (1645–1714), and was applied to **forestry.**

Sources: http://www.environmentandsociety.org/tools/keywords/hans-carl-von-carlowitz-and-sustainability
https://commons.wikimedia.org/wiki/File:Spruce_forest_at_Holma.jpg

Sustainability – Domains or Pillars

largely agreed on:

environmental, economic and social

with subdomains

cultural, technological and political

(our focus domains underlined)

Sources: https://en.wikipedia.org/wiki/Sustainability

The Sustainable Development Goals,
adopted on 25 September 2015 as a part of the UN 2030 Agenda.

Sources:
https://en.wikipedia.org/wiki/Sustainable_Development_Goals

Sustainability – Contradictions

Already at this point – there are **contradictions**:

the **”ability to exist constantly”** implies
lack of change, or at least **a circle.**

How does this concept relate to
”development” or **”growth”?**

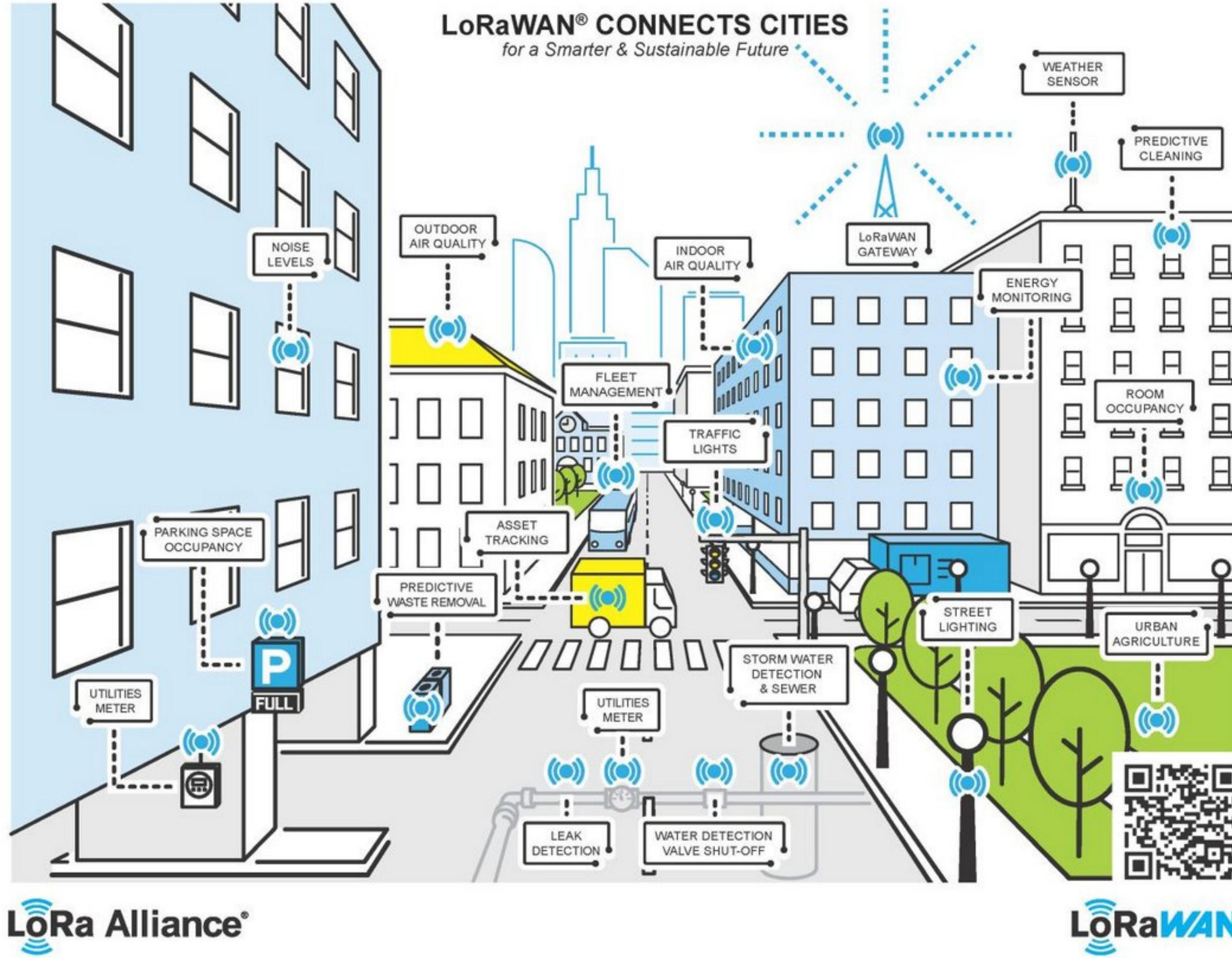
In any finite system, constant growth per definition can not be sustainable.

A possible issue

A well accepted and repeated commonplace that Digitalization, IoT, sensors, data, some form of "smartness" are a part of the "green transition".

A/ Do we have the metrics to prove it? Is the smart house more sustainable? Are smart lights using less energy?
B/ The IT sector is using energy and natural resources at a fast growing rate.
The very tool we claim will help us tackle climate change is responsible for further driving it.

Smartness



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IoT and Energy / Cloud worries

IoT relies heavily on

infrastructure,

data centers,

networks ...

The “cloud” ...

From a time where video was our biggest worry ... →

Dirty streaming: The internet's big secret

Figures suggest that IT now generates as much CO2 as flying, with some arguing it's nearly double.

bbc.co.uk

Exact description or estimation of the IT environmental footprint is hard

A personal experience:

someone asked me about **energy footprint of keeping their pictures and videos in the cloud** - Is it like a light bulb? A fridge? A car?

I couldn’t answer initially
and neither could my colleagues.
Can you? Take 1 TB of images – what does it compare to?

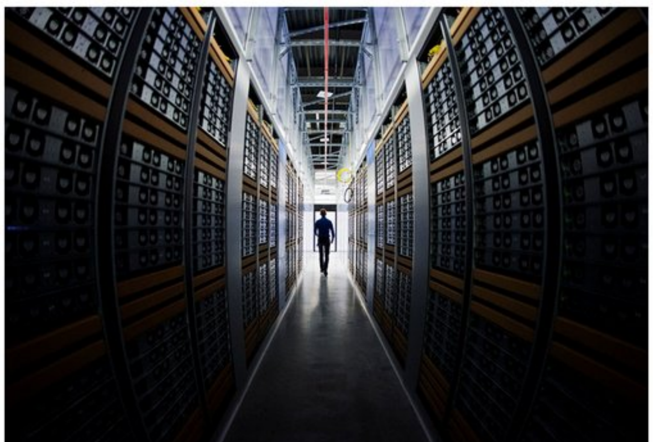
ICTs use ~10%* of global electricity

NEWS FEATURE · 12 SEPTEMBER 2018 · CORRECTION 13 SEPTEMBER 2018

How to stop data centres from gobbling up the world's electricity

The energy-efficiency drive at the information factories that serve us Facebook, Google and Bitcoin.

Nicola Jones



A Facebook data centre in Luleå, Sweden. Credit: Jonathan Nackstrand/AFP/Getty

ENERGY SCALE

Global electricity demand

20,000 TWh

Electricity use by ICT

2,000 TWh

Data-centre electricity demand

200 TWh

Bitcoin use by mid-2018

20 TWh

©nature

Figures are approximate.

Sources: IEA/A. Andrae/Ref. 6

Excellent start point for reading: **https://www.nature.com/articles/d41586-018-06610-y**

*** with huge uncertainty**

Sources: https://www.iea.org/ https://eia.gov
https://yearbook.enerdata.net/electricity/electricity-domestic-consumption-data.html
https://ember-climate.org/wp-content/uploads/2020/03/Ember-2020GlobalElectricityReview-Web.pdf
https://www.nature.com/articles/d41586-018-06610-y

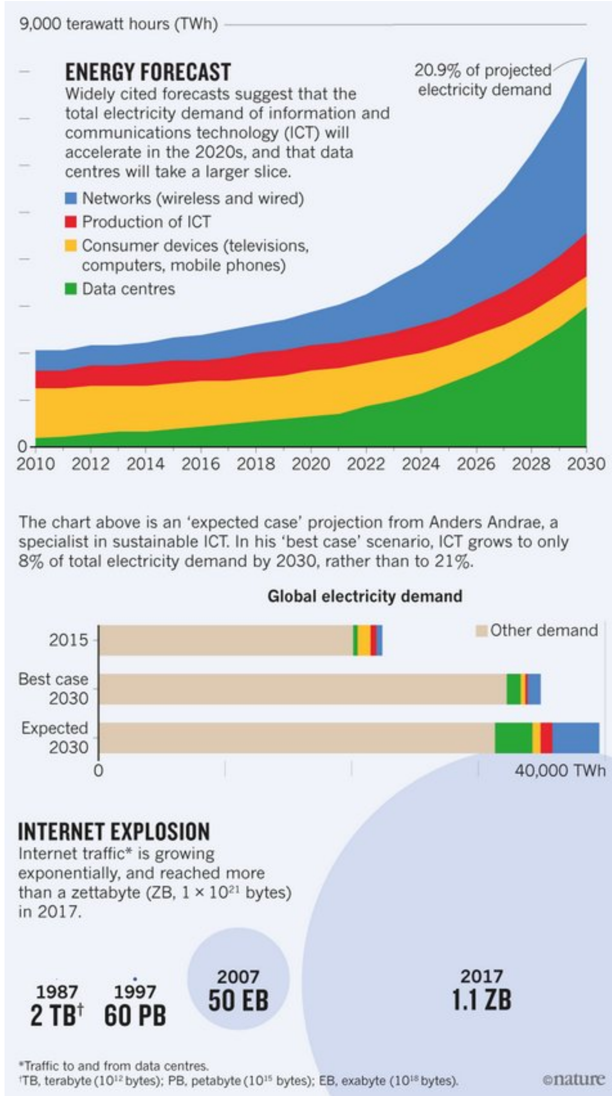
Some key sources

Andrae et al. (Huawei) have supplied data which is widely used and discussed

Andrae, A.S.G.; Edler, T.
On Global Electricity Usage of Communication Technology Trends to 2030.
Challenges 2015, 6, 117–157.
https://www.mdpi.com/2078-1547/6/1/117

Total Consumer Power Consumption Forecast
October 2017
Conference: Nordic Digital Business Summit
Project: Global Forecasting of ICT footprints
Anders S.G. Andrae
https://www.researchgate.net/publication/320225452_Total_Consumer_Power_Consumption_Forecast

key message:
centralized data & networks are drivers,
not consumer devices and production



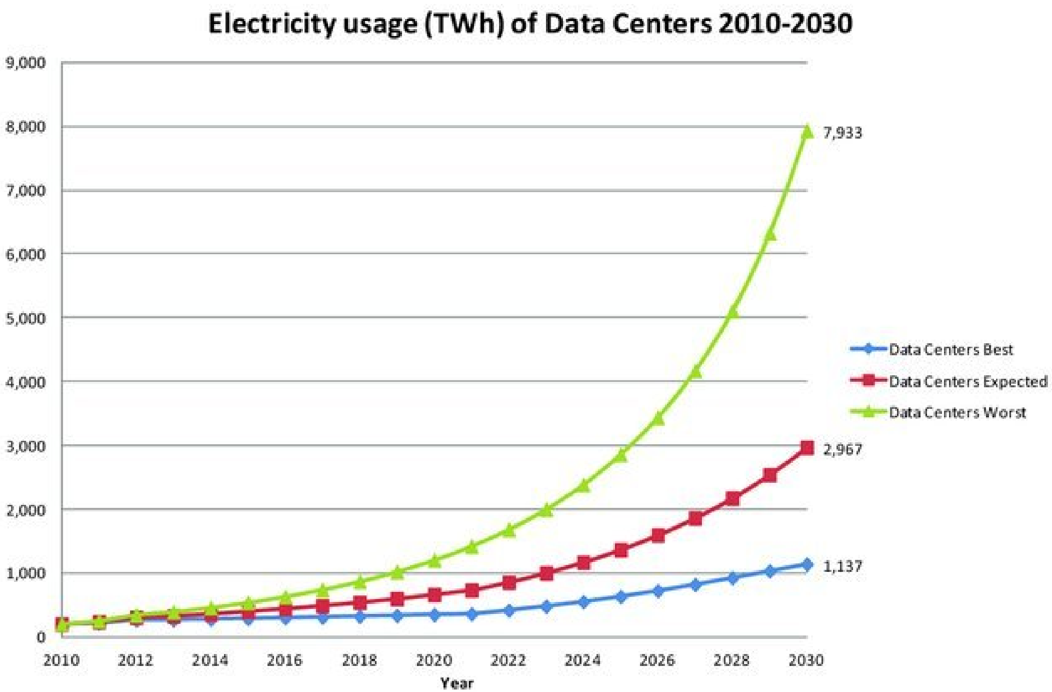
Central role of Data Centers: growing 10% per year

Environment

Global warming: Data centres to consume three times as much energy in next decade, experts warn

416.2 terawatt hours of electricity world's data centres used last year was far higher than UK's total consumption

Tom Bawden Environment Editor | @BawdenTom |
Saturday 23 January 2016 22:37 |



Data centres of the world will consume 1/5 of Earth's power by 2025

Joao Lima

12 Dec 2017 (Updated: 25 Jun 2020)
1 minute read

Alarming new research suggests that failure to source renewable energy could make data centres one of the biggest polluters in just seven years.

The rapid adoption of data-hungry machines and services is driving the need for more power to keep the lights on in the data centres of the world. As analysts estimate as many as 50 billion devices to be connected by 2020, with some statistics pointing to more than 100 billion a further five years down the line, new alarming research suggests that data centres will be one of the biggest energy consumers on the planet, beating many countries' energy consumption levels. According to a paper to be published by US researchers before the end of the year, the ICT industry is posed to be responsible for up to 3.5% of global emissions by 2020, with this value potentially escalating to 14% by 2040, according to Climate Change News. Researchers say this will be directly related to the fact that the data centre sector could be using 20% of all available electricity in the world by 2025 on the back of the large amounts of data being created at a fastest speed than ever before seen. The figures meet those published by Swedish researcher and Senior Expert Life Cycle Assessment at Huawei, Anders Andrae in 2016 in his "Total Consumer Power Consumption Forecast". Andrae predicts that by 2025, data centres will amount to ICT's largest share of global electricity production at 33%, followed by smartphones (15%) networks (10%) and TV (9%). As for the wider global usage, Andrae also expects data centres to use 20% of the world's energy, however, he places their carbon footprint at 5.5% of the global value, should adoption of more efficient energy sources not evolve at speed. The exponential utilisation of energy by data centres is not new, with the amount of power consumed increasing 9% between 2010 and 2015, according to KPN Integrated. On the global scale, data centres are poised to be the largest global energy users by 2025 at 4.5%, an increase from just 0.9% in 2015, according to Andrae's report. In comparison, consumer devices, fixed access wired services, wireless networks and production are all set to lag behind data centres in terms of energy usage. Globally, data centres were in 2014 responsible for around 1.62% of the world's utilised energy that year, according to Yole Développement. That has increased today to more than 3% of the world's energy (around 420 terawatts) and data centres are also responsible for 2% of total greenhouse gas emissions.

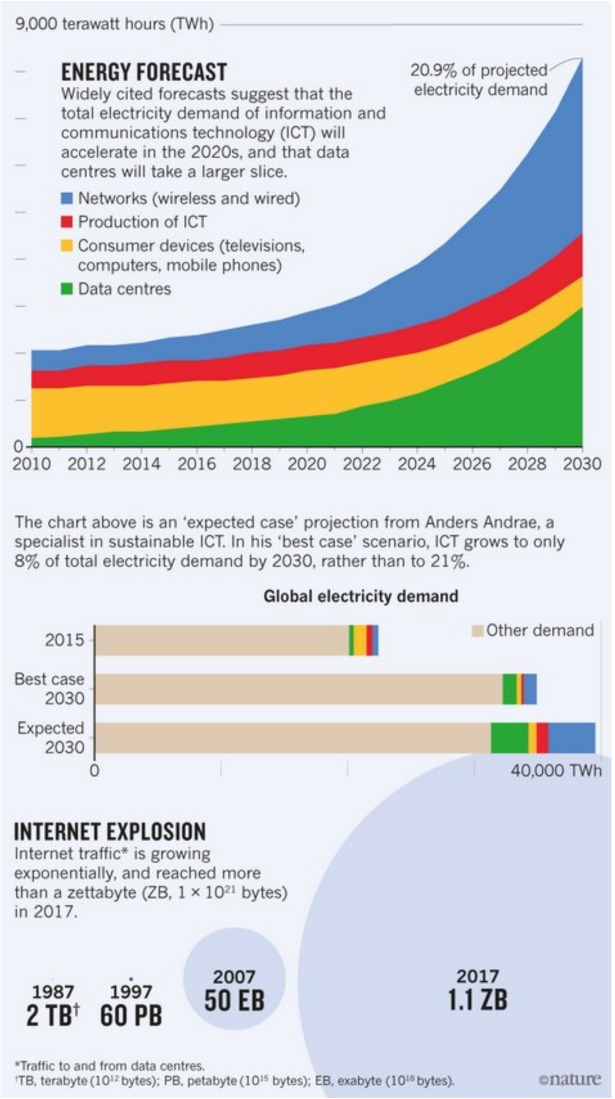
Sources:
https://www.independent.co.uk/environment/global-warming-data-centres-to-consume-three-times-as-much-energy-in-next-decade-experts-warn-a6830086.html
https://www.broad-group.com/data/news/documents/b1m2y6qlx5dv5t
https://www.researchgate.net/publication/320225452_Total_Consumer_Power_Consumption_Forecast

Difficult predictions

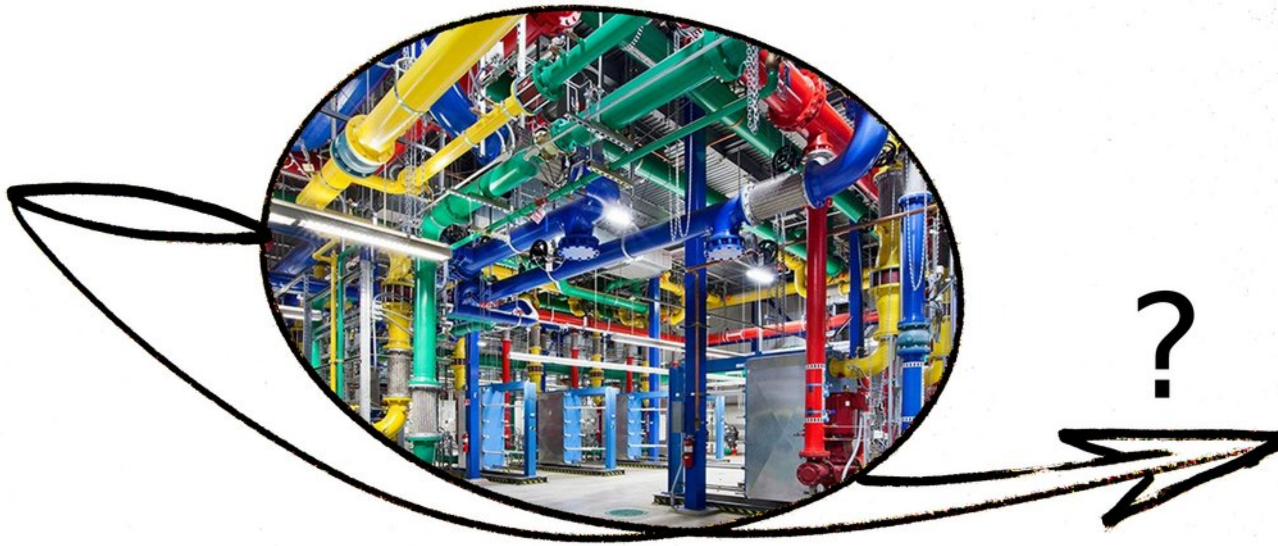
Some important studies are from 2017-2020.
We did not even see ChatGPT coming at that point.
Video and Bitcoin seemed the biggest contributions.

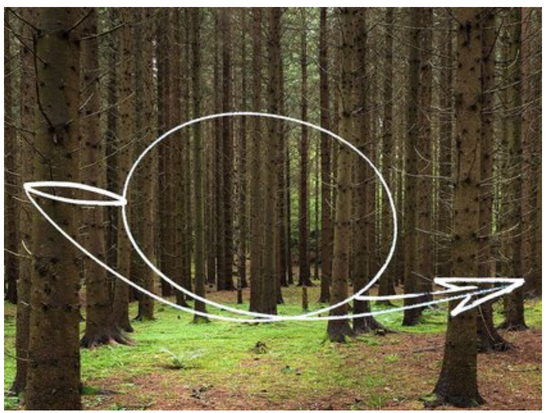
Koot, Martijn, and Fons Wijnhoven.
"Usage impact on data center electricity needs: A system dynamic forecasting model."
Applied Energy 291 (2021): 116798.
https://www.sciencedirect.com/science/article/pii/S0306261921003019

We have a very rough idea that
IT will be a 10% (or more?) part of global electricity consumption.



Perhaps the most fundamental problem: What are the INs and OUTs of IT?

