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Towards hundred Thousand-fold improvement in energy performance for the coming ronnabyte era?

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Abstract: This research estimates the associated primary energy consumption for different combinations of dynamic switching energy for storage (J/bit), for processing (J/computation) and global computation intensity (computations/s). Bottom-up extrapolation is used. With ≈10 ronnacomputations/s in 2050, the J/computation should improve ≈36% per year from 2024 to 2050 to ≈50 attoJ/computation to keep computing processing energy flat. Also the dynamic switching energy needs a similar reduction rate to keep the computing processing energy flat. Hence, a paradigm shift is required to reduce the power used by computing. Technology could keep the use of primary energy flat if global computations and stored data grow slower than expected and especially if 50 aJ/computation and 1 nJ/bit can be delivered in 2050.
Keywords: integrated circuits, computing, energy, power, processing, storage, semiconductor

I. INTRODUCTION

The alleged energy challenge and opportunity posed by evermore bit generation is widely recognized [1]-[5]. Computing (processing and storage) is presently not yet, but may within a decade rise to the same share of global electricity use as air conditioning and lighting, i.e. >10%. Generally computing consists of processing computations and storage of bits. This would make computing one of the most important users of electricity on a global scale. However, admittedly the fields of computing primary energy and electricity footprint estimations are currently characterized by ideas which are not provable on the global scale.

The entanglement of the energy trends in the Complementary Metal-Oxide Semiconductor (CMOS) logic chip world is a very challenging task. The memory chips are similarly difficult in this regard. The total global operational primary energy use of IoT semiconductors is projected to decrease significantly (from 118 TWh to 1 TWh between 2016 and 2025) with the development of smaller transistor size, low-power devices, and faster wireless data communication technology [6].

Additionally, video streaming is one of the most popular digital services driving demand for traffic and eventually communication infrastructure [7] [8] [9]. Combinations of cryptocurrency mining, Internet of Things (IoT), Artificial Intelligence (AI), and Virtual Reality (VR) are drivers evermore.

I.1 Overall computing energy and electricity

Previously most research and predictions have looked at the electricity use. This prediction will focus on primary energy.

Data centers do processing and storage both. Moreover, users' behavior may increase the data center electricity use from 292 TWh in 2016 to just 353 TWh in 2030 [8]. However, the presupposed end of Moore's law - and rise of IoT – would cause data center electricity use going up to 1287 TWh in 2030 [8], much closer to the best case scenario in [1] and [2] than 353 TWh.

Exascale computing and beyond requires a shift from considering only computation time when optimizing code, to also consider more efficient use of electric energy [10].

The optimistic scenario from 2030 in Fig.1 requires new energy-efficient computational concepts.