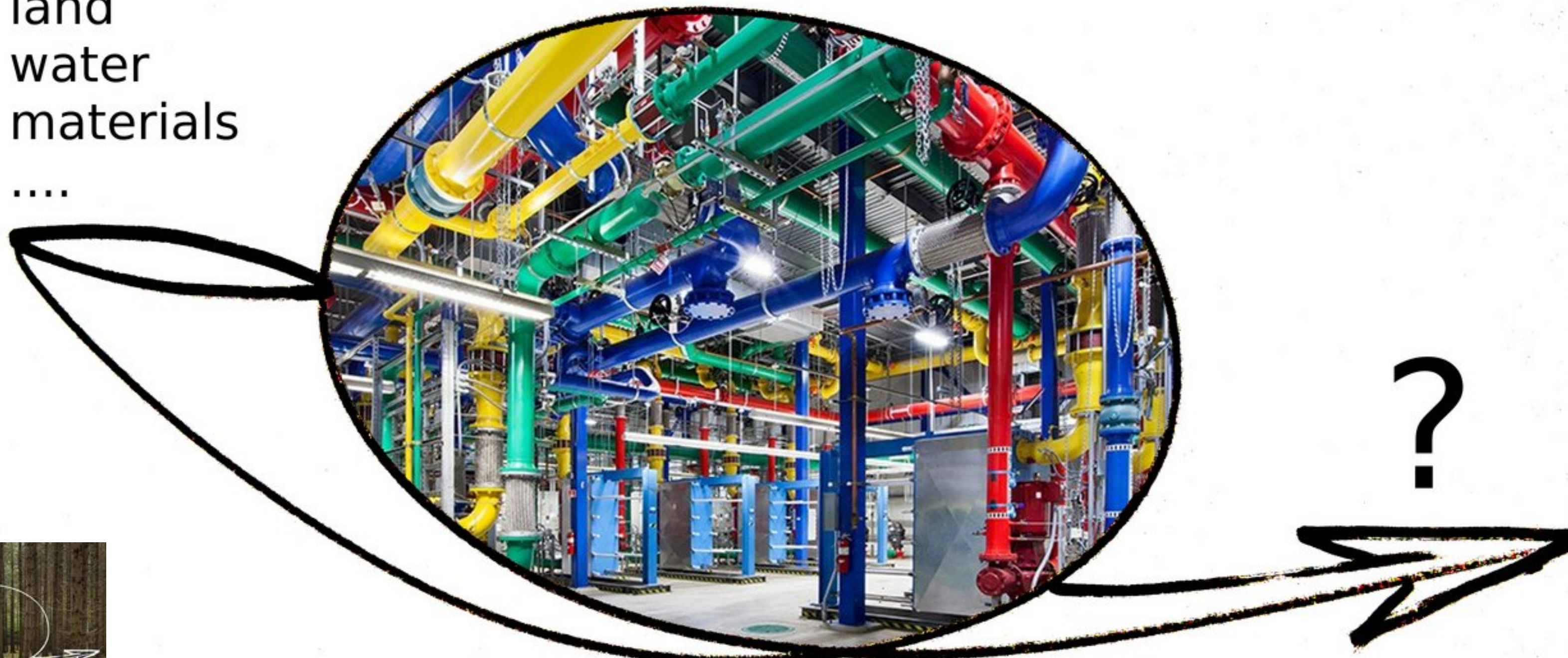




Sources: https://en.wikipedia.org/wiki/Sustainability
http://www.un-documents.net/ocf-ov.htm#1.2

Perhaps the most fundamental problem

energy
land
water
materials
....



Unlike e.g. agriculture, forestry, energy sectors,

IT can not produce any of its own input resources

Sources: https://en.wikipedia.org/wiki/Sustainability
http://www.un-documents.net/ocf-ov.htm#1.2

The concept of footprint and handprint

”In environmental management and sustainability there is an increasing interest in measurement and **accounting of beneficial impact**—as an incentive to action, as a communication tool, and to move toward a positive, constructive approach focused on opportunities rather than problems. One approach uses **the metaphor of a “handprint,**” complementing the notion of environmental footprints, which have been widely adopted for impact measurement and accounting.”

Source: Guillaume, Joseph HA, et al. "Giving legs to handprint thinking: Foundations for evaluating the good we do." Earth's Future 8.6 (2020): e2019EF001422.

The concept of footprint and handprint

”**The “handprint” has been suggested as a way of looking at the good we do**, to complement the negative impacts captured by environmental “footprints.” There are many ways we could try to assess a handprint, which capture different perspectives on the world, and the potential role of the handprint assessment in moving toward sustainability.”

Source: Guillaume, Joseph HA, et al. "Giving legs to handprint thinking: Foundations for evaluating the good we do." Earth's Future 8.6 (2020): e2019EF001422.

IoT and Energy / IT energy consumption

Many creative attempts at mitigating the problem,

however significant countertrends, e.g.

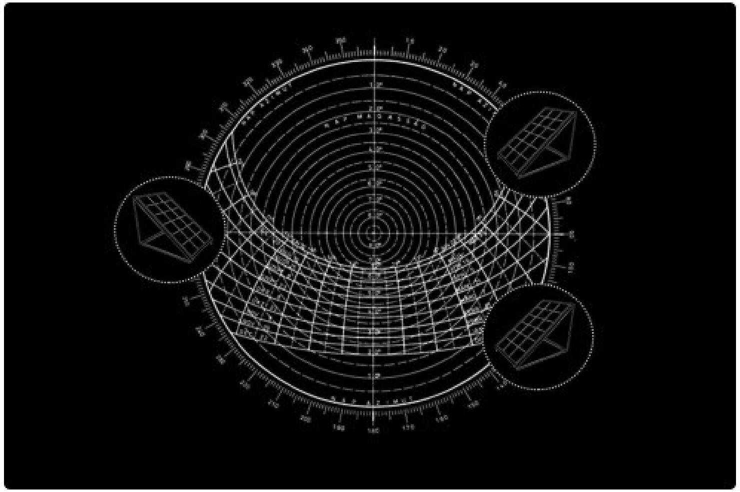
cloud at large, video streaming, 5G, blockchain, ...

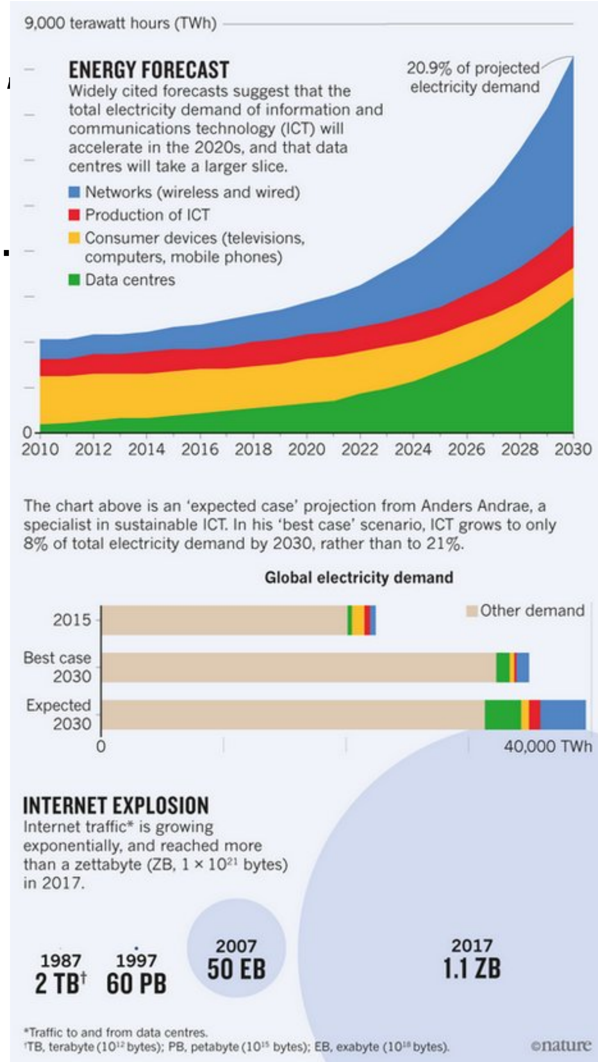
(and this was before we knew about AI!!!)

solarprotocol.net

Solar Protocol

A naturally intelligent network. A website hosted across a network of solar powered servers and served from wherever there is the most sunshine.





IoT and Energy / IT energy consumption

Read more: https://github.com/ITU-DASYALab/IT-sustainability

Andrae, A.S.G.; Edler, T.
On Global Electricity Usage of Communication Technology Trends to 2030.
Challenges 2015, 6, 117-157.
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How to stop data centres from gobbling up the world's electricity

The energy-efficiency drive at the information factories that serve us Facebook, Google and Bitcoin.

Nicola Jones

Difficult to estimate infrastructure energy usage

POLICY FORUM | ENERGY

Recalibrating global data center energy-use estimates

Eric Masanet[1,2], Arman Shehabi[3], Nuoa Lei[1], Sarah Smith[3], Jonathan Koomey[4]
+ See all authors and affiliations

Science 28 Feb 2020:
Vol. 367, Issue 6481, pp. 984-986
DOI: 10.1126/science.aba3758

But we know it s a lot ...

AI as the new driver of power consumption

The New Era of AI and its Impact on Data Centres

By Marcus Law
February 29, 2024 • 6 mins

The New Era of AI and its Impact on Data Centres

With Data Centres Serving as the Critical Infrastructure Supporting the AI Ecosystem, Innovative Solutions Are Needed to Tackle Sustainability Challenges

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AUTHOR
Marcus Law ›

AI sparks huge increase in U.S. energy consumption and is straining the power grid; transmission/distribution as a major problem

Posted on March 16, 2024 *by* Alan Weissberger

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Newsletter

AI Emerges as Next Shiny Thing in the Energy World

Executives gathered at CERAWeek say the technology has potential to become a huge source of demand, as well as reshape production.

An offshore oil and gas platform off California. Energy executives say AI can revamp exploration, drilling and pumping, as well as create new sources of demand. *Photographer: Eric Thayer/Bloomberg*

DAILY COMMENT

THE OBSCENE ENERGY DEMANDS OF A.I.

How can the world reach net zero if it keeps inventing new ways to consume energy?

By Elizabeth Kolbert
March 9, 2024

It's been estimated that ChatGPT is consuming more than half a million kilowatt-hours of electricity per day. Photograph by Mark Felix / AFP / Getty

IoT Life Cycle Assessment – a case

Life Cycle Assessment or Analysis (LCA)

Definition:
a methodology for assessing environmental impacts associated with all the stages of the life cycle of a commercial product, process, or service. [wikipedia]

Term: **”Cradle to Grave”**

How to include ”handprints”?
==> Case: TinyML Sustainabiliy

Is TinyML sustainable?

TinyML is seen as bearing a promise of positive impact with regards to SDGs.

Platform	Freq.	Memory	Storage	Power	Price	CO_2-eq Footprint
Cloud	GHz	10+GB	TBs-PBs	~1 kW	$1000+	Hundreds of kgs
Mobile	GHz	Few GB	GBs	~1 W	$100+	Tens of kgs
Tiny	**MHz**	**KBs**	**Few MB**	**~1 mW**	**$10**	**Single kgs**

Table 1. Cloud and mobile ML systems compared with TinyML across frequency, memory, storage, power, price, and footprint. The footprint of TinyML systems is far less.

If TinyML has significant negative footprint,
let us look at offsetting it by
positive handprint.

→ Lifecycle Assessment

Source: Prakash, Shvetank, et al. "Is TinyML Sustainable? Assessing the Environmental Impacts of Machine Learning on Microcontrollers." arXiv preprint arXiv:2301.11899 (2023).

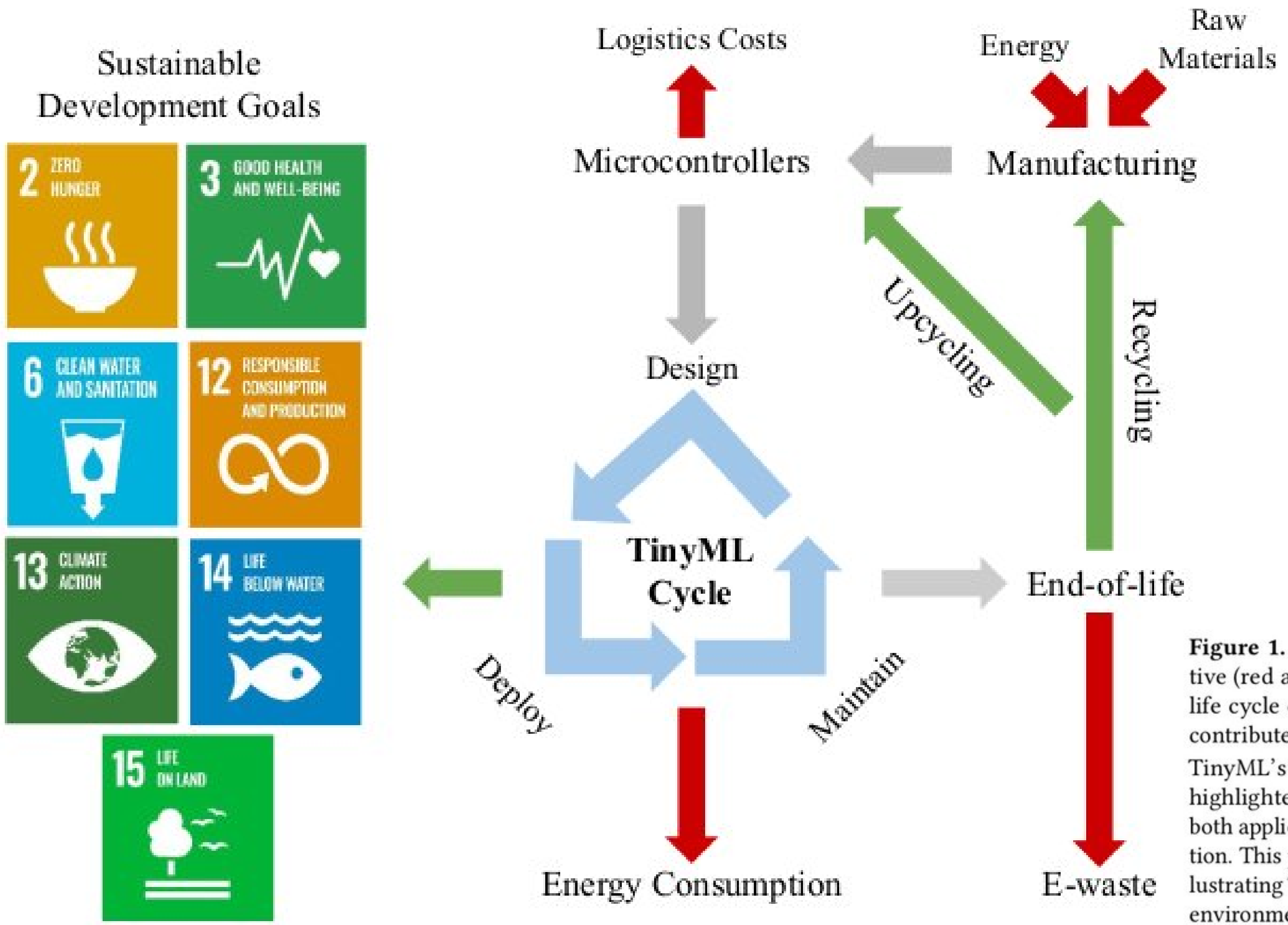


Figure 1. We show the positive (green arrows) and negative (red arrows) environmental footprint of the complete life cycle of TinyML systems as well as how TinyML can contribute to the UN's environmental sustainability goals.

TinyML's operational benefits for sustainability are often highlighted, it is crucial to consider the entire life cycle of both applications and hardware to ensure a net carbon reduction. This paper contributes by (1) presenting case studies illustrating TinyML's sustainability benefits, (2) examining the environmental impacts of TinyML at both MCU and system levels through a life cycle analysis (LCA), and (3) identifying future research directions for sustainable TinyML.

Source: Prakash, Shvetank, et al. "Is TinyML Sustainable? Assessing the Environmental Impacts of Machine Learning on Microcontrollers." arXiv preprint arXiv:2301.11899 (2023).

Lifecycle Assessment

1. Identify positive handprint

Zero Hunger & Good Health and Well-Being
(SDG #2 & #3)

Precision agriculture, plant & animal diseases,
harvest efficiency,
Malaria prevention (insect identification)

Source: Prakash, Shvetank, et al. "Is TinyML Sustainable? Assessing the Environmental Impacts of Machine Learning on Microcontrollers." arXiv preprint arXiv:2301.11899 (2023).

Lifecycle Assessment

1. Identify positive handprint

Life on Land & Below Water (SDG #14 & #15)

Wildlife Conservation, conflict mitigation, poaching detection, deforestation detection

Source: Prakash, Shvetank, et al. "Is TinyML Sustainable? Assessing the Environmental Impacts of Machine Learning on Microcontrollers." arXiv preprint arXiv:2301.11899 (2023).

Lifecycle Assessment

1. Identify positive handprint

Climate Action (SDG #13)

side remark:
collision of aspects of sustainability?

we just replaced 150-160 employees ...

3.3 Climate Action (SDG #13)

Take urgent action to combat climate change and its impacts.

TinyML is well-suited to efforts aimed at combating climate change and its impacts through environmental monitoring applications. For example, Ribbit Network recently launched an effort to crowdsource the world's largest greenhouse gas emissions dataset through distributed intelligent sensors which enabled cheap, accurate, and actionable local data on emissions. Similarly, the SmartForest project utilizes a remote monitoring system to provide information on tree growth. This replaced the need for 150 – 160 employees to regularly go into the field with a single trip to install the sensors [13], significantly reducing human impact on the ecosystem while increasing data quality.

Source: Prakash, Shvetank, et al. "Is TinyML Sustainable? Assessing the Environmental Impacts of Machine Learning on Microcontrollers." arXiv preprint arXiv:2301.11899 (2023).

Lifecycle Assessment

2. Identify negative footprint

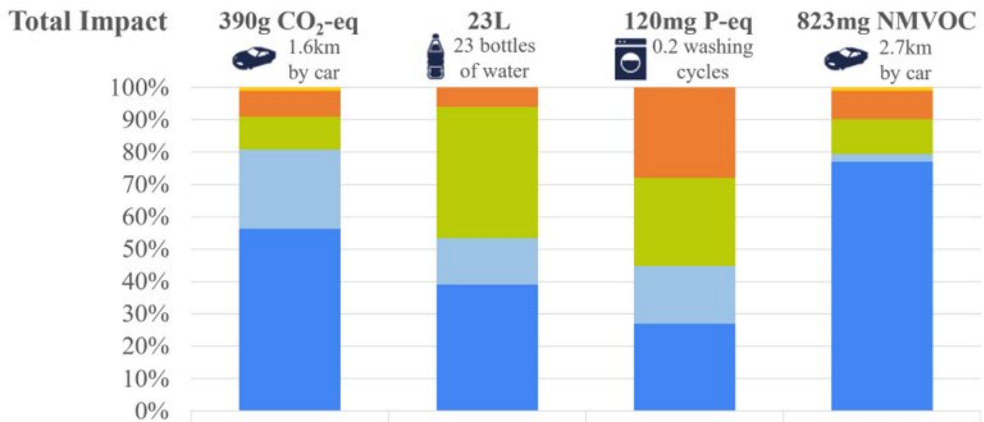
LCA with 5 phases

Raw Materials
Manufacturing
Transportation
Operating
End of Life / E-waste

Focus on the **MCU (Micro Controller Unit)**

Source: Prakash, Shvetank, et al. "Is TinyML Sustainable? Assessing the Environmental Impacts of Machine Learning on Microcontrollers." arXiv preprint arXiv:2301.11899 (2023).

Lifecycle Assessment / MCU



	Climate Change	Water Demand	Freshwater Eutrophication	Protochemical Oxidant Formation
End of Life	<1%	<1%	<1%	<1%
Logistics	1%	<1%	<1%	1%
Use	8%	6%	28%	8%
Raw Materials	10%	41%	27%	10%
Production: Other	25%	15%	18%	2%
Production: Energy Consumption	56%	39%	27%	71%

Figure 3. Four different environmental indicators measuring the impact of MCUs on our environment. Each footprint contains both the operational and embodied footprint of the device, including the five-stage life cycle of an MCU. Data courtesy of STMicroelectronics [44]. The data from other MCU providers follow the same operational and embodied footprint trends.

Source: Prakash, Shvetank, et al. "Is TinyML Sustainable? Assessing the Environmental Impacts of Machine Learning on Microcontrollers." arXiv preprint arXiv:2301.11899 (2023).

Raw materials and production outweighs use

This is the same for consumer IT, e.g. a laptop:

The manufacture of a laptop is between 75% – 85% of the overall carbon footprint.

Sources: https://circularcomputing.com/news/carbon-footprint-laptop/

A short discourse

Putting 390 grams of CO_2 for an MCU in perspective:

The average kWh of electricity in Denmark? *
(Carbon Intensity)

Fossil fuel car per 100 km?

Electric car per 100 km?

* what’s your household then?

A short discourse

Putting grams of CO_2 in perspective:

The average kWh of electricity in Denmark? 180 g*
(Carbon Intensity)

Fossil fuel car per 100 km? 10 kg

Electric car per 100 km? 2.5 kg

* what's your household then?

Sources: https://ourworldindata.org/grapher/carbon-intensity-electricity , https://www.europarl.europa.eu/news/en/headlines/society/20190313STO31218/co2-emissions-from-cars-facts-and-figures-infographics

The MCU is not all

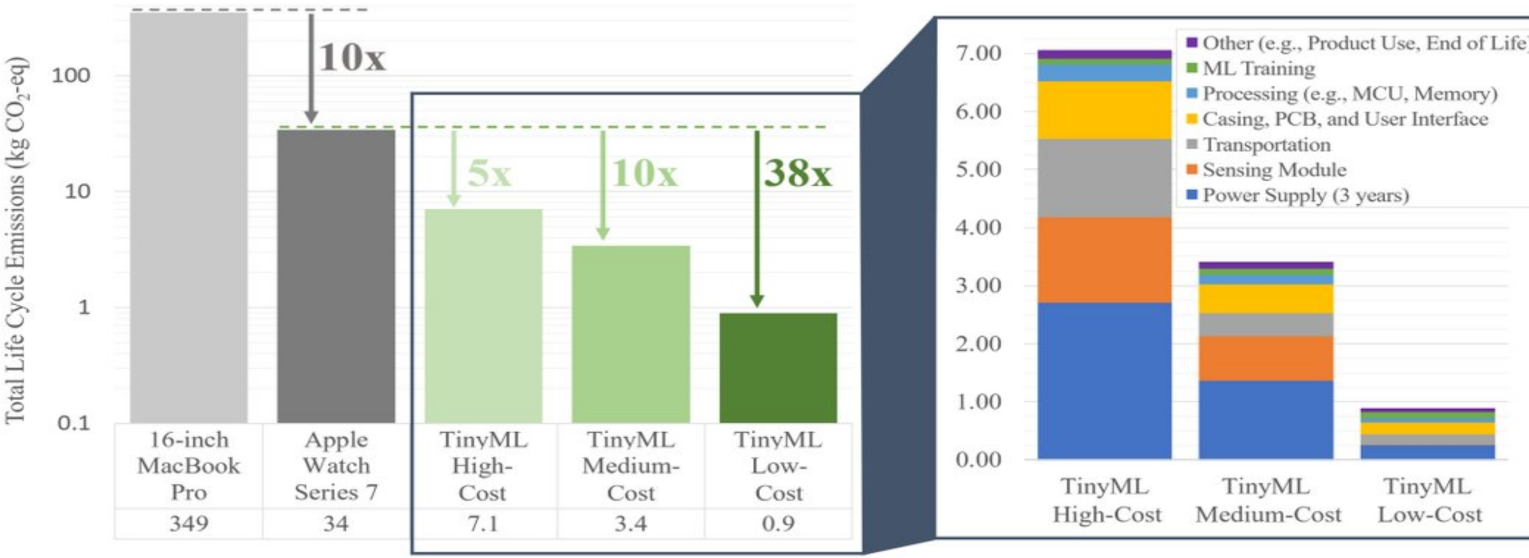


Figure 4. A breakdown of different TinyML system footprints highlights that the footprint is largely attributable to the embodied footprint of the power supply, onboard sensors, and transportation. Note that actuator and connectivity blocks from Pirson and Bol [32] are encapsulated in "Other" and "Processing", respectively, while "Product Use" captures the operational footprint. The carbon footprint of Apple's Series 7 Watch [22] and 16-inch MacBook Pro [21] are also provided for reference. For more details and to compute the footprint of your own TinyML system, see https://github.com/harvard-edge/TinyML-Footprint.

Source: Prakash, Shvetank, et al. "Is TinyML Sustainable? Assessing the Environmental Impacts of Machine Learning on Microcontrollers." arXiv preprint arXiv:2301.11899 (2023).

Total lifecycle results for CO2 emissions

TinyML devices estimated to produce

1 .. 10 kg CO2-equivalent over lifetime
(depending on size of system)

Source: Prakash, Shvetank, et al. "Is TinyML Sustainable? Assessing the Environmental Impacts of Machine Learning on Microcontrollers." arXiv preprint arXiv:2301.11899 (2023).

Balance footprint vs handprint

Figure 5. If all 250 billion MCUs were TinyML systems with three-year lifespans, their worst-case footprint would be 1765 million metric tons of CO_2. If these systems enabled a 20% emissions reduction for the residential sector and only a 0.6% reduction for all other sectors (Figure 2), the total footprint would be net-zero. Anything larger (e.g., 20%) results in more carbon savings from TinyML than emissions.

Source: Prakash, Shvetank, et al. "Is TinyML Sustainable? Assessing the Environmental Impacts of Machine Learning on Microcontrollers." arXiv preprint arXiv:2301.11899 (2023).

Discussion / Limitations of study

Lack of reliable LCA data for digital devices

Jevons’ paradox

In economics, the Jevons paradox occurs when technological progress or government policy increases the efficiency with which a resource is used (reducing the amount necessary for any one use), but the falling cost of use induces increases in demand enough that resource use is increased, rather than reduced. [wikipedia]

Comparison is made beween

TinyML intervention vs *No intervention*

ignoring possibility of other interventions

Source: Guillaume, Joseph HA, et al. "Giving legs to handprint thinking: Foundations for evaluating the good we do." Earth's Future 8.6 (2020): e2019EF001422.

Discussion / Other limitations

Discuss!

Source: Guillaume, Joseph HA, et al. "Giving legs to handprint thinking: Foundations for evaluating the good we do." Earth's Future 8.6 (2020): e2019EF001422.

Discussion / Other limitations

Footprint is de-facto – Handprint is mere potential
”if it were used in this way …”

Realization of benefits is not achieved by mere deployment of TinyML – in fact, it might only be the first initial step, e.g. in building sector

Optimal/correct usage of technology is assumed. This is rarely the case.

Source: Guillaume, Joseph HA, et al. "Giving legs to handprint thinking: Foundations for evaluating the good we do." Earth's Future 8.6 (2020): e2019EF001422.

Discussion / Other limitations

While TinyML devices have some degree of autonomy, they still depend on a lot of infrastructure that is not taken into account.

Examples given actually mention the use of EdgeImpulse.

Generally, models will not be developed and trained on tiny devices, but in conventional datacenters.

Discussion / Other limitations

Personal view, Sebastian:

While the paper makes the important attempt to quantify the somewhat diffuse hope that IoT & TinyML might be beneficial,
the work remains too
tech-centric and likely overly optimistic (?).

Practical work with energy on device level

More pragmatically, **devices need power**

- **Fundamentals of power engineering**
- **Classes of operation**
- **Harvesting techniques**
- **Optimizing power consumption**

We need some fundamentals:

Simplified, but useful:

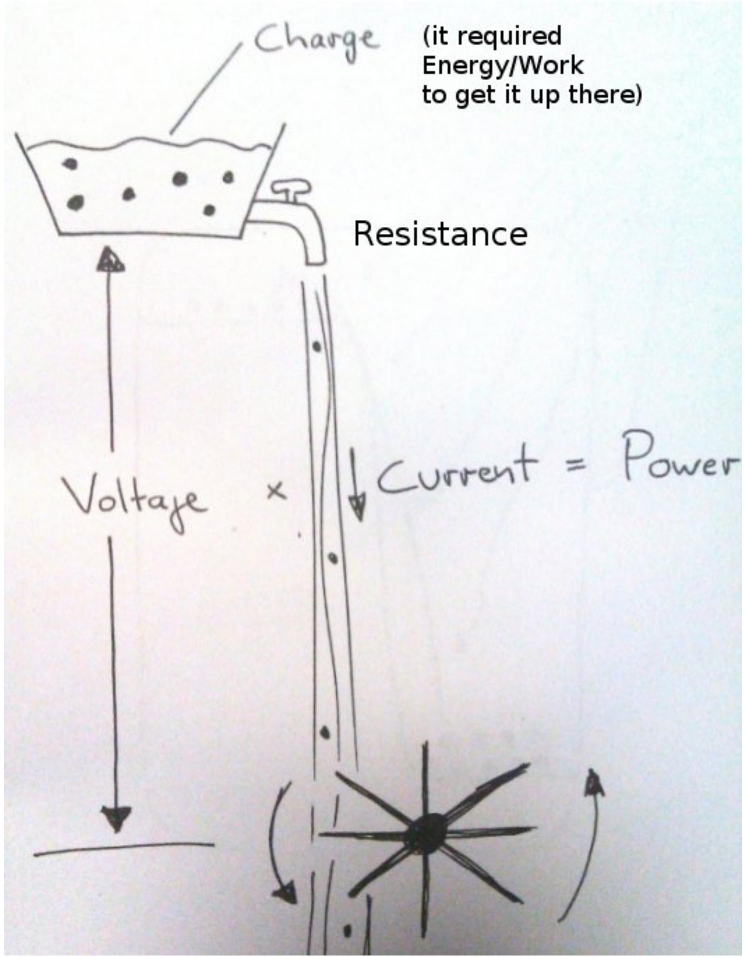
Charge

Current

Voltage

Power

Energy



SI base unit for all things electrical

Current I, measured in Ampere [A]

Power P, measured in Watt [W]

Voltage U, measured in Volt [V]

P = U x I

I = P / U

U = P / I

Sensors / Reminder of prerequisites

- SI UNIT system
- Powers of ten

International System of Units (SI)

SI Base Units

Base Quantity	Name	Symbol
Length	meter	m
Mass	kilogram	kg
Time	second	s
Electric current	ampere	A
Temperature	kelvin	K
Amount of substance	mole	mol
Luminous intensity	candela	cd

SI Derived Units

Derived Quantity	Name	Symbol	Equivalent SI units
Frequency	hertz	Hz	s^{-1}
Force	newton	N	$m \cdot kg \cdot s^{-2}$
Pressure	pascal	Pa	N/m^2
Energy	joule	J	N·m
Power	watt	W	J/s
Electric charge	coulomb	C	s·A
Electric potential	volt	V	W/A
Electric resistance	ohm	Ω	V/A
Celsius temperature	degree Celsius	°C	K*

*Unit degree Celcius is equal in magnitude to unit kelvin.

SI Prefixes

Factor	Name	Symbol	Numerical Value
10^{12}	tera	T	1 000 000 000 000
10^{9}	giga	G	1 000 000 000
10^{6}	mega	M	1 000 000
10^{3}	kilo	k	1 000
10^{2}	hecto	h	100
10^{1}	deka	da	10
10^{-1}	deci	d	0.1
10^{-2}	centi	c	0.01
10^{-3}	milli	m	0.001
10^{-6}	micro	μ	0.000 001
10^{-9}	nano	n	0.000 000 001
10^{-12}	pico	p	0.000 000 000 001

- Adapted from NIST Special Publication 811
- SI rules and style conventions recommend using spaces rather than commas to separate groups of three digits.

FLINN SCIENTIFIC, INC
"Your Safer Source for Science Supplies"

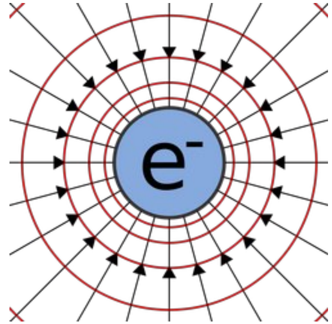
SI base unit for all things electrical:

Current I, measured in Ampere [A].

The Current I s the result of a charge of

1 Coulomb flowing per second:

Ampere = Coulomb / Second



SI base unit for all things electrical:

Current I, measured in Ampere [A].

Given the definition of the second,

The duration of 9192631770 periods of the radiation corresponding to the transition between the two hyperfine levels of the ground state of the caesium-133 atom

And the definition of electric charge:

Under the 2019 redefinition of the SI base units, which took effect on 20 May 2019,[2] the elementary charge (the charge of the proton and of the electron, but also of other fundamental particles) is exactly 1.602176634×10−19 coulombs. Thus the coulomb is the charge of exactly 1/(1.602176634×10−19) elementary charges

Energy / Fundamentals

Charge, measured in Coulomb [C]

elementary charge: that of one electron

Energy/Work E, measured in Joule [J] or Wh

E = P x t

Resistance R, measured in [Ω Ohm]

R = U / I Ohm’s Law

(Battery) Capacity, measured in [Ah]

C = I x t

Energy/Work E, measured in Joule [J] or Wh -

Relation Joule to Wh:

Because of the hour = 3600 seconds,

you have a factor of 3600 between

1 Wh = 3600 Ws = 3600 J

Simple, but useful - test yourself:

www.menti.com and use the code 3759 9556

Your annual electricity bill?

....

Capacity of your phone battery?

....

Power of your charger?

....

Simple, but useful - test yourself:

Your annual electricity bill (kWh)?

~ some 100 to 1000s of kWh

Capacity of your phone battery?

some 1000 mAh, *often 2600, 3700 mAh*

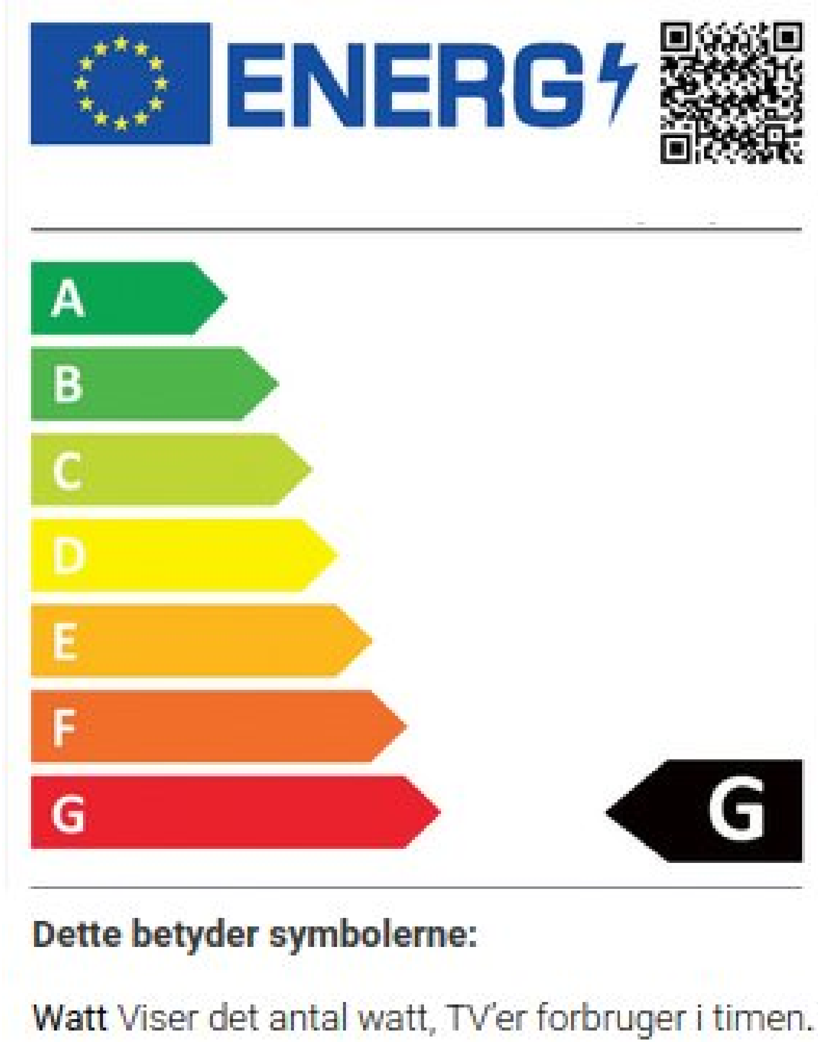
Power of your charger?

0.5 – 2 Watt

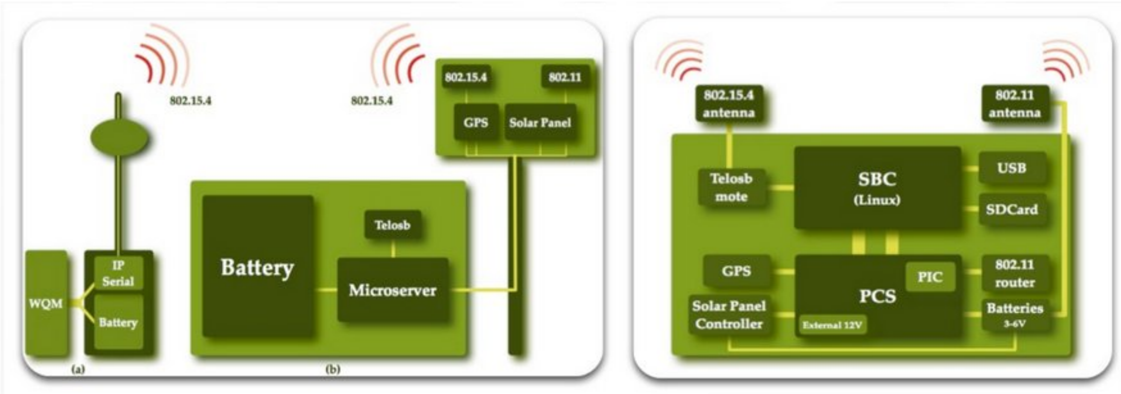
Energy / Fundamentals – often wrong

What's wrong here?

....



Experience from MANA project



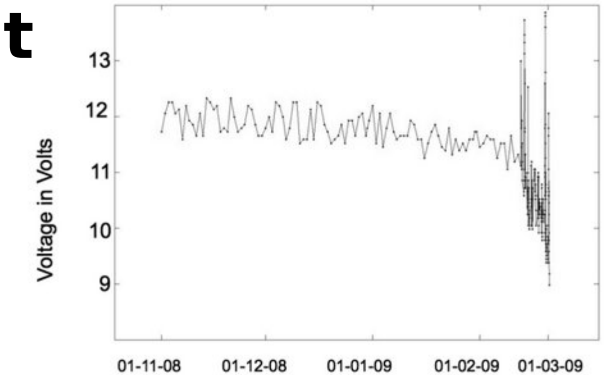


Figure 3: Voltage readings during Winter 2009

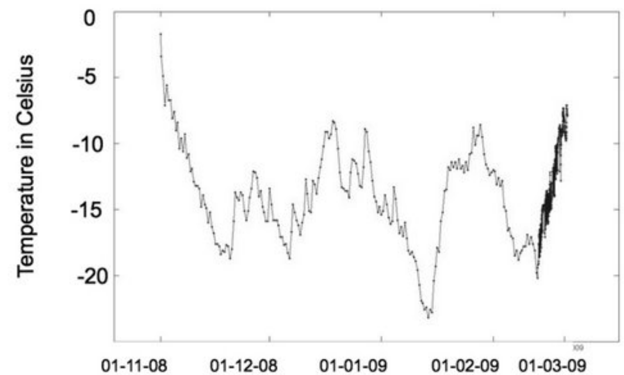
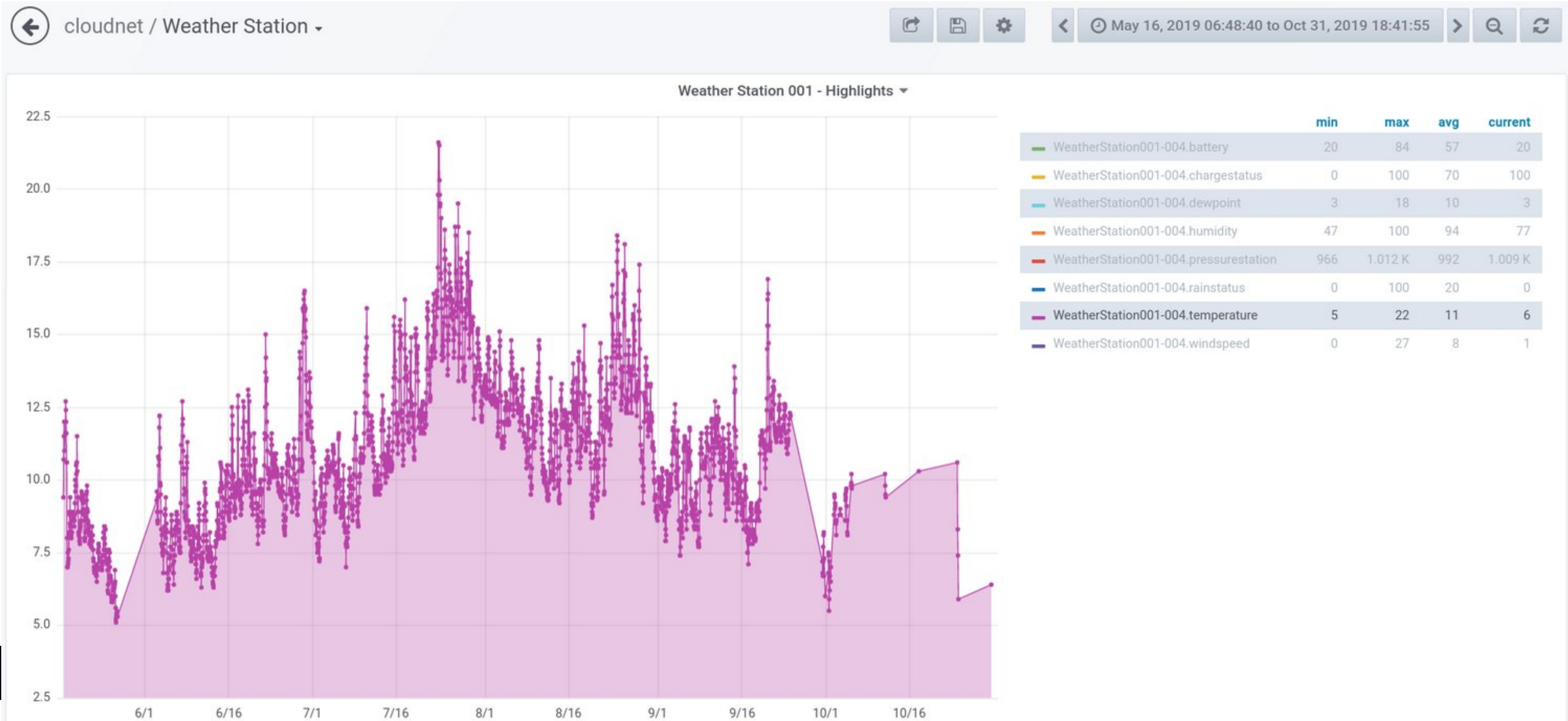