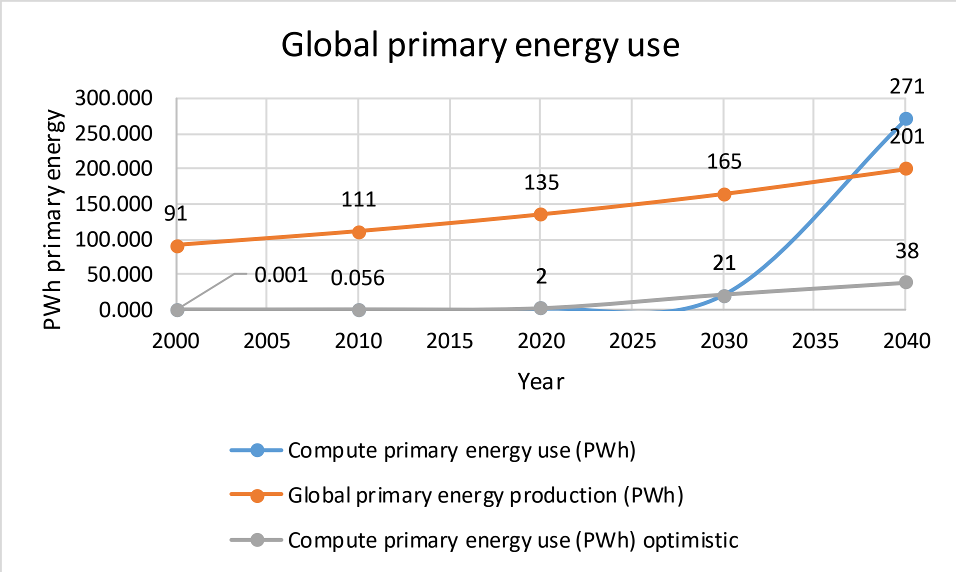

Figure 1. Actual and possible trends for primary energy for computing and total global from 2010 to 2040.

So is it within reason that Bitcoin (BTC) could use 761 TWh electricity already in 2030, i.e. some 2000 TWh primary energy which would be around 10% of computing energy? 21000 TWh computing primary energy corresponds to ≈8000 TWh electricity in 2030 which seems very unreasonable. 8000 TWh is near the expected case scenario for 2030 for communication technology in [1]. Such high predictions are not consistent with rapidly declining power use in line with aims of processor producers [6].

However, Fig. 2 shows an estimation based on the sum of global accumulated data growing more than 4000 times between 2025 and 2050, the electricity intensity for handling the data improving on average 15% per year from 0.01 kWh/GB in 2025 to 1.8×10^{-4} kWh/GB in 2050. Anyway, the top-down electricity intensity for the internet should not be applied to the accumulated stored bits. Another intensity is J/transistor (dynamic switching energy) for which [3] assumed 2.88×10^{-21} (the minimum energy required to write one bit, i.e. the so called Landauer limit) in the future applied to writing and storing each bit of information. The processing (J/computation) and the storage (J/bit, J/transistor) are here assumed to be two separate energy parameters by which the total computation energy can be estimated. In 2007 the global computations/s were $\approx2.25\times10^{20}$ and the accumulated stored data were $\approx2.83\times10^{21}$ bits. The growth rate for these are expected to be ≈56% and ≈40%, respectively.

Interestingly, for 2020 and 2030 the best case data center J/bit from [2] gives similar results as [3] for information energy totals.

The difference between the latest chips (≈5470 fJ/computation) and plasmoid graphene (≈0.5 fJ/bit) is around 10000 times. Another combination is between ≈490 fJ/computation and future superconduction (≈0.024 fJ/bit) resulting in around 20000 times improvement potential. For some chips the improvement potential could be 100000 in between 2024 and 2050. How far will 0.5 fJ/computation and 0.5 fJ/bit storage writing go in relation to the global computing primary energy?

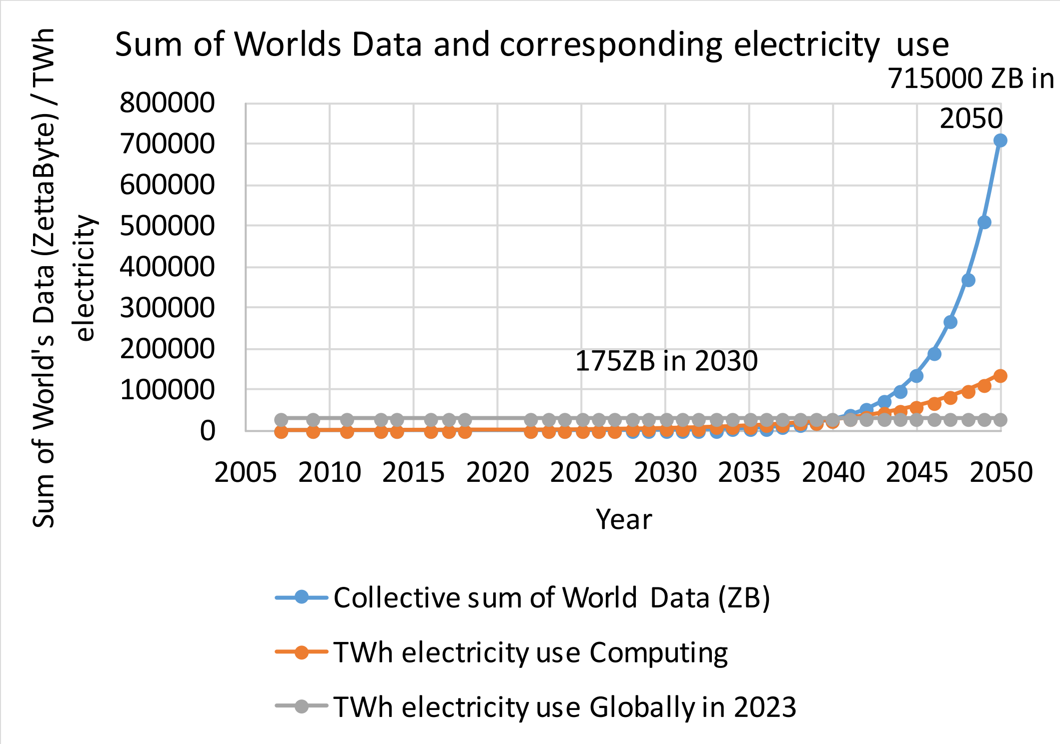

Figure 2. Actual and possible trends for data and electricity use towards 2050.

Here some other approaches will be used to estimate the trends for 2050.

A. Trends for J/computations

Neural network design using attojoules per bit [11] has been proposed. A prototype microprocessor has been presented using superconductor devices that are about 80 times more energy efficient (≈0.186 pJ/computation) than the state-of-the-art semiconductor devices (≈15 pJ/computation) found in the microprocessors of today's high-performance computing systems [12].

In 2022 certain computer systems obtained 15.95 pJ/computation [13]. In 2024 Graphical Processing Units (GPUs) used for processing in data centers can achieve 5.47 pJ/computation. 0.49 pJ/computation in 2025 has also been proposed.

B. Trends for dynamic switching energy J/transistor

It has been demonstrated experimentally that the Landauer bound (primary energy required to erase a 1-bit memory), 2.88 zJ/transistor (dynamic switching energy), can be reached with a very high accuracy in a short time [14]. Moreover, 409 zJ/transistor has been predicted [15] for CMOS 3D design.

A 1-trit ternary full adder designed with an anti-ambipolar switch device shows a power–delay product performance of around 122 aJ [16]. The power consumption of such a circuit is 7 times lower than a reference circuit [16].Likely [12] chip manufacturers may be ahead of roadmaps of 1000 zJ/transistor in 2030 [15], and the J/transistor (dynamic switching energy) is correlated to the power use of chips.

Synchronization of large spin Hall nano-oscillator (SHNO) arrays is an approach toward ultrafast non-conventional computing paving the way for human-like computers with high energy efficiency [17]. It is not clear if SHNO is close to the Shannon-von Neumann-Landuaer (SNL) limit.

C. Bitcoin energy intensity trends

Bitcoin (BTC) is a digital asset which uses energy/hash. A hash is a function that converts an input of letters and numbers into an encrypted output of a fixed length. These hashes are here assumed to add to the global computations growth, i.e. the growth of $A_{computations}$ in (7). BTC energy use estimations and modelling are important as they suggest that contemporary energy use predictions of data center and blockchain technologies have been underestimated as the BTC effect is excluded.

Table 1 assumes that 900 BTC was mined per day 2019 to 2021, that 400 BTC will be mined per day from 2022 to 2035, and that the annual electricity intensity improvement of TWh/BTC is 20% per year from a 2021 baseline of 103.73 TWh.

Table 1. Projections for electricity used to mine bitcoins 2022 to 2035.