Figure 4: Internal temperature readings during Winter 2009

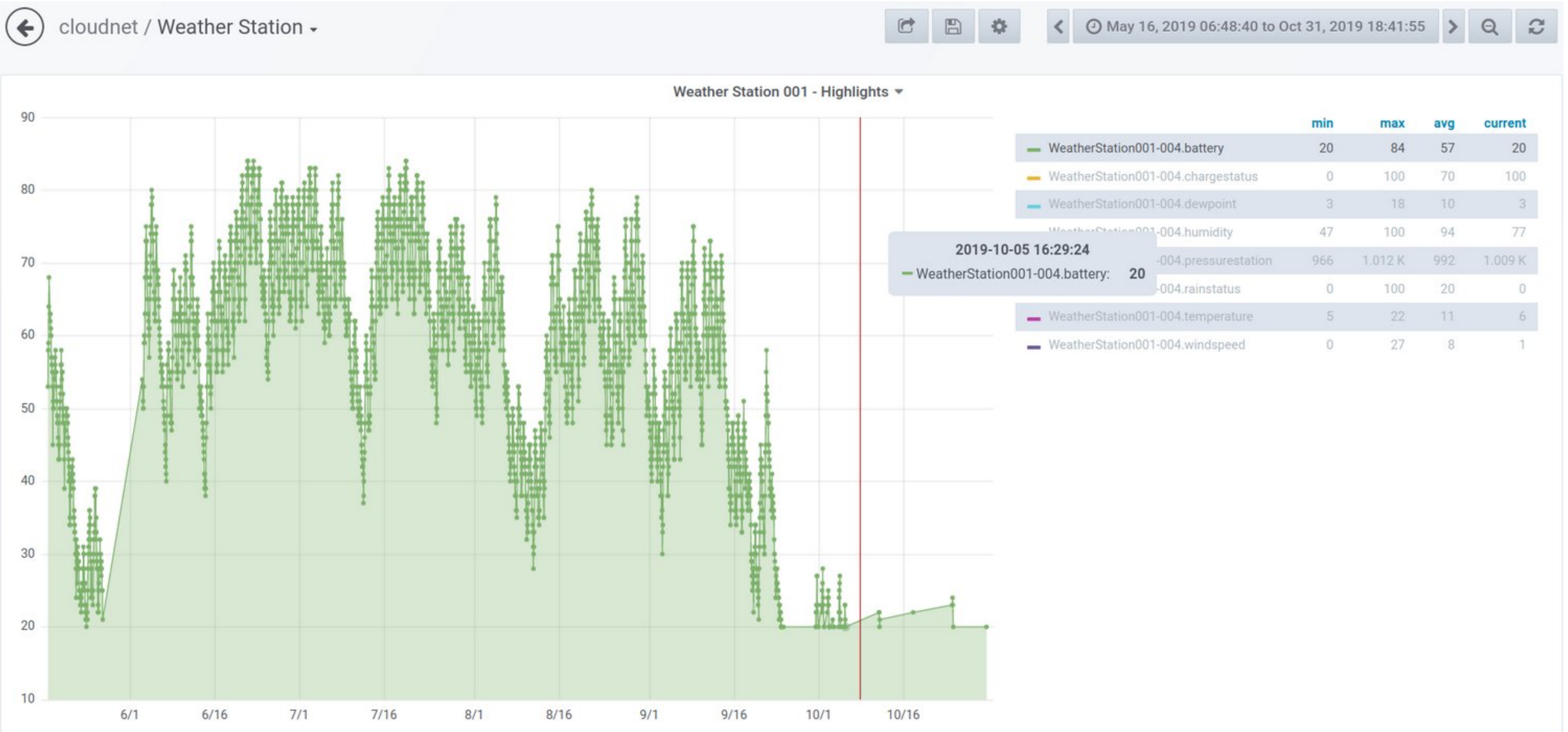
Energy / Powering devices

Experience from Orkney (Weather Station from Spain :)



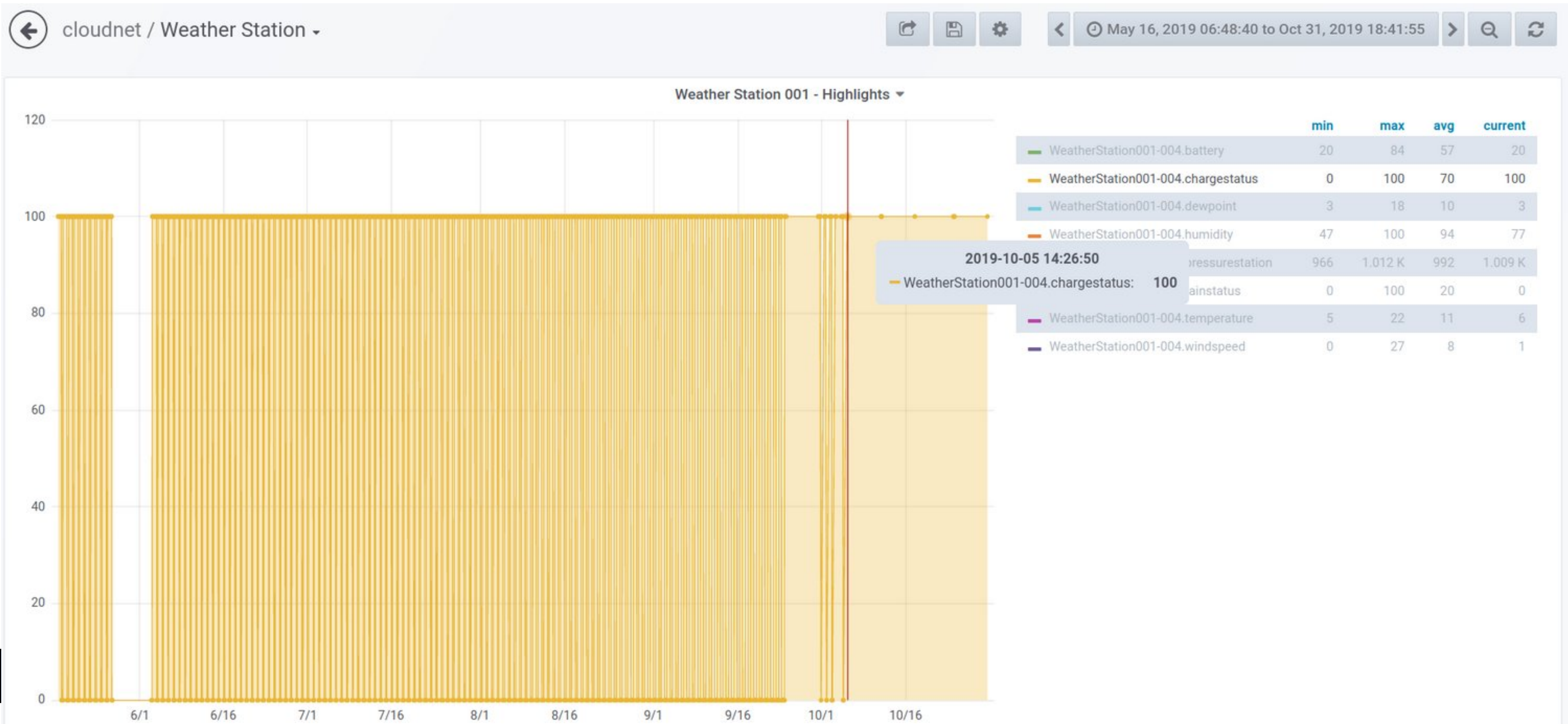
Energy / Powering devices

Experience from Orkney (Weather Station from Spain :)



Energy / Powering devices

Experience from Orkney (Weather Station from Spain :)



Energy / Classes of Operation

Grid

dependent

Battery / Storage

Temporarily autonomous

Autonomous

Semi: Parasiting

Fully: Harvesting

From object of sensing, or independent

Grid

Preferred option for operation in/near

buildings/infrastructure,

however

Consider dependencies and cross-impacts

If I am to measure power consumption profiles in

offices, should I depend on office power?

Energy / Classes of Operation / Battery

Battery (electrochemical)

Supercap (electrostatic)

Characterized by a.o.

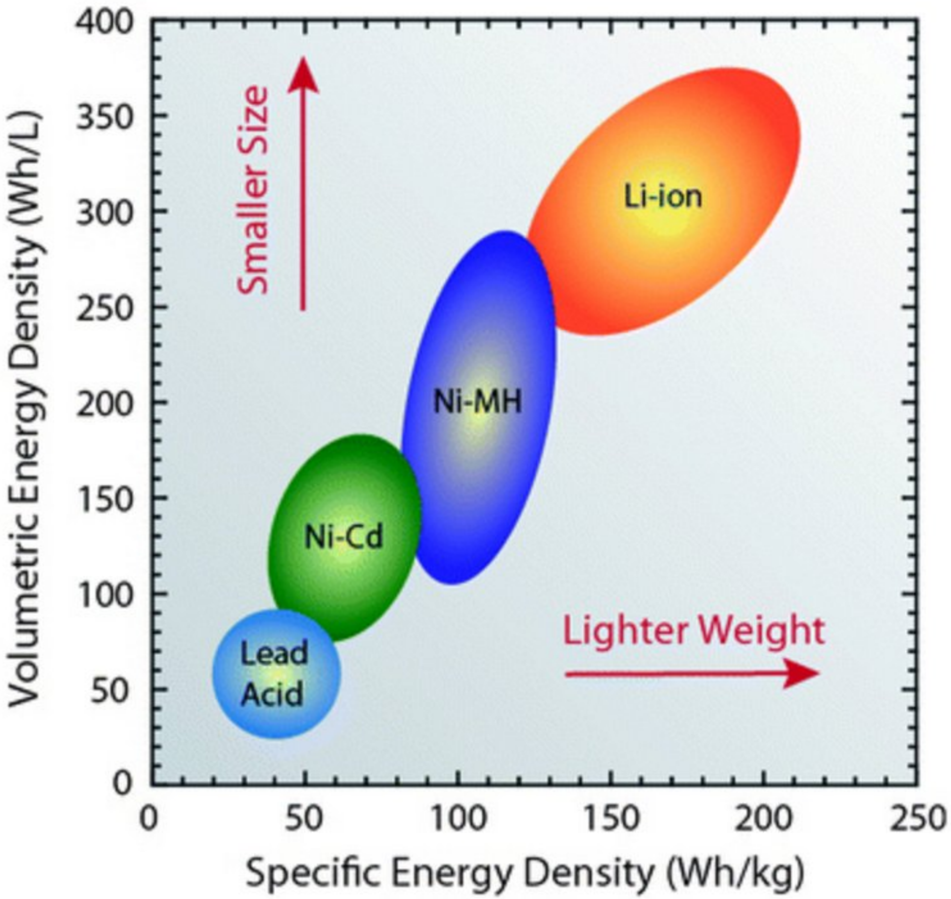
- Capacity, in [Ah], [mAh]
- Energy Density = Energy/volume
  Energy/mass (*specific energy*)
- Maximum Current
- Time charactaristics (Trickle, peaks, etc)

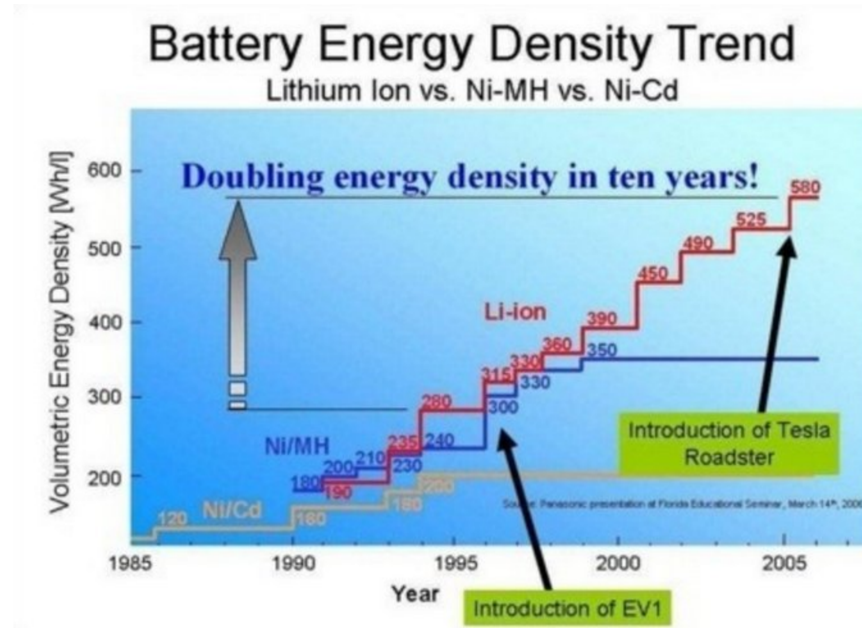
Energy Density = Energy/volume

also used for Energy/mass (***specific energy***)

Claus Ableiter / Wikimedia Commons

Energy / Classes of Operation / Battery





Energy / Classes of Operation / Supercaps

Lower specific energy than batteries, but constantly improving

Good for peak, trickle operations

Unit: F Farad

$$\mathrm{F} = \frac{\mathrm{s}^4\cdot\mathrm{A}^2}{\mathrm{m}^2\cdot\mathrm{kg}} = \frac{\mathrm{s}^2\cdot\mathrm{C}^2}{\mathrm{m}^2\cdot\mathrm{kg}} = \frac{\mathrm{C}}{\mathrm{V}} = \frac{\mathrm{A}\cdot\mathrm{s}}{\mathrm{V}} = \frac{\mathrm{W}\cdot\mathrm{s}}{\mathrm{V}^2} = \frac{\mathrm{J}}{\mathrm{V}^2} = \frac{\mathrm{N}\cdot\mathrm{m}}{\mathrm{V}^2} = \frac{\mathrm{C}^2}{\mathrm{J}} = \frac{\mathrm{C}^2}{\mathrm{N}\cdot\mathrm{m}} = \frac{\mathrm{s}}{\Omega} = \frac{1}{\Omega\cdot\mathrm{Hz}} = \frac{\mathrm{S}}{\mathrm{Hz}} = \frac{\mathrm{s}^2}{\mathrm{H}},$$

Energy / Classes of Operation / Battery

Storage material	Energy type	Specific energy (MJ/kg)	Energy density (MJ/L)	Uses
Deuterium (in Fusion reactor)	Nuclear fusion	87,900,000[3]	15,822[4]	Experimental
Uranium (in breeder)	Nuclear fission	80,620,000[5]	1,539,842,000	Electric power plants
Thorium (in breeder)	Nuclear fission	79,420,000[5]	929,214,000	Experimental
Plutonium 238	Nuclear decay	2,239,000	43,277,631	RTGs
Tritium	Nuclear decay	583,529	158[6]	Experimental, thermonuclear weapons
Hydrogen (liquid)	Chemical	142	10	Rocket engines, Fuel Cells, H2 Storage/Transport
Hydrogen (compressed at 700 bar)	Chemical	142	9.17	Fuel Cells, Natural Gas Heating Supplement
Methane or Liquefied natural gas (compressed)	Chemical	55.5	22.2	Cooking, home heating, electric power plants
Diesel	Chemical	48	35.8	Automotive engines, electric power plants
LPG (including Propane / Butane)	Chemical	46.4	26	Cooking, home heating, automotive engines, lighter fluid
Gasoline (petrol)	Chemical	46.4[2]	34.2	Automotive engines, electric power plants
Jet fuel (Kerosene)	Chemical	42.8[7]	37.4	Aircraft engines
Fat (animal/vegetable)	Chemical	37	34	Human and animal nutrition
Coal (anthracite or bituminous)	Chemical	~30	~38	Electric power plants, home heating
Methanol	Chemical	19.7	15.6	Fuel engines
Carbohydrates (including sugars)	Chemical	17	43	Human and animal nutrition
Protein	Chemical	16.8	~17	Human and animal nutrition
Wood	Chemical	16.2[8]	13	Home heating, cooking
Gunpowder	Chemical	4.7–11.3[9]	5.9-12.9	Explosives, Ammunition
TNT	Chemical	4.184	6.92	Explosives
Lithium metal battery	Electrochemical	1.8	4.32	Portable electronic devices
Lithium-ion battery	Electrochemical	0.36–0.875[12]	0.9–2.63	Automotive motors, portable electronic devices, RC vehicles
Flywheel	Mechanical	0.36–0.5	5.3	Power plants, Gyrobusses
Alkaline battery	Electrochemical	0.48[13]	1.3[14]	Portable electronic devices, flashlights
Nickel-metal hydride battery	Electrochemical	0.41[15]	0.504–1.46[15]	Portable electronic devices, flashlights
Lead-acid battery	Electrochemical	0.17	0.56	Automotive engine ignition
Supercapacitor (EDLC)	Electrical (electrostatic)	0.01–0.036[22]	0.05–0.06[23]	Electronic circuits
Electrolytic capacitor	Electrical (electrostatic)	0.00001–0.0002[24]	0.00001–0.001[27]	Electronic circuits

Source:https://en.wikipedia.org/wiki/Energy_density

Energy / Classes of Operation / Battery

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Electrolytic capacitor	Electrical (electrostatic)	0.00001–0.0002[24]	0.00001–0.001[27]

Specific Energy tangible:

Assume you can afford 100 g -

You run on 5 Volts -

How much capacity

(and thus time)

can you fit in?

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Assume a Li-Ion battery with 0.5 MJ/kg

www.menti.com - code 6736 8196

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Assume a Li-Ion battery with 0.5 MJ/kg

www.menti.com - code 6736 8196

Specific Energy made tangible, for 100 g battery

Assume LiPo battery with 200 Wh/kg =~ 0.72 MJ/kg

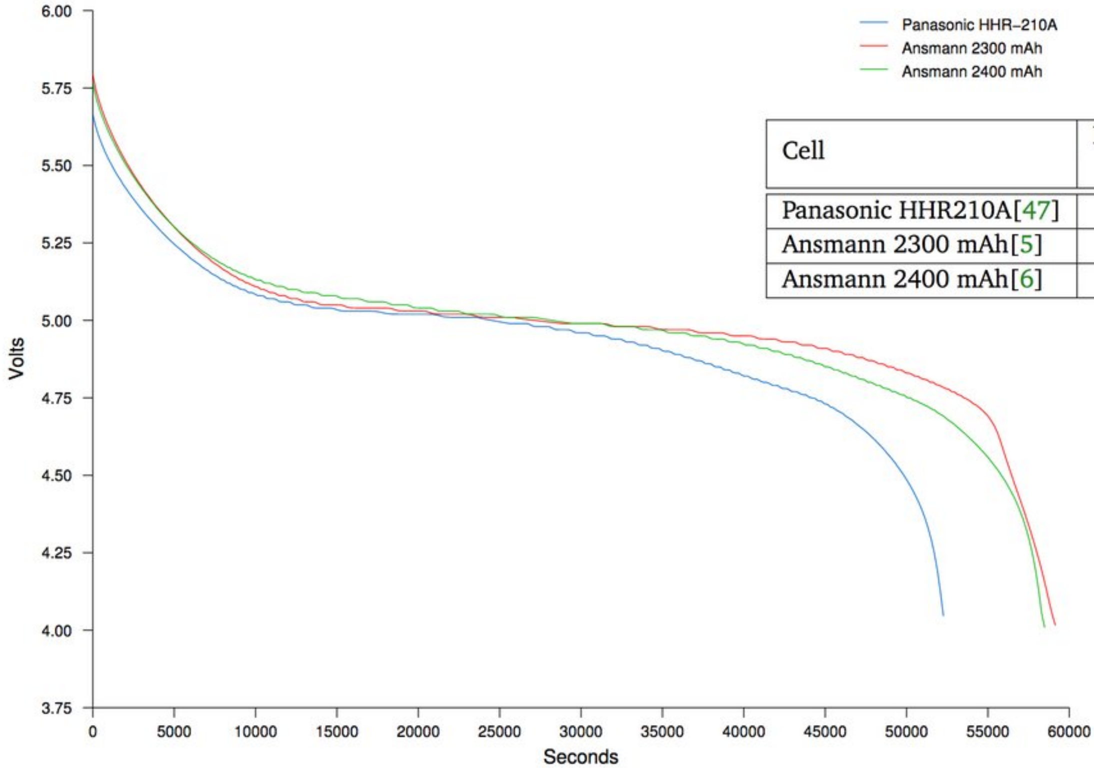
(because 100 Wh = 100 * 3600 Ws = 360000 J)

==> 20 Wh for 100 g

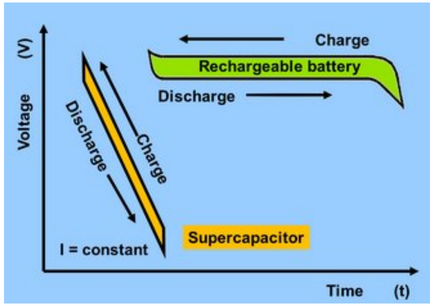
at 5 V:

4 Ah or 4000 mAh for 100 g

Time characteristics



Cell	Nominal Voltage	Manufacturer Capacity		Weight
Panasonic HHR210A[47]	1.2 V	2080 mAh	2496 mWh	29 g
Ansmann 2300 mAh[5]	1.2 V	2300 mAh	2760 mWh	28 g
Ansmann 2400 mAh[6]	1.2 V	2400 mAh	2880 mWh	30 g



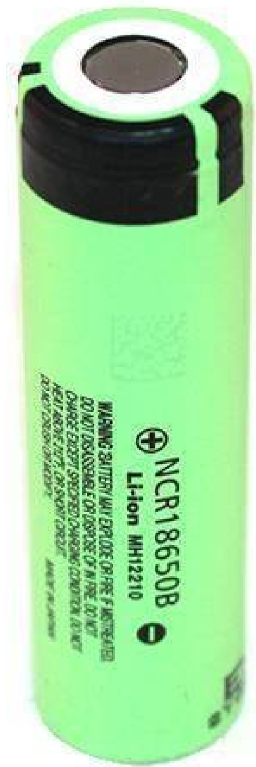
Data sheet

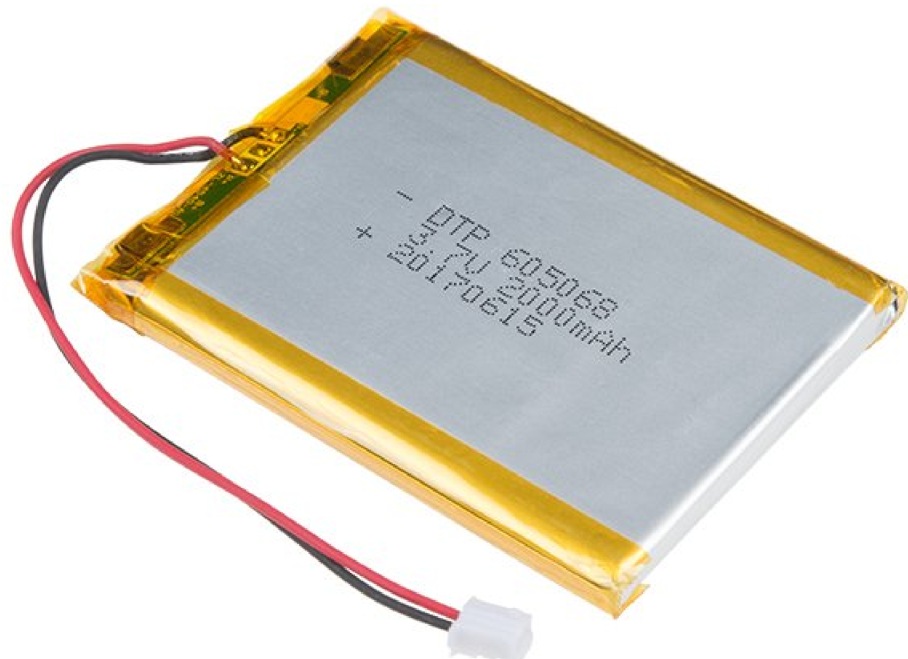
Item		Specifications	Remark
Nominal Capacity		2200mAh ±2%	$0.2C_5A$ discharge，25℃
Nominal Voltage		3.7V	Average Voltage at $0.2C_5A$ discharge
Standard Charge Current		$0.2\ C_5A$	Working temperature：0～40℃
Max Charge Current		$1C_5A$	Working temperature：0～40℃
Charge cut-off Voltage		4.2V	CC/CV
Standard Discharge Current		$0.5C_5A$	Working temperature：25℃
Discharge cut-off Voltage		2.75V	
Cell Voltage		3.7-3.9V	When leave factory
Impedance		≤35mΩ	AC 1KHz after 50% charge,25℃
Weight		Approx:48.0g	
Storage temperature	≤1month	-10～45℃	Best 20±5℃ for long-time storage
	≤3month	0～30℃	
	≤6month	20±5℃	
Storage humidity		65±20% RH	

* the notation $0.5C_5A$: C = the capacity of a battery
C_5 = capacity of a battery measured over 5 hours.
$0.5C_5A$ means: charge at 0.5 x that battery capacity/hour.
Example: 2200mAh battery, charge at 1100mA.

https://cdn-shop.adafruit.com/datasheets/1781Battery_2200mAh.pdf

Popular types





Energy / Classes of Operation / Autonomous

Semi-autonomous

e.g. car sensor depending on car power

Bicycle sensor on dynamo

Fully autonomous (and renewable) - **“Harvesting”**

Dependent or independent

of the system that is being sensed.

(Consider advantages/disadvantages)

Energy / Harvesting

Solar

Kinetic/mechanical

Thermal

RF / wireless

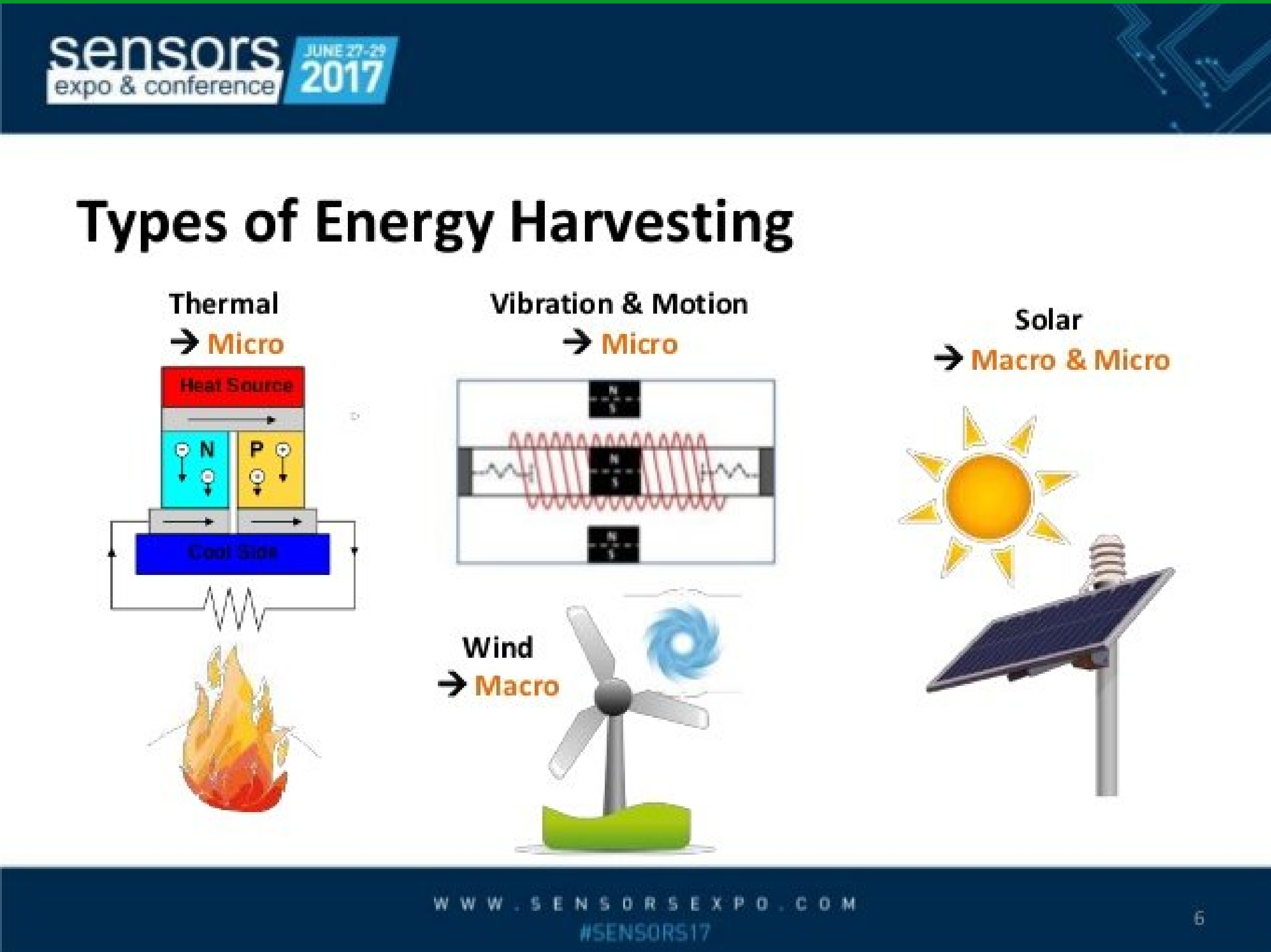
Hydro

Wind **a.o.**

(sometimes combined, all typically with temporary storage)

Good intro: https://www.electronicdesign.com/power/these-5-iot-energy-harvesting-options-stand-out-field

Energy / Harvesting



Energy / Harvesting

Energy-Harvesting Sources Today			
Energy Source	**Characteristics**	**Efficiency**	**Harvested Power**
Light	Outdoor Indoor	10~24%	100 mW/cm^2 100 μW/cm^2
Thermal	Human Industrial	~0.1% ~3%	60 μW/cm^2 ~1-10 mW/cm^2
Vibration	~Hz–human ~kHz–machines	25~50%	~4 μW/cm^3 ~800 μW/cm^3
RF	GSM 900 MHz WiFi	~50%	0.1 μW/cm^2 0.001 μW/cm^2

Courtesy of Texas Instruments

Energy / Harvesting / Criteria for choice

Power needed

Space / weight available

Availability of source – location?

Durability

Maintenance

Moving parts?

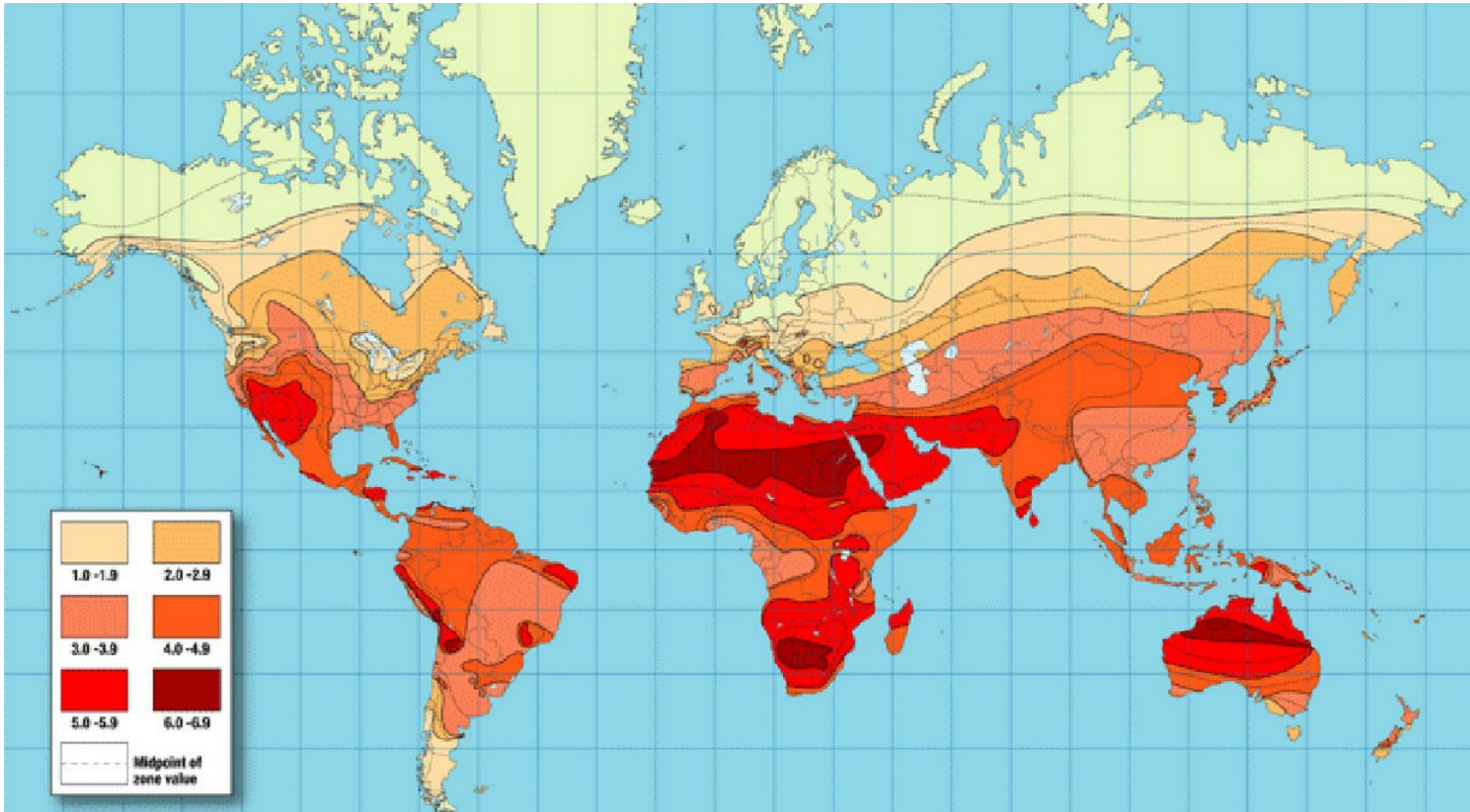
Among the most important power sources

Key figures:

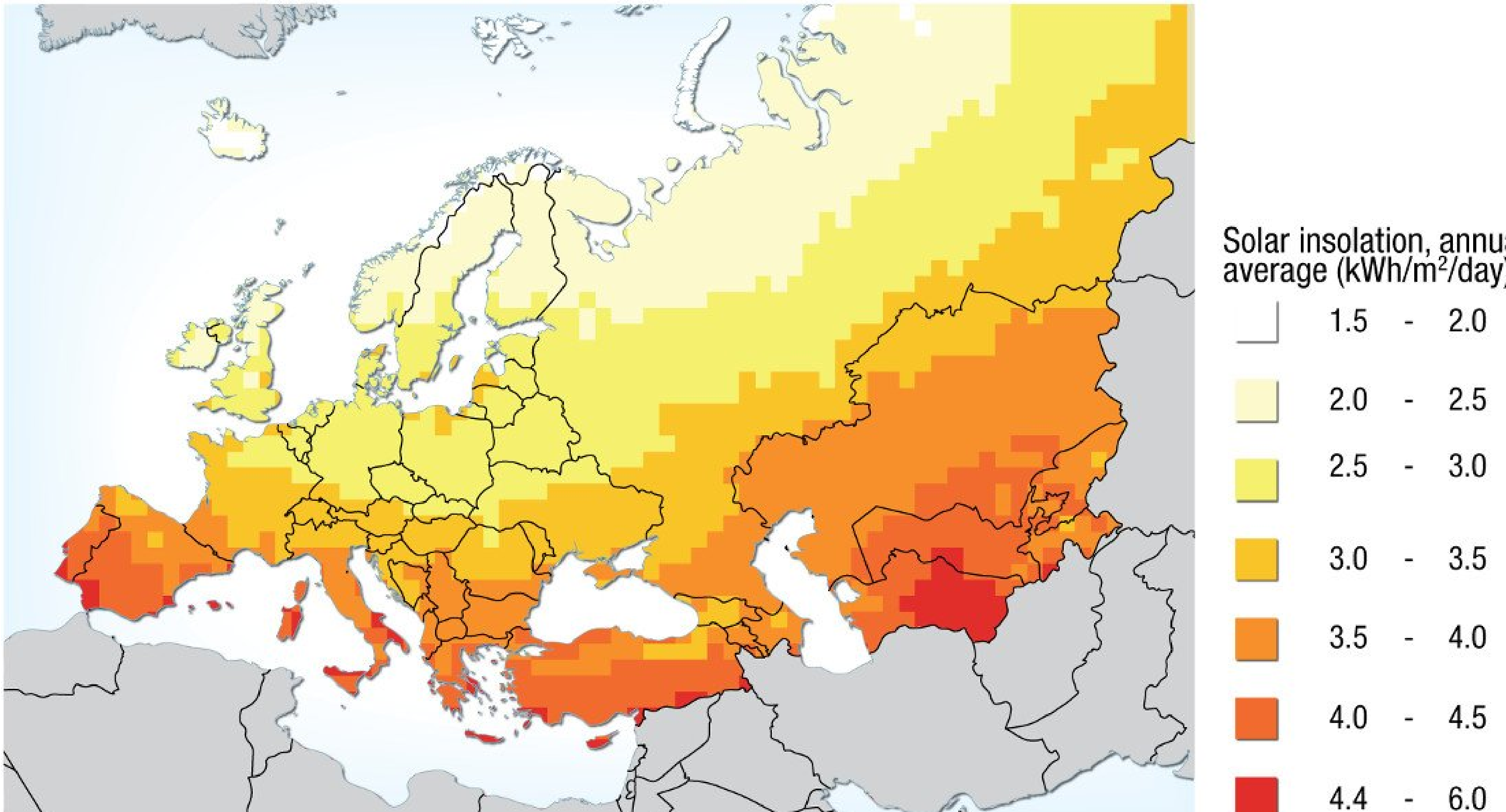
- **Insolation / Irradiation: 1kW/m^2**
- **Efficiency: … 15-20%**
- **Cost: < EUR 1/Watt**

Types: mono-, polychrystalline, amorphous, thin film, organic, ..