Year	**TWh electricity used**	**BTC mined of 21 million**	**TWh/BTC**
2019	45.75	18057343	1.39×10^{-4}
2020	58.49	18385843	3.88×10^{-5}
2021	130.73	18714343	2.20×10^{-4}
2022	*276.37*	*18860343*	9.98×10^{-4}
2023	*392.89*	*19006343*	7.98×10^{-4}
2024	*486.10*	*19152343*	6.38×10^{-4}
2025	*560.67*	*19298343*	5.11×10^{-4}
2026	*620.33*	*19444343*	4.09×10^{-4}
2027	*668.05*	*19590343*	3.27×10^{-4}
2028	*706.23*	*19736343*	2.62×10^{-4}
2029	*736.78*	*19882343*	2.09×10^{-4}
2030	*761.21*	*20028343*	1.67×10^{-4}
2031	*780.76*	*20174343*	1.34×10^{-4}
2032	*796.40*	*20320343*	1.07×10^{-4}
2033	*808.91*	*20466343*	8.57×10^{-5}
2034	*818.92*	*20612343*	6.86×10^{-5}
2035	*826.92*	*20758343*	5.85×10^{-5}

In Table 1, based on the trend from 2019 to 2021, the TWh needed to mine BTC in 2022 is derived as 130.73 TWh+400 BTC/day×365 days/year×2.20×10^{-4}TWh/BTC×0.8^{1} × ($2.20\times10^{-4}/3.88\times10^{-5}$) = 276.37 TWh.
The electricity needed to mine BTC in 2023 is derived as 276.37 TWh+400 BTC/day×365 days/year×2.20×10^{-4}TWh/BTC×0.8^{2} × ($2.20\times10^{-4}/3.88\times10^{-5}$) = 392.89 TWh.

The BTC electricity use prediction in Table 1 will be compared to later findings in this research about the electricity needed to sustain the BTC network.

It was recently estimated that BTC mining energy use in 2024 in China will be 296.59 TWh [18]. This suggests that the calculation model for Table 1 is reasonable.

For estimating the energy needed to sustain the BTC network, once the BTC have been mined, another estimation technique can be used based on the hash rate, i.e. total number of hashes per second needed to sustain the BTC network and the best available J/hash. The lowest BTC network power use in 2018 at the average hash rate 26 million terrahashes (quintillion) per second is estimated to 2.55 GW [19], e.g. 0.098 nJ/hash in 2018 for bitcoin technology. The hash rate (humber of hashes per second) is expected to rise and the J/hash is expected to decline. Additionally, the number of integer operations per hash is also expected to rise. In February 2022 the bitcoin hash rate was 248.11 exahashes/s [19], i.e. the average global hash rate may have grown 76% per year between 2018 and 2022. Additionally, it has been reported that one of the latest mining chips will achieve 55 J/Terrahash, i.e. 0.055 nJ/hash [20]. Bitcoin miners used some 0.034 nJ/hash in 2022. Consequently, the best available J/hash was reduced 23% per year between 2018 [19] and 2022 [20]. The actual bitcoin mining efficiency seems to have been improved 23.4% per year from 2018 to 2021, 0.098 to 0.044 J/Ghash [20]. The improvement rate is worse than the theoretical prediction of 36 in 2018 to 6.15 pJ/computation in 2022, i.e. 36%

per year [15],[21]. Still, the J/hash follows well the improvement trends reported by chip manufacturers for J/computation.

The main aim of the present research is to outline which path the energy consumption of computing is following and likely is about to follow.

Compared to previous investigations the present research will add the storage energy separately and expand the temporal scope from 2030 to 2050.

The principal conclusion is that 24 aJ/computation for processing - and dynamic switching energy of 0.003 zJ/transistor and 1 nJ/bit for storage – will be enough for reduced energy use of computing in 2050 compared to 2024. The rebound effect of software is implicitly included in the modelling via overestimation of global computations per second and stored bits.

The trends indeed look very promising for dynamic switching energy and energy use per computation. However, what trajectory is required to keep the computing electricity use flat between 2024 and 2050?

II. THEORETICAL FRAMEWORK

(1) and (2) show definitions of the dynamic switching energy (E_{tr}) of processor architectures and (3) the so called E_{factor}. (4) and (5) show how the power use of a chip and the global power use of chips used in global computing is estimated. (6) and (7) show how the global energy use from computing related to processing is estimated from the power use of chip and its FLOP/s and annual computations per second.

$$E_{tr} = C \times V^2 + \frac{1}{sp \times Clock_{chip}} \times I_{off} \times V \qquad (1)$$

$$E_{tr} = E_{factor} \times k_b \times T \qquad (2)$$

$$E_{factor} = \frac{C \times V^2 + \frac{1}{sp \times Clock_{chip}} \times I_{off} \times V}{k_b \times T} \qquad (3)$$

$$W_{chip} = N_{transistors.chip} \times Clock_{chip} \times E_{tr} \times CompUE \qquad (4)$$

$$W_{computing} = N_{chips,computing} \times W_{chip} \times PUE \qquad (5)$$

$$E_{computation} = \frac{1}{\left(\frac{FLOPS_{chip}}{W_{chip}}\right)} \qquad (6)$$

$$E_{computing} = E_{computation} \times A_{computations} \times 24 \times 365 \times 3600 \qquad (7)$$

Where

E_{tr}= Dynamic switching energy (J/transistor).

C = Load Capacitance (As/V)

V = Voltage across the gate, (V)

sp = switching probability.

$Clock_{chip}$= Clock frequency (1/s)

I_{off}= Leaking current drawn by each switch in the off-state (A)

E_{factor}= Dimensionless primary energy/enthropy factor.

k_b= Boltzmann's constant (J/K).

T= Temperature at which the transistor is operating (K).

W_{chip}= Power consumption of one chip (W), energy.

$N_{transistors.chip}$= Number of transistors in one chip (#).

$CompUE$ = Computational use effectiveness.

$W_{computing}$= Power used by global computing (W)

$N_{chips,computing}$= Number of chips running at the same time globally doing computing (#).

PUE = Power use effectiveness of data centers and alike.

$E_{computation}$ = energy use per floating point operation, energy use per computation, energy use per hash (J/computation).

$FLOPS_{chip}$= floating point operations per second performance per chip (computations/s).

$E_{computing}$ = annual energy use for computing related to processing (J/year).

$A_{computations}$ = global computations done per second, (computations/s).

Figs. 2a and 2b show the relation between E_{tr} and feature size as estimated from 1989 to 2022.

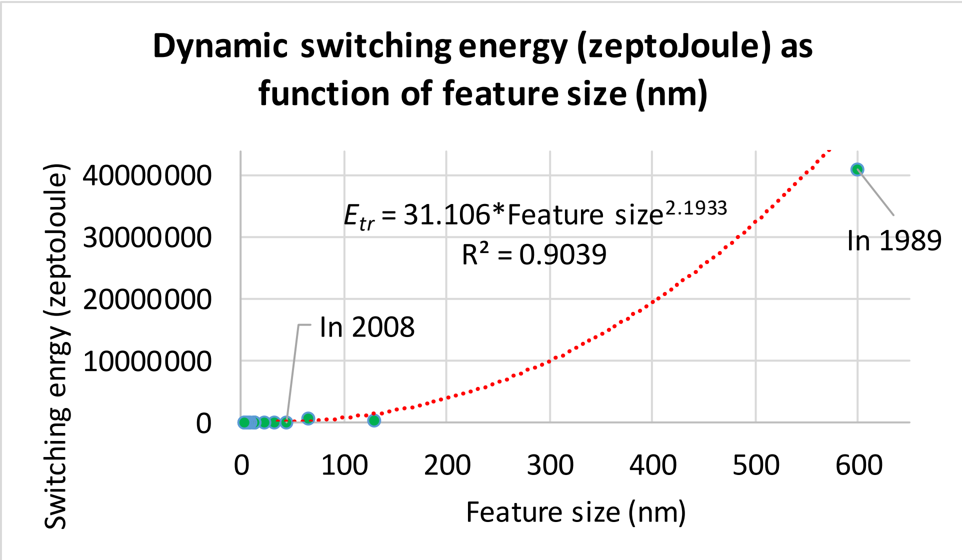

Figure 2a. Dynamic switching energy (zeptoJoule) as function of feature size (nm) from 1989 to 2024.