Concept of “peak hours”: Equivalent of an hour in full sun

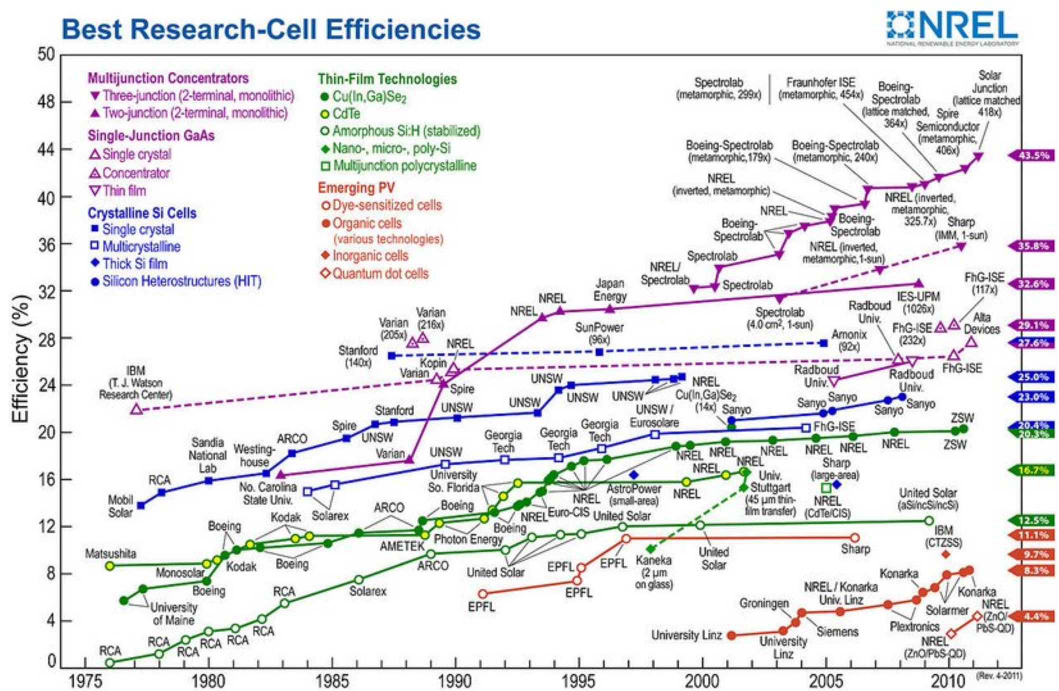


Energy / Harvesting / Solar / Insolation

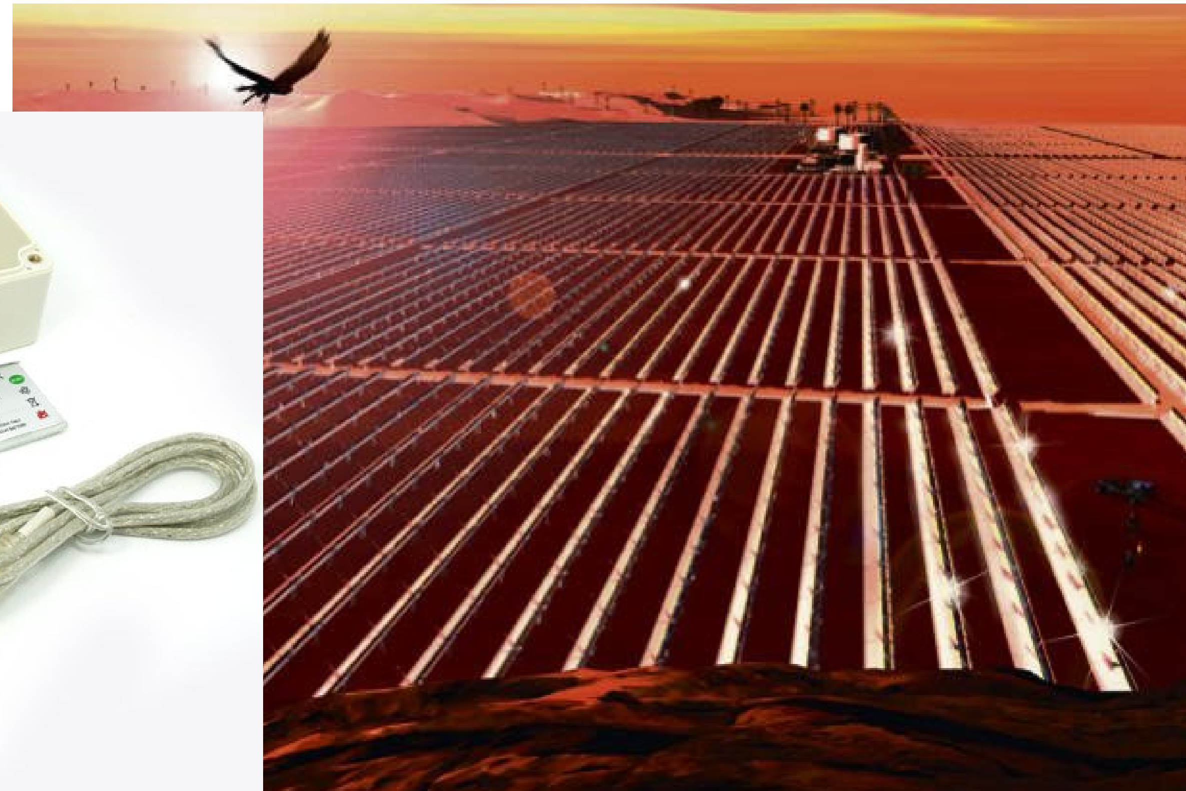


Energy / Harvesting / Solar / Efficiencies

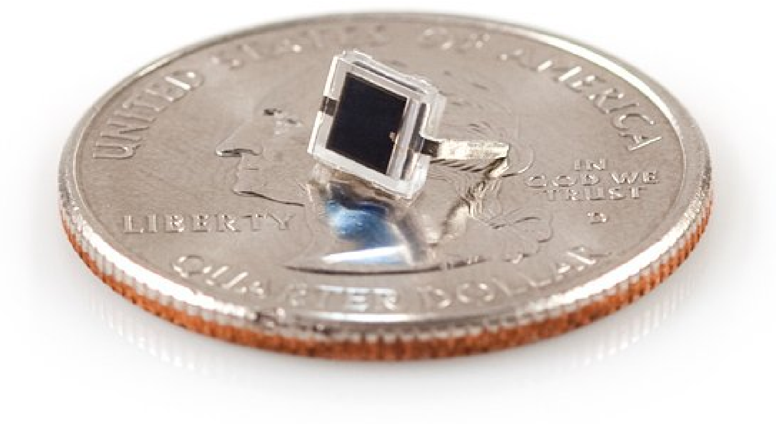
Manufacturer Name	Module Model Number	PTC	Area (sqft)	PTC/ Sqft	Description
SunPower Corporation	SPR-230-WHT-U	209.5	13.395	15.64	230W Monocrystalline Module, White Backsheet
SunPower Corporation	SPR-225-BLK-U	201.9	13.395	15.073	225W Monocrystalline Module, Black Backsheet
Sanyo Electric Co. Ltd.	HIP-215NKHA1	199.6	13.486	14.801	215W HIT Power N Hybrid Amorphous/Monocrystalline
SunPower Corporation	SPR-220-WHT-U	198.2	13.395	14.797	220W Monocrystalline Module, White Backsheet
SunPower Corporation	SPR-220-BLK-U	197.3	13.395	14.729	220W Monocrystalline Module, Black Backsheet
Sanyo Electric Co. Ltd.	HIP-210NKHA1	194.9	13.486	14.452	210W HIT Power N Hybrid Amorphous/Monocrystalline
SunPower Corporation	SPR-215-WHT-U	193.5	13.395	14.446	215W Monocrystalline Module, White Backsheet
Sanyo Electric Co. Ltd.	HIP-205BA19	190.7	13.486	14.141	HIT Power 205W - Hybrid Amorphous/Monocrystalline
SunPower Corporation	SPR-210-WHT-U	189	13.395	14.11	210W Monocrystalline Module, White Backsheet
Sanyo Electric Co. Ltd.	HIP-205NKHA1	190.2	13.486	14.104	205W HIT Power N Hybrid Amorphous/Monocrystalline
SunPower Corporation	SPR-210-BLK-U	188.1	13.395	14.043	210W Monocrystalline Module, Black Backsheet
SunPower Corporation	SPR-205-BLK-U	183.6	13.395	13.707	205W Monocrystalline Module, Black Backsheet
Schuco USA LP	SPV 210 SMAU-1	192.1	15.766	12.184	210W Monocrystalline Module, Black Frame
Siliken California Corp	SLK60P6L 235 Wp	210.7	17.476	12.056	235W Polycrystalline Module
Siliken California Corp	SLK60P6L 230 Wp	206.1	17.476	11.793	230W Polycrystalline Module
REC ScanModule AB	REC230AE-US (BLK)	200.7	17.025	11.789	230W Polycrystalline Module, High Performance
Solon Ag Fuer Solartechnik	P220/6+/01 235Wp	208	17.653	11.783	235W Polycrystalline Module
Suntech Power Co.	STP280-24/Vb-1	246	20.908	11.766	280W Polycrystalline Module, MC Connectors
ET Solar Industry, Ltd	ET-P672270	241.8	20.908	11.565	270W Polycrystalline Module
aleo solar AG	S18.230	204.5	17.689	11.561	230W Polycrystalline Module
REC ScanModule AB	SCM225	196.5	17.025	11.542	225W Polycrystalline Module
Siliken California Corp	SLK60P6L 225 Wp	201.5	17.476	11.53	225W Polycrystalline Module
Solon Ag Fuer Solartechnik	P220/6+/01 230Wp	203.4	17.653	11.522	230W Polycrystalline Module
ET Solar Industry, Ltd	ET-P672265	237.1	20.908	11.34	265W Polycrystalline Module
Suntech Power Co.	STP270-24/Vb-1	236.9	20.908	11.331	270W Polycrystalline Module, MC Connectors
aleo solar AG	S18.225	199.9	17.689	11.301	225W Polycrystalline Module
Sharp Corporation	ND-U230C1	198	17.541	11.288	230W Polycrystalline Module, Locking Connector
Solartech Power Inc.	SPM230P	197.9	17.541	11.282	230W Polycrystalline Module
REC ScanModule AB	SCM220	192	17.025	11.278	220W Polycrystalline Module
Siliken California Corp	SLK60P6L 220 Wp	197	17.476	11.272	220W Polycrystalline Module



Photovoltaics scale from nW to 100s of MW



1 kW/m² insolation



= how much per mm²?

Energy / Harvesting / Solar for TinyML

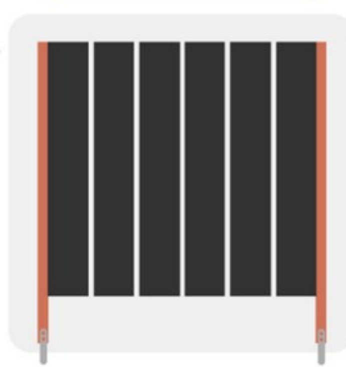
Low Power IoT
Sustainability
TinyML is (soon) becoming an option for
battery-less, energy-harvesting approaches to IoT

DRACULA TECHNOLOGIES

Standard demokit performance

DEMOKIT #6 PERFORMANCES BETWEEN 50 - 1000 LUX

Illumination (lux)	Voc (V)	Isc (µA)	Vmax (V)	Imax (µA)	Pmax (µW)
50	3	17	2,35	13	31
200	3,4	72	2,7	59	160
500	3,65	171	2,8	138	386
1000	3,7	322	2,85	263	750



source: Dracula OPV

Energy / Harvesting / Kinetic

Principle: convert any form of movement/vibration into electrical energy,

By means of piezo effect

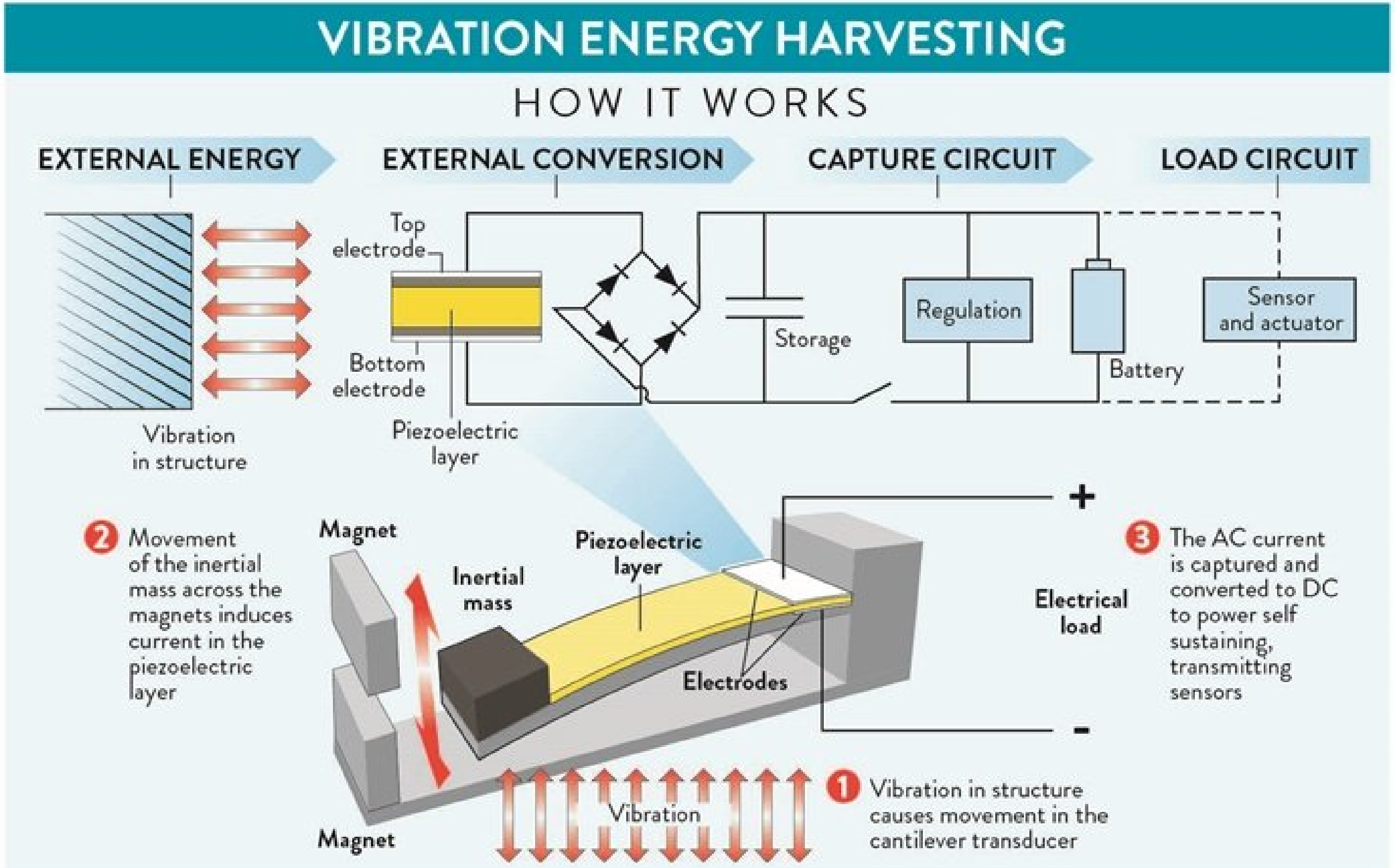
MEMS

Typically well below < 1mW, ~100 uW

in appropriate size constraints (~ 100 $mm^{2)}$)

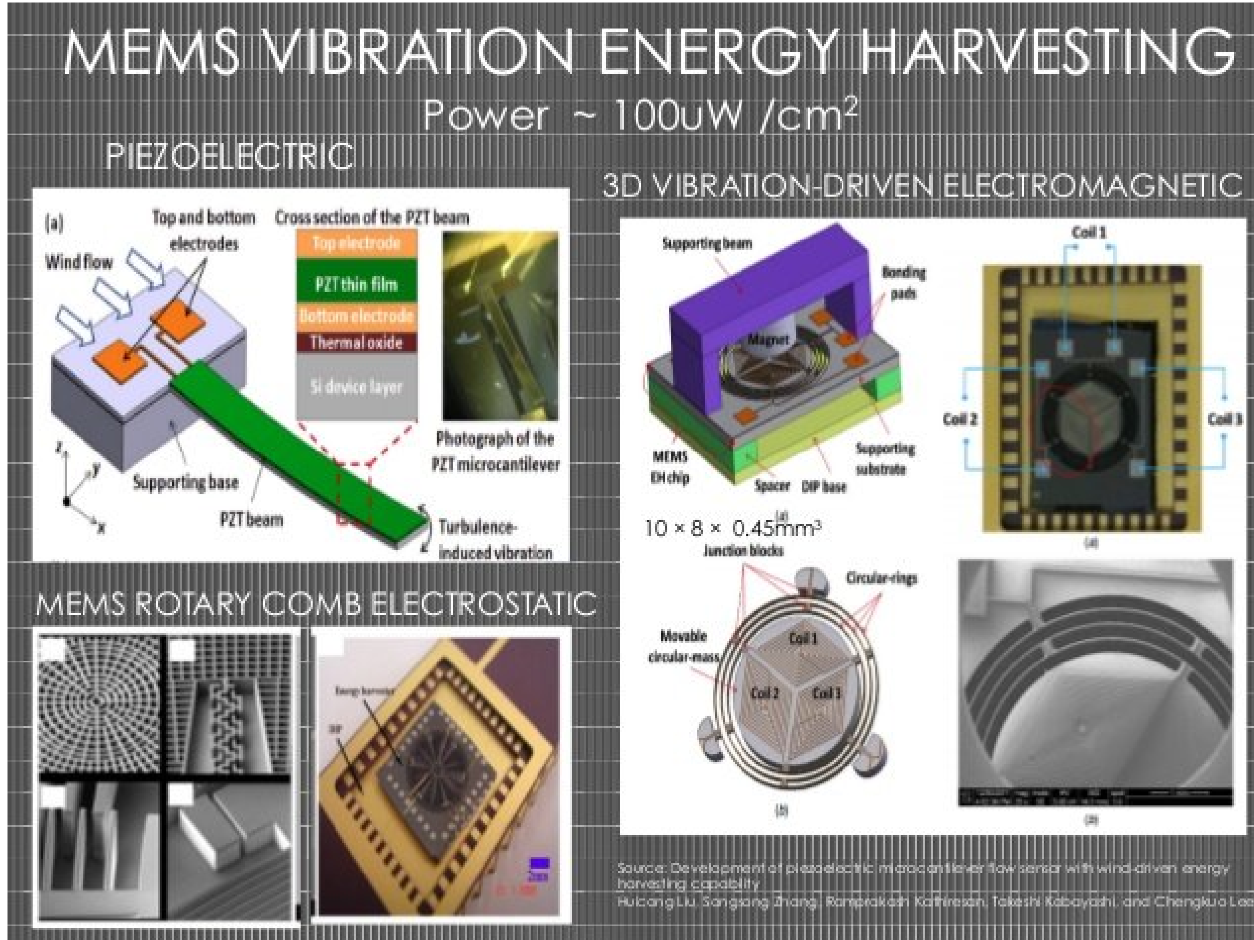
sources: https://spectrum.ieee.org/nanoclast/energy/renewables/a-mems-vibration-energy-harvester-for-the-iot
https://www.analog.com/en/technical-articles/microgen-s-piezo-mems-vibration-energy-harvesters-enable-linear-technology-smartmesh-ip-wireless.html
https://www.analog.com/en/parametricsearch/11503
https://www.newcivilengineer.com/technical-excellence/smart-infrastructure-vibration-energy/10008070.article

Energy / Harvesting / Kinetic

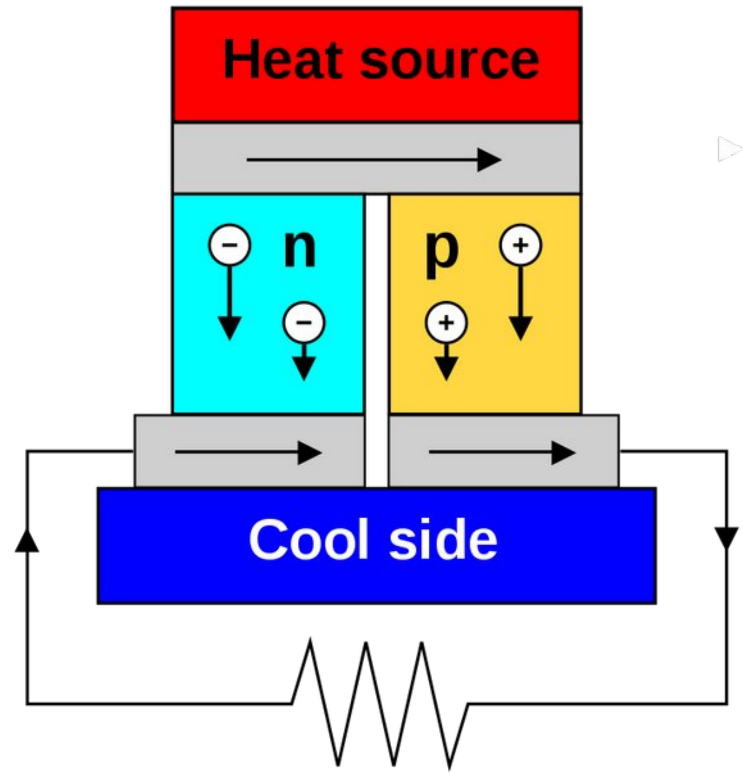


sources:
https://www.newcivilengineer.com/technical-excellence/smart-infrastructure-vibration-energy/10008070.article

Energy / Harvesting / Kinetic

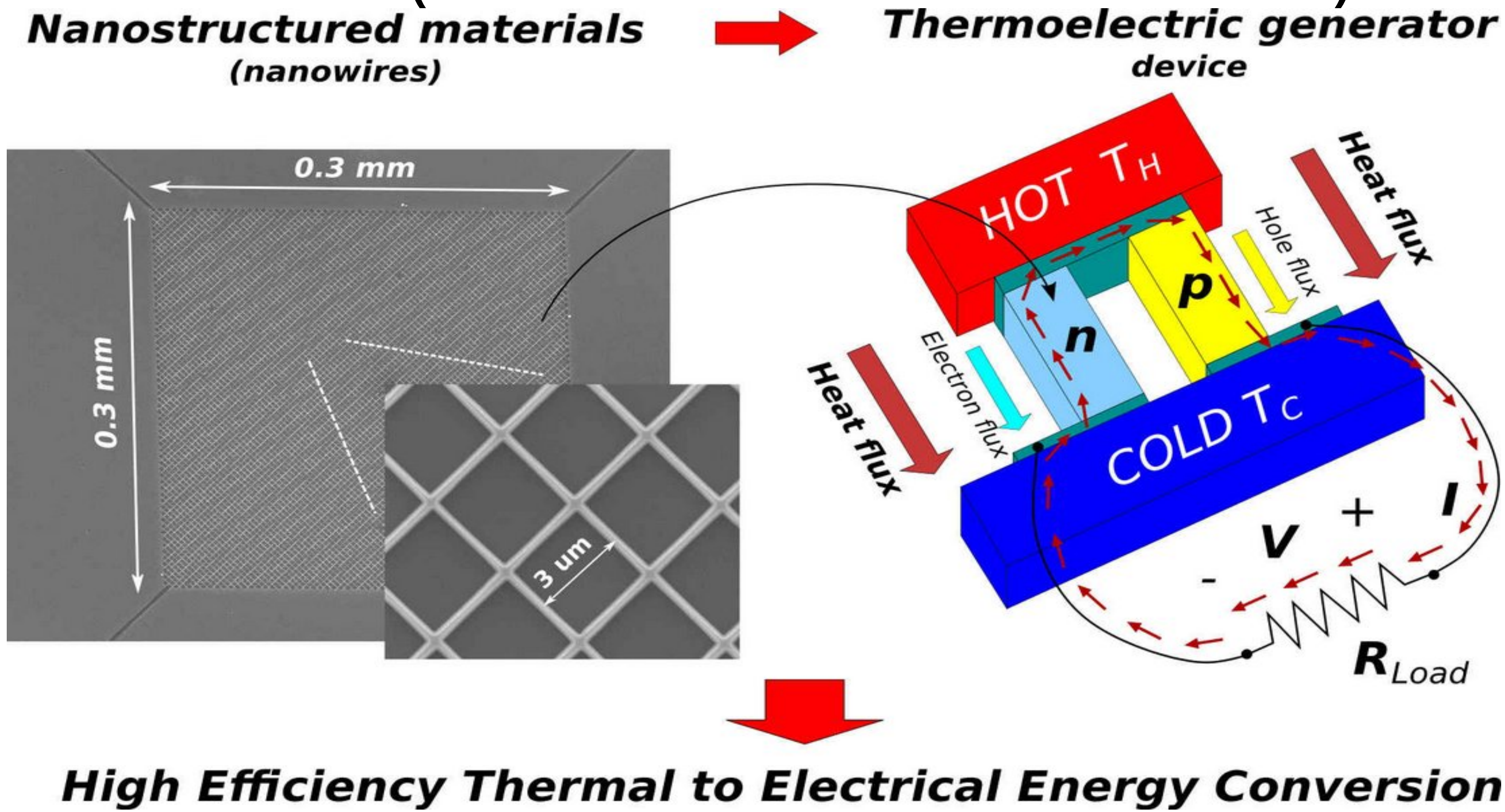


Thermolectric (Peltier / Seebeck / Thomson) effect

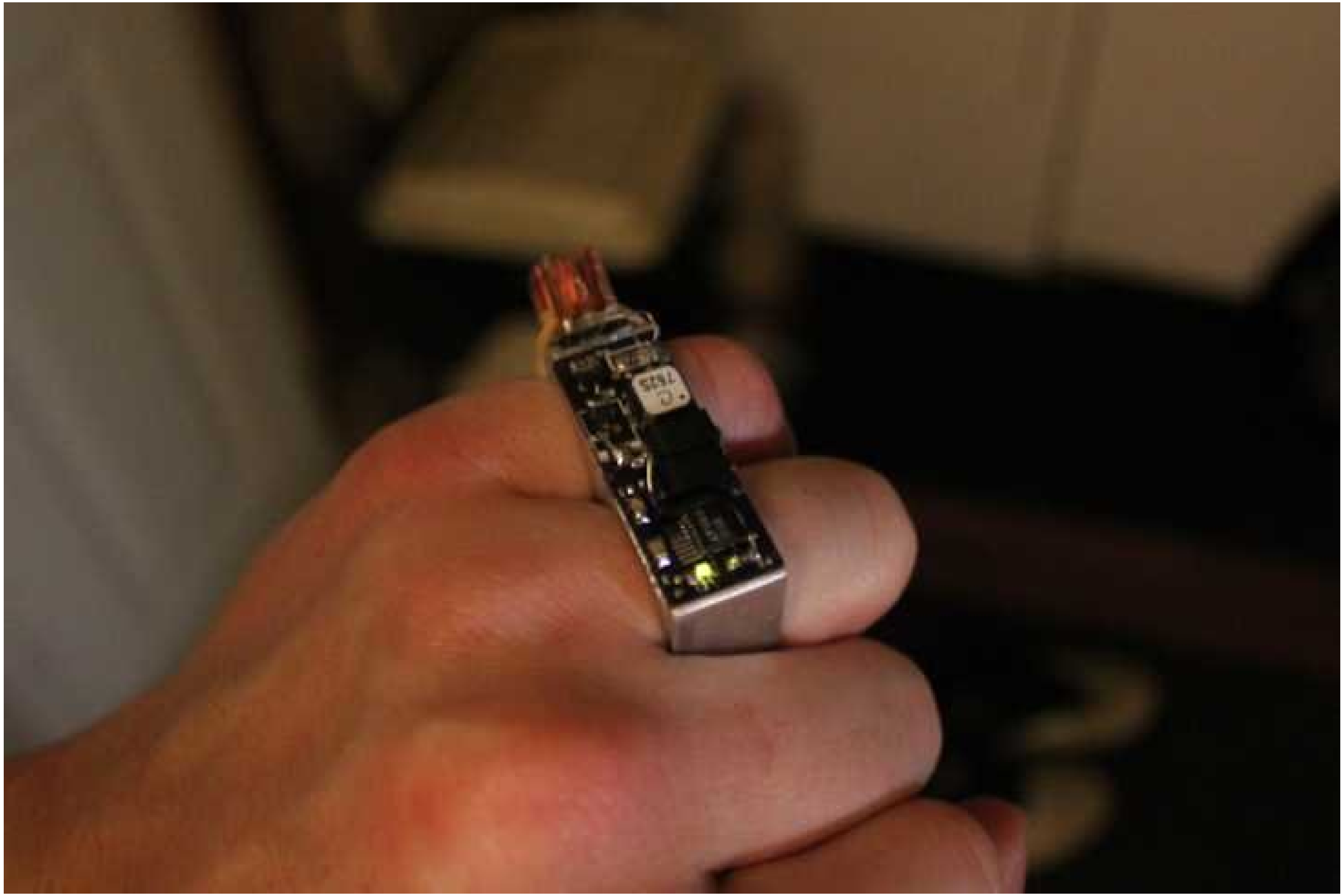


Key figures:

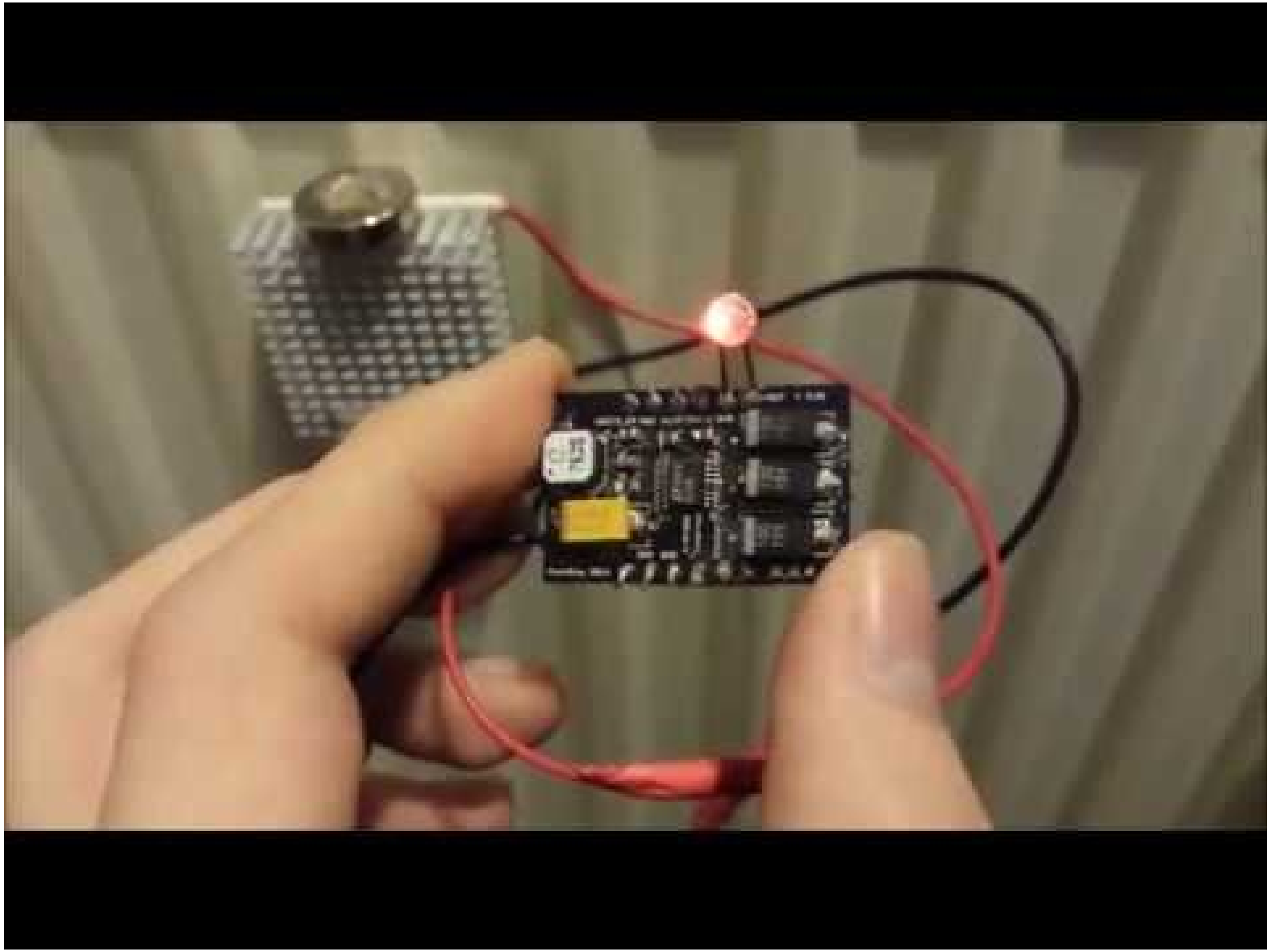
Thermolectric (Peltier / Seebeck / Thomson) effect



Energy / Harvesting / Thermal



Energy / Harvesting / Thermal



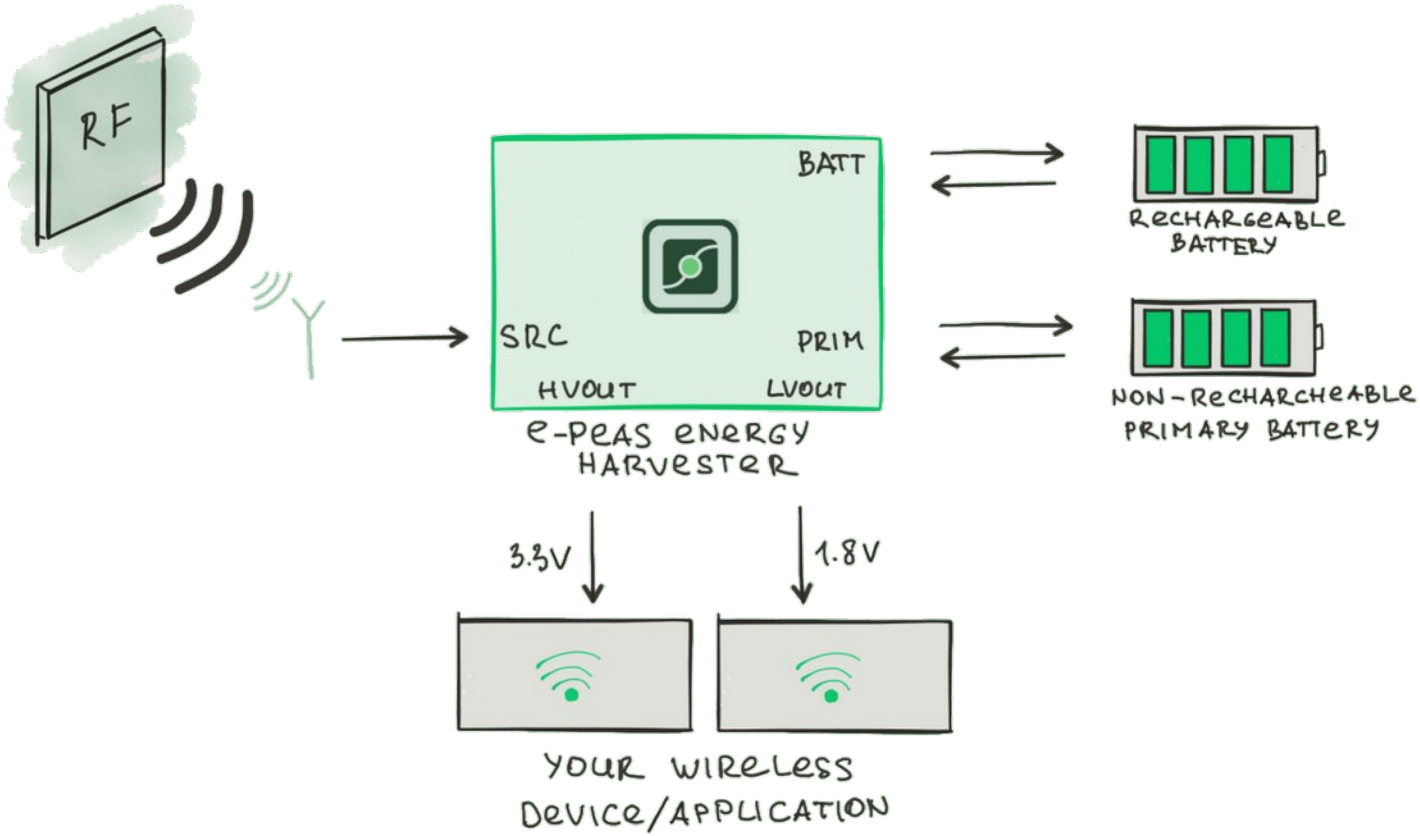
Energy / Harvesting / RF, Wireless

Any wireless receiver is de-facto harvesting energy - just not with a goal of supplying power.

Depends on **presence of RF/wireless “noise”**, such as 433 / 868/915 MHz / 2.4 GHz

10 uW .... mW, depending on source, size, antenna

Energy / Harvesting / RF, Wireless



Source: https://e-peas.com/types/energy-harvesting/rf/

Energy / Harvesting / RF, Wireless

Source:
https://www.arrow.com/en/research-and-events/articles/the-future-of-energy-harvesting-iot-applications

Hydro & Wind

tend to be less important in IoT,

More suitable for macro scale,

however micro scale is possible.

Minimizing energy consumption, by implementing effective

duty cycles:

(Deep) Sleep cycles

~mA for normal sleep

(modem sleep, light sleep)

~uA for deep sleep

Wake-up on

Timer/clock (on-board)

External interrupt, event, network, ..

Power & Networking - Wi-Fi

The main power cost is transmission/networking

(no rule without exception though – need to verify!)

Processor: typically < 1 nJ per Instruction (calculate by comparing MIPS and power)

Acquiring a digital data sample from a sensor: order of 1 nJ

Networking: Example: Wi-Fi

100 mW (pure radio power, no periphery) gives you in the range of 10 Mb/s

==> 10 nJ/bit ==> 100 nJ / 10bit sample

Power uptake of radio chips is typically several times the radio output power (scales quadratically with distance)

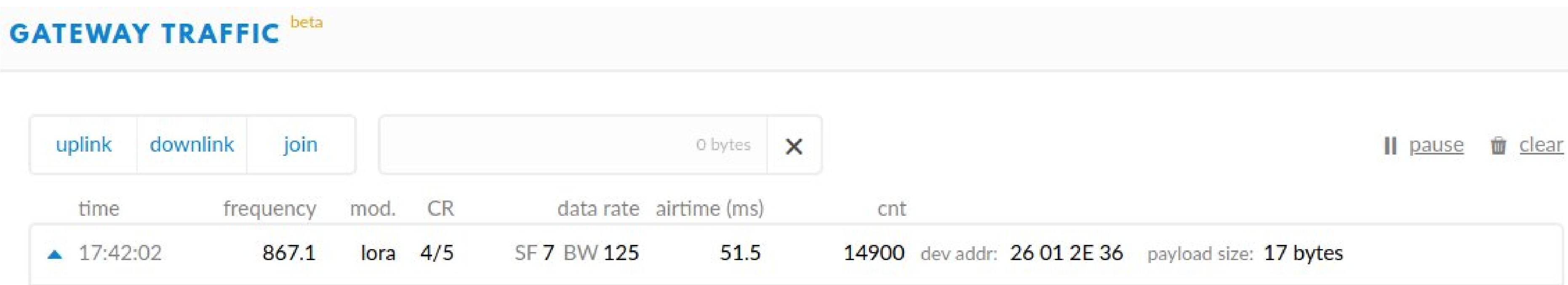
==> Sending the sample requires 100x more power than sampling it!

Power & Networking - LoRa

Networking: Example: LoRa

14 dBm = 25 mW (pure radio power, no periphery) gives you in the range of kb/s ==>

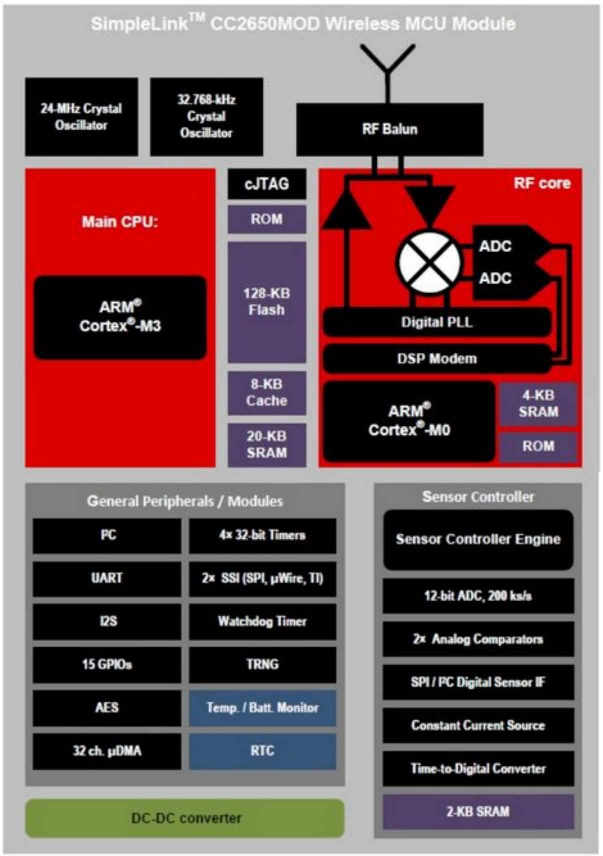
Example 50 ms on air for 17 bytes (one 4 byte measurement plus headers)

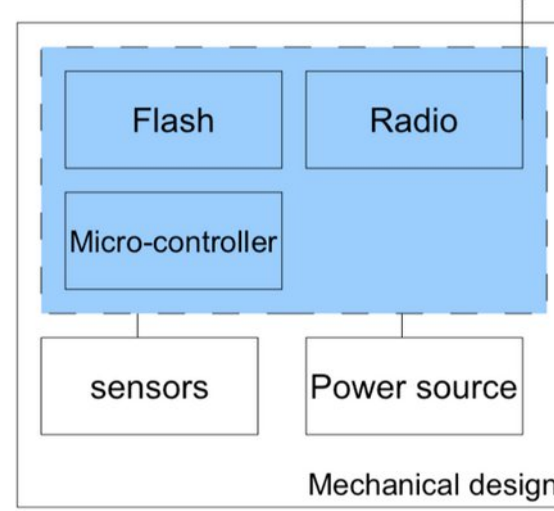


50 ms x 25 mW = 0.00125 Ws = 1 mWs per measurement

IoT and Energy / Minimizing power

Duty cycles: components





PARAMETER		TEST CONDITIONS	MIN	TYP	MAX	UNIT
Peripheral Current Consumption (Adds to core current I_{core} for each peripheral unit activated)[1]						
I_{peri}	Peripheral power domain	Delta current with domain enabled		20		µA
	Serial power domain	Delta current with domain enabled		13		
	RF core	Delta current with power domain enabled, clock enabled, RF Core Idle		237		
	µDMA	Delta current with clock enabled, module idle		130		
	Timers	Delta current with clock enabled, module idle		113		
	I²C	Delta current with clock enabled, module idle		12		
	I2S	Delta current with clock enabled, module idle		36		
	SSI	Delta current with clock enabled, module idle		93		
	UART	Delta current with clock enabled, module idle		164		

IoT and Energy / Minimizing power

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http://uk.farnell.com/calculating-battery-life-in-iot-applications

LoRa case study: Spreading factor & battery life

Case:

- Housing Cooperative buys 150+ water meters
- **battery life, optimal usage**: 15+ years
- what defines optimal usage*?

  most of all, **Spreading Factor** SF7

  SF12 has 26 times the airtime! ($2^{12}/2^{7}$ = 32, some correction due to preamble etc)

  Spreading factor determined by gateway positioning, signal strength

  → external to the sensor node, out of control for vendor or user
- Spreading Factor directly impacts battery life
- sensor nodes are single-use devices with regards to battery –

  when battery empty, you throw them out

  (reason: warranty for IP6x waterproofness – whole device is sealed)

- huge implications both economically and environmentally!

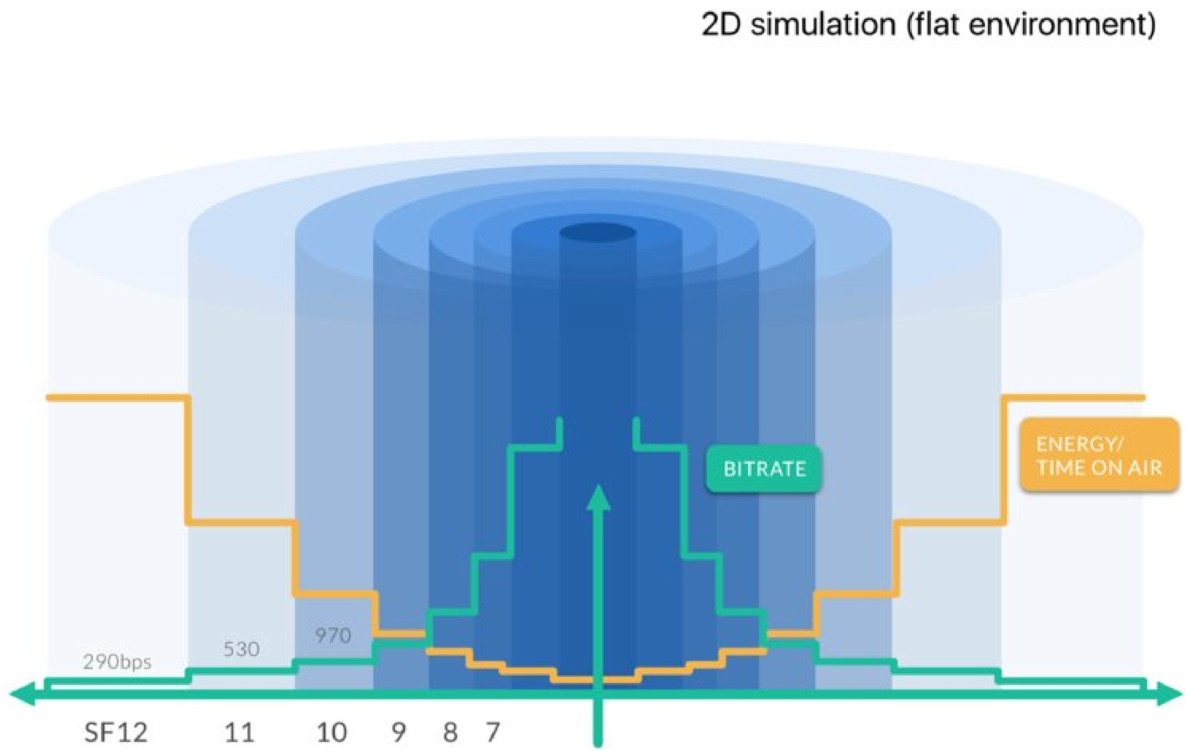
- * other factors: temperature, environment

LoRa case study: Spreading factor & battery life

Example : Axioma datasheet

Laskennalliset parametrit							LoRa patterinkesto kun lähetyksiä		
Spreading Factor	BW	Physical Bit Rate (bit/s)	Payload Length	Transmission time (ms)	Patterin kapasiteetti	Patterin purkautuminen	1 lähetys / vrk	6 lähetystä / vrk	12 lähetystä / vrk
SF 12	125kHz	250	37 bytes	1952	2700mAh	2% vuodessa	> 16 vuotta	> 15 vuotta	> 7 vuotta
SF 11		440		1109				> 16 vuotta	> 10 vuotta
SF 10		980		498					> 16 vuotta
SF 9		1760		277					
SF 8		3125		156					
SF 7		5470		89					

LoRa case study: Spreading factor & battery life

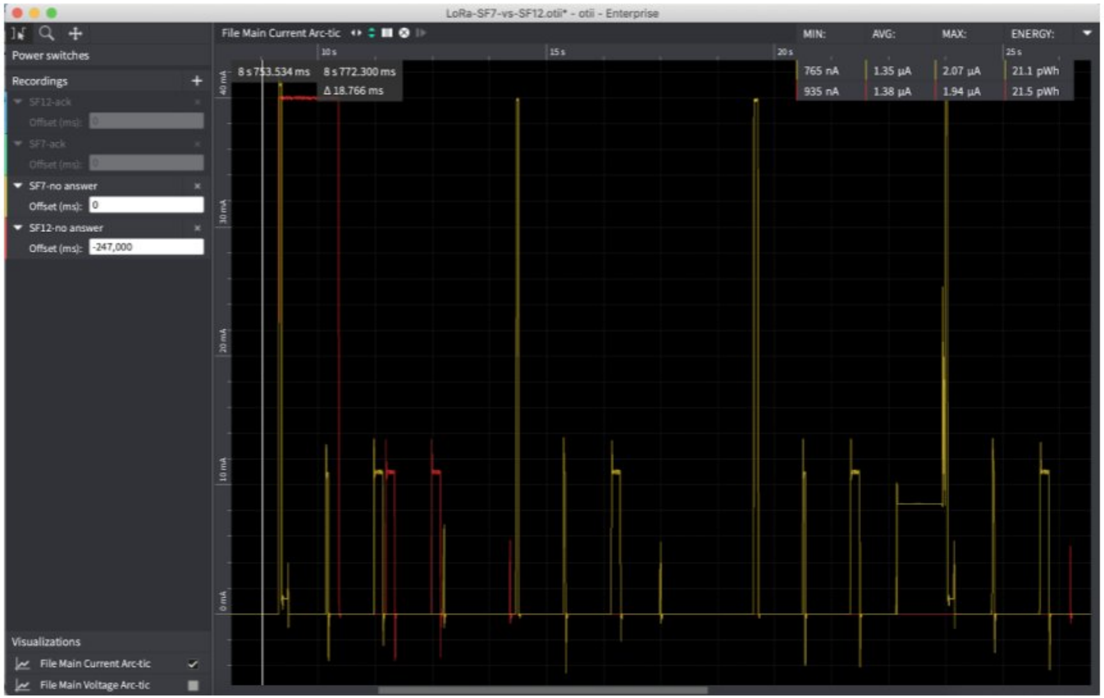


source : Qoitech / Otii

Power measurements

Because of network/environment/antenna dependencies,

only measurement gives real data!