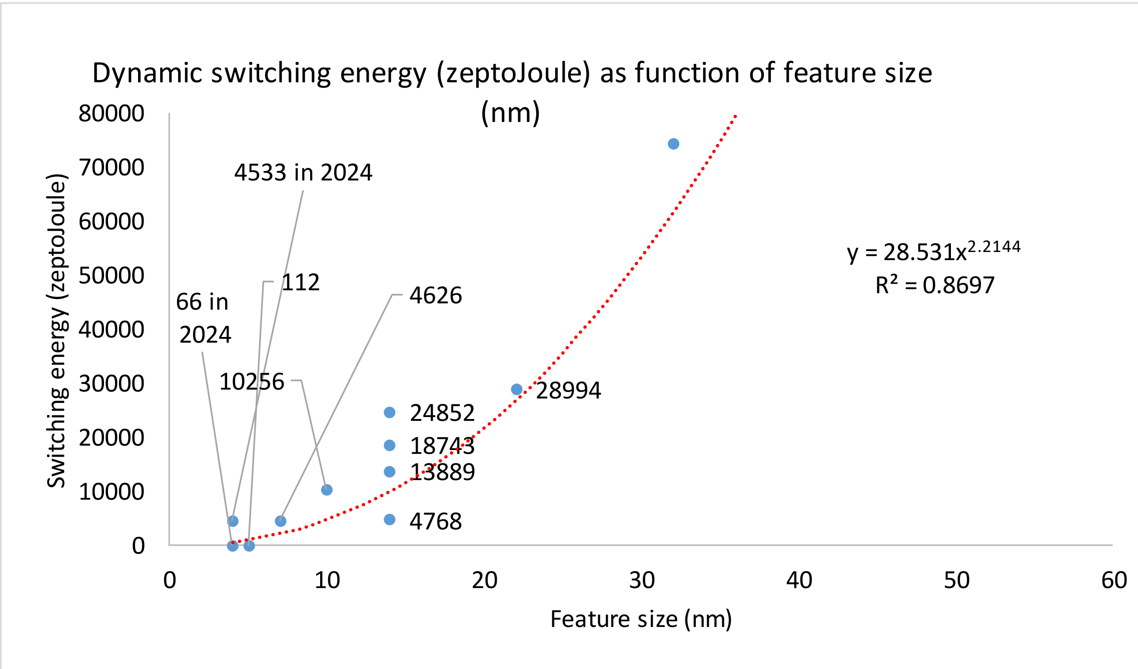

Figure 2b. Dynamic switching energy (zeptoJoule) as function of feature size (nm) from 2008 to 2024.

Figure 2b suggests that from around 2008 the dynamic switch energy has improved faster than suggested by the historical trend.

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There are only two practical ways today for lowering E_{tr} of traditional CMOS: either changing the physics of the transistor, with significant effect on voltage lowering (Equation 1), or operating at much lower temperatures (cryogenic electronics) (Equation 2) [24].

In 2007 E_{tr} was ≈250 attoJoule (aJ), and currently about ≈11 aJ and the prediction is ≈1 aJ by 2030 [15]. Table 2 suggests that the semiconductors are already better performing much better than ≈9000 zeptoJoules/transistor predicted for 2020 [15].

Table 2. Theoretical estimations of historical computation power metrics.