Power measurements

How long can you run your sensor node on a 5 V/10000 mAh power bank?

Minutes? Hours? Years?

(There isn’t one correct answer – it s all about the discussion of how you implement!)

www.menti.com - 8102 5165

IoT and Energy Transition

Main challenge:

Transition from stable centralized fossile energy

to

Renewables dependent on environmental factors

Matching demand and supply.

Flexibility. Storage. Temporality.

Hybrid networks (e.g. El/Heat)

IoT and Energy / ”Smart Grid”

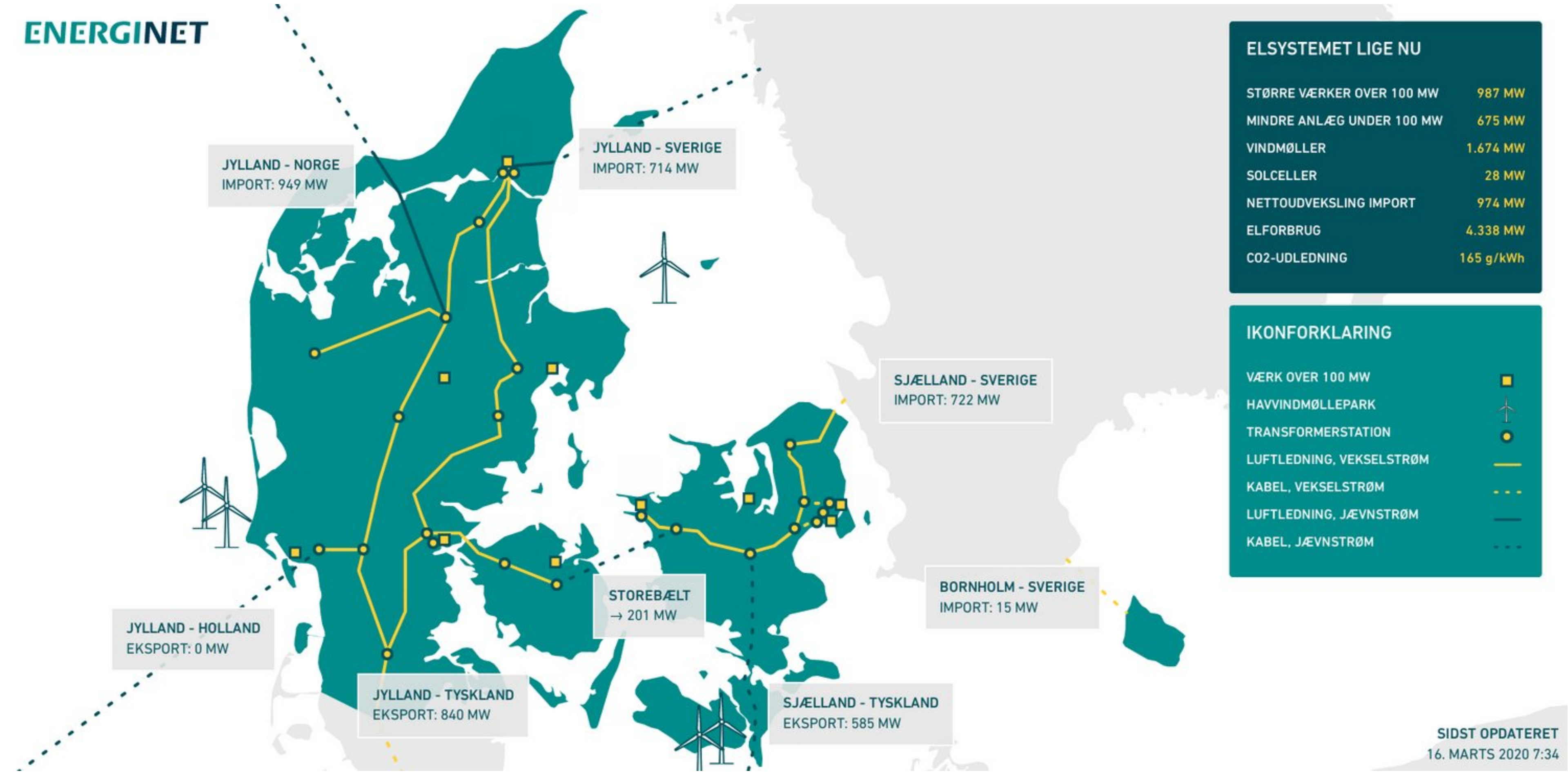
Collaborative Innovation

IBM er en af de væsentligste deltagere i ECOGRID - EU's største satsning på Smart Grid.

24

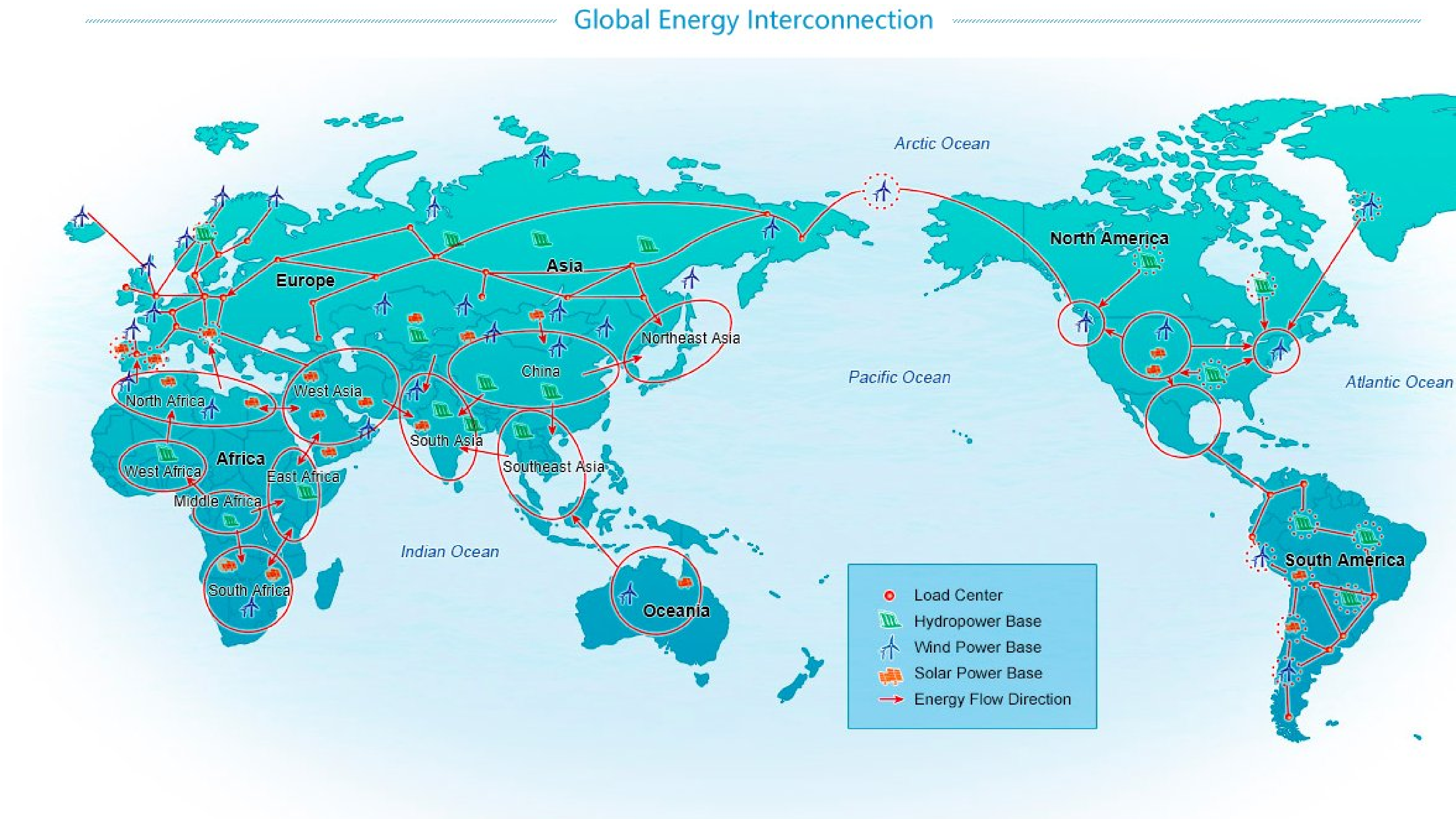
IoT and Energy / ”Smart Grid”

IoT and Energy / Energinet



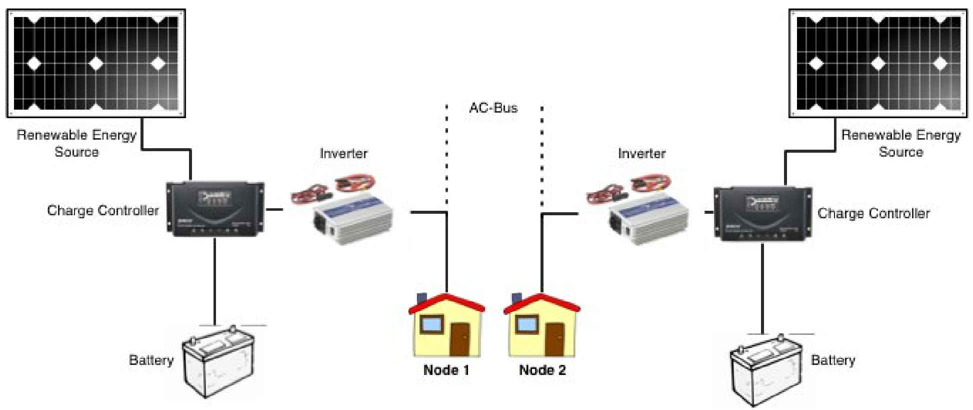
source: energinet.dk

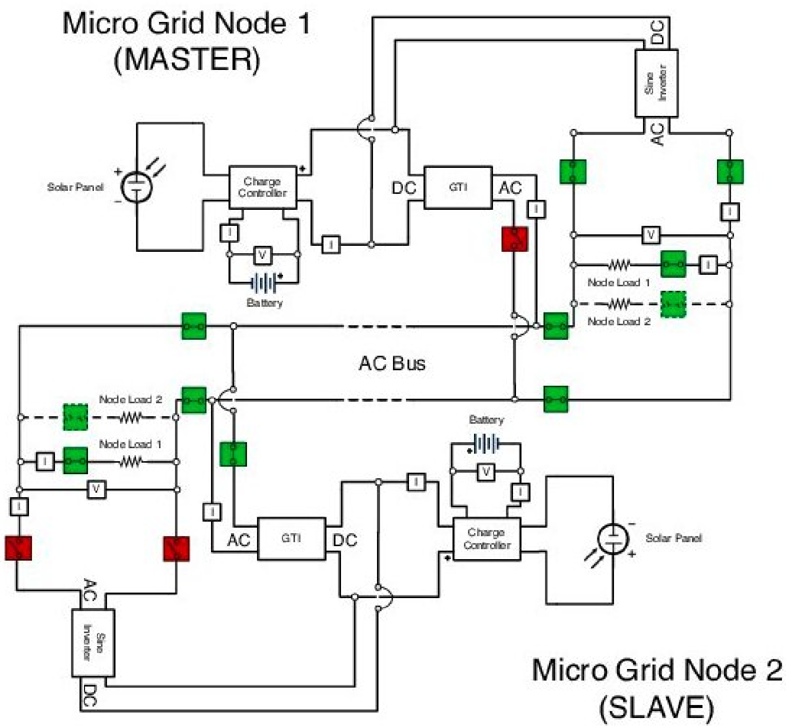
IoT and Energy / Global scale



source: geidco.org

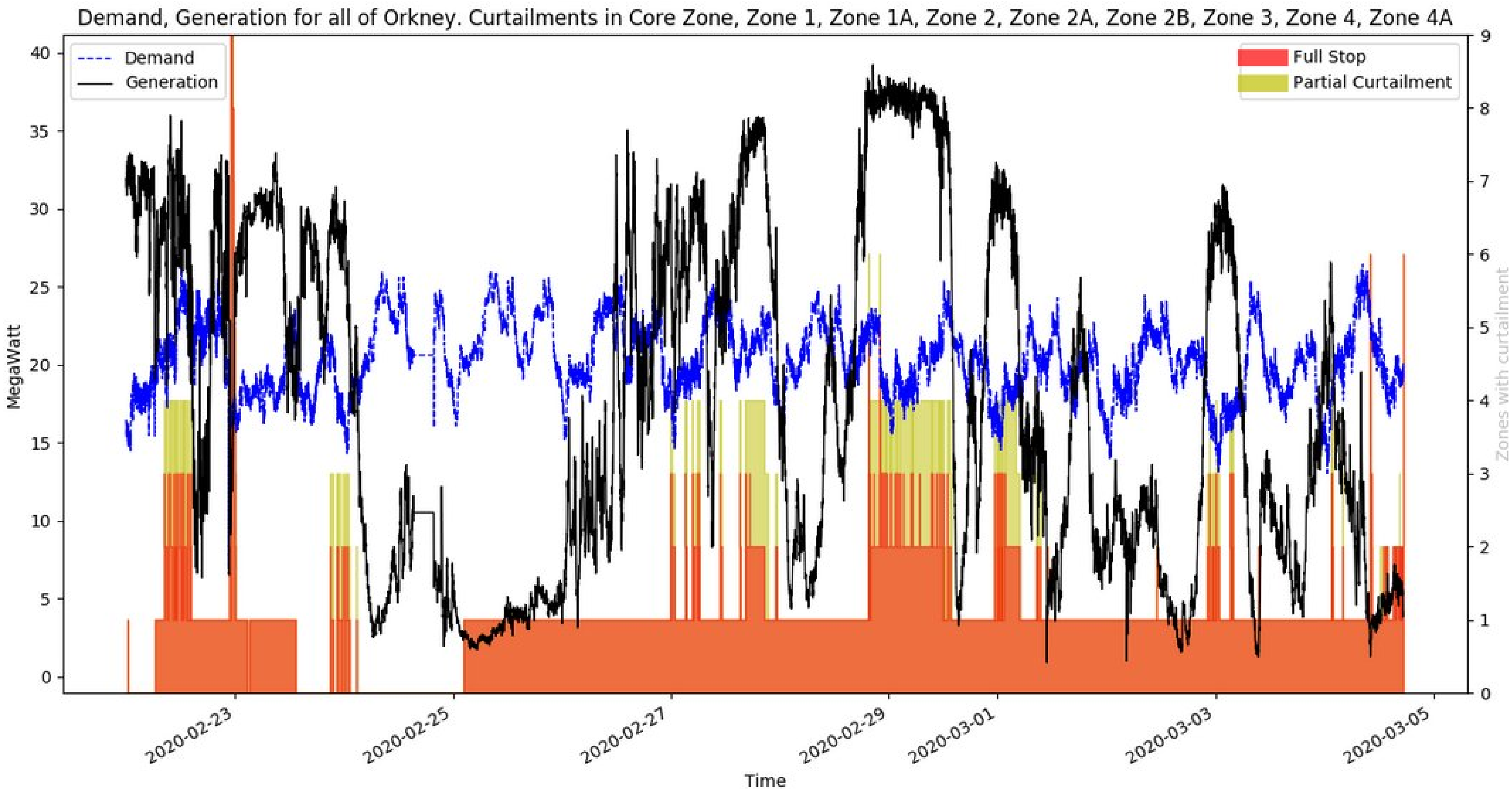
IoT and Energy / ITU COSMGrid





COSMGrid: Bonnet, Fürst, Büttrich 2013

IoT as optimizer: Orkney curtailment modeling



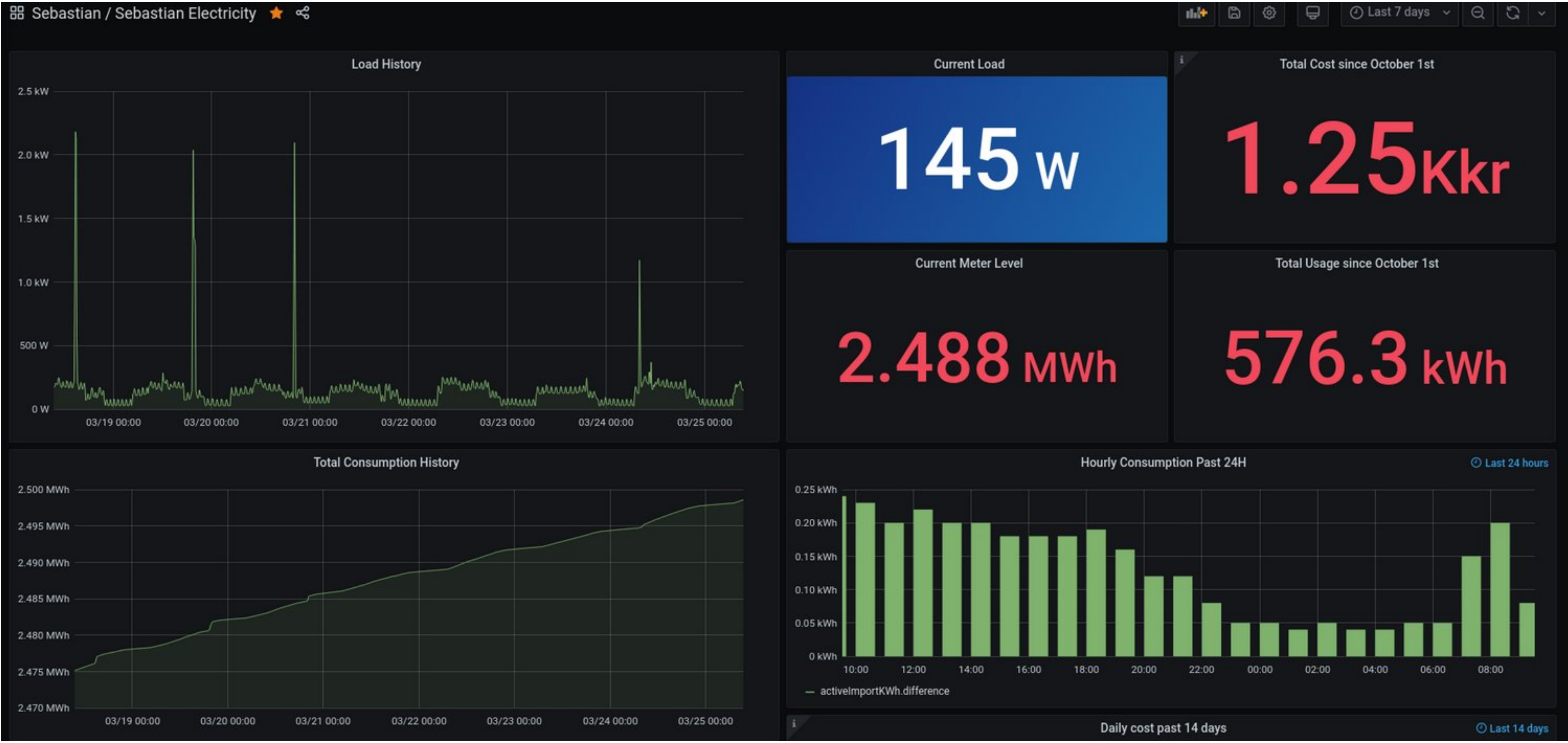
IoT as optimizer: smart meters in Denmark

- **European law demands remote readable meters**
- **(To be) deployed in 1.x million households in Denmark**
- **Mostly wireless, Wireless MBUS, 440 MHz, communication via Concentrators (= gateways), approx 300 devices per concentrator**

IoT as optimizer: DIY data work

- **Wemos / Lolin board, WiFi**
- **Powered by meter (75 mA)**
- **Supercapacitor as power assistance**

IoT as optimizer: DIY data work



IoT as optimizer: smart meters in Denmark

- **Smart meters = valuable data source**
- **Modern meters have 50+ sensors**
- **Highly personal data,**

  in context of GDPR
- **Technically, aggregation over some 10 households could be sufficient for modeling and controlling, however other interests are at play**

Smart meters & GDPR

"The operation of smart meters entails the processing of 'personal data' and needs to comply, as specifically required by Directive (EU) 2019/944 of the European Parliament and of the Council of 5 June 2019 on common rules for the internal market for electricity and amending Directive 2012/27/EU with the EU data protection rules."

https://platform.dataguidance.com/opinion/eu-edps-tech-dispatch-smart-meters-smart-homes

https://edps.europa.eu/data-protection/our-work/publications/techdispatch/techdispatch-2-smart-meters-smart-homes_en

Fratini et al:

Data protection and smart meters: the GDPR and the 'winter package' of EU clean energy law

https://eulawanalysis.blogspot.com/2018/03/data-protection-and-smart-meters-gdpr.html

Eoghan McKenna, Ian Richardson, Murray Thomson,

Smart meter data: Balancing consumer privacy concerns with legitimate applications,

Energy Policy,Volume 41,2012,Pages 807-814,

ISSN 0301-4215,

https://doi.org/10.1016/j.enpol.2011.11.049.

Mateev, Mihail. International Multidisciplinary Scientific GeoConference : SGEM; Sofia Vol. 17, : 921-927. Sofia: Surveying Geology & Mining Ecology Management (SGEM). (2017) DOI:10.5593/sgem2017H/63

Energy / Harvesting / Kinetic

- IoT and Energy relation – multiple dimensions
- Large scale: IoT and general ICT power consumption
- Handprints – Footprints – LCA
- Practical on device level
  - How to power devices – options:
  - Classes of operation
    - Energy Harvesting, sources
      (solar, thermal, kinetic, RF, ..)
  - Energy optimization: sleep, network