Year	**Feature size (nm)**	$N_{transistors.chip}$ **(billions)**	$Clock_{chip}$ **(Ghz)**	$FLOPS_{chip}$ **(GigaFLOP/s)**	W_{chip} **(W)**	$E_{computation}$ **(pJ/computation)**	E_{tr} **(zeptoJoule/transistor)**
2017	14	4.4	0.65	403.2	15	37.2	4767
2020	7	26.8	2.2	20700	300	14.49	4626
2020	7	5.99	4.4	546	90	164.84	3104
2020	7	30	2	20500	330	16.10	5000
2023	4	80	1.76	25610	700	27.33	4533
2024	4	80	1.76	128050	700	5.47	1743

Moreover, Table 2 even suggests that there may already be chips which perform much better than earlier roadmaps for 2030 of 1000-3300 zeptojoule per transistor for E_{tr}[15].

The present research aims to clarify and simply the results in[15],[22] by removing assumptions about transistor per instruction, by focusing on published and estimated W_{chip}, $Clock_{chip}$, $N_{transistors.chip}$ and $FLOPS_{chip}$performance for microchip processors, and by interpreting global estimation of instructions/second [23] as $A_{computations}$ computations/second.

Clearly $A_{computations}$ is increasing while $E_{computation}$ and E_{tr} are decreasing.

Performance metrics for different semiconductor technologies and the corresponding use in 2030 are herein modelled. Table 3 shows different processor architectures promises for 2022, 2025, 2030, 2040 and 2050.

Table 3. Theoretical predictions of computation power metrics 2025, 2030, 2040 and 2050.

Processor architecture	**Year**	**Feature size (nm)**	$N_{transistors.chip}$ **(billions)**	$Clock_{chip}$ **(Ghz)**	$FLOPS_{chip}$ **(GigaFLOP/s)**	W_{chip} **(W)**	$E_{computation}$ **(pJ/computation)**	E_{tr} **(zeptoJoule/transistor)**
	2025	5	50	2.2	57600	28	0.49	231
[15]	2030	5	80	5	57600	180	3.125	409
[15]	2030	1.5	80	5	57600	*440*	7.63	1000
[15]	2030	1.5	80	5	57600	*191*	3.31	434
[15]	2030	1.5	80	5	57600	*77*	1.33	175
[12]	2030	1.5	80	5	57600	*10.45*	0.181	24
[15]	2030	1.5	80	5	57600	*1.35*	0.023	2.88
Reversible	2030	1.5	80	5	57600	0.08	0.0014	0.182
Superconducting	2030	1.5	80	5	57600	0.0014	0.000024	0.003
Plasmoid graphene	2040						0.0005	

Superconducting	2050						0.000024	0.003

The controversial and diverging hypotheses concern to which degree the total global generated bits/year and computations/s are on an unsustainable path when compared to the paths of J/computation and J/transistor and J/bit. The main aim of the present research is to outline which paths the energy consumption of computing are following and are most likely about to follow. The principal conclusion is that the likely achievable $E_{computation}$ (J/computation) will not be enough for a flat energy use of computing in 2050 compared to 2024. However, eventual increase of the energy use of computing will likely be driven by the number of computations and stored bits, and not by lack of performance of the hardware.

III. RESULTS

III.1 Processing primary energy

Table 4 shows some extrapolations done by using two diverging trends, the increase of $A_{computations}$ and the decrease of E_{tr}.

Table 4. Theoretical estimations of computation energy use 2007, 2020, 2030, 2040 and 2050.

Year	$A_{computations}$ **(Exa computations/s)**	E_{tr} **(zJ/transistor)**	$E_{computing}$ **(TWh)**
2007	195	250000	216 [25]
2020	*≈42456*	*4626*	*870*
2030	2671474	1000	11837
2030	2671474	231	2734
2040	167771905	2.88 (Landauer limit)	2141
2040	167771905	0.182 (reversible)	135
2050	10546503870	25.5	1190631
2050	10546503870	2.88 (Landauer limit)	134580
2050	10546503870	0.182 (reversible)	8505
2050	10546503870	0.003 (superconducting)	149

Table 4 suggests that something like reversible computing in 2040 and superconducting in 2050 are sustainable from a power standpoint.

Table 5 shows some estimations for $E_{computing}$ as a result of variable $E_{computation}$ and fixed $A_{computations}$ in 2020, 2024, 2030 and 2040 and 2050.

For the same value of $A_{computations}$, the values for $E_{computing}$ in 2030 are similar for E_{tr}= 1000 zJ/transistor (Table 4).

Table 5. Theoretical estimations of computation primary energy use trends 2020 to 2050

Year	**Comment**	**GFLOP/s/W**	$E_{computation}$ **(pJ/computation)**	$A_{computations}$ **Computations/s**	$E_{computing}$ **(TWh)**
2020	Overestimates TWh	69	14.49	4.89×10^{22}	6213
2024	Overestimates TWh	183	5.47	1.12×10^{23}	5369

2030	What it takes at least to reduce to 2024 level TWh	5000	0.2	3.08×10^{24}	5396
2040		3.1×10^{5}	3.2×10^{-4}	1.93×10^{26}	5410
2050	What it takes at least to reduce to 2024 level TWh	2×10^{7}	5×10^{-5}	1.22×10^{28}	5343
	Bitcoin network primary energy use				
Year	**Energy power (GW)**	**Ghashes/s/W**	**pJ/hash (energy efficiency)**	**Global BTC hashrate**	**TWh (primary energy)**
2020	3.96	22.7	44	90×10^{18} hashes/s [19]	35
2030	21.3	2326	0.43	4.96×10^{22} hashes/s	187
2040	13.7	2000000	0.0005	2.73×10^{25} hashes/s	120
2050	362	4.17×10^{7}	0.000024	1.51×10^{28} hashes/s	3175

The results for BTC in Table 5 is much different from Table 1 which uses a top-down approach to estimate the electricity use of BTC mining. Table 5 suggests that the lowest BTC network power use in 2020 at the average hash rate 90 million terrahashes (quintillion) per second is estimated to 3.96 GW. In 2030, the lowest BTC network power use at the average hash rate 49600 million terrahashes (quintillion) per second is estimated to 21.328 GW. For 2040 it is assumed that 0.5 fJ/hash can be achieved and in 2050 the 0.024 fJ/hash is accomplished with superconducting computing.

III.2 Storage primary energy

Data centers do both processing and storage. Table 6 shows how the energy estimation technique from [2] can be used to generate numbers for storage primary energy. The J/bit in [2] for data centers are multiplied by 2.7 to arrive at primary energy. It is assumed that bits accumulated in the data centers can use the average energy intensity of the data centers to estimate the storage energy.

Table 6. Primary energy use trends 2024,2030,2040 and 2050 for data storage based on data center energy intensity.

Year	***Bits accumulated in data centers***	***J/bit i data centers, [2]***	***(TWh)/year, primary energy***
2024	1.23×10^{24}	6.32×10^{-6}	2157
2030	9.79×10^{24}	3.16×10^{-6}	8602
2040	2.57×10^{26}	1.78×10^{-7}	12719
2050	6.75×10^{27}	1.00×10^{-8}	18808

Table 7 shows how Fig.2 in [3] is used as an alternative energy estimation technique for storage primary energy. [3] argues that the minimum energy to write a bit is 2.88 zJ. Fig.2 in [3] has log10 for power on the Y-axis and year on the X-axis in which 10 corresponds to 2030. From Table 2 E_{tr} in 2020 is 4626 zJ. Hence the power use for information creation (TW) which corresponds to X=10 can be identified as $Y=10^{-5}$. 10^{-5}corresponds to 0.08 TWh which is too small. Instead a correction factor is used consisting of the relation between the average E_{tr} and the minimum E_{tr}. The correction factor is multiplied with the TW in column three as shown in Table 7.

Table 7. Primary energy use trends 2024,2030,2040 and 2050 for data storage based on power for information creation and switching energy relation.

Year	E_{tr}, **zJ**	**Power (TW) for information creation based on [3]**	**(TWh)/year, primary energy, TW×8760 hours/year**
2020	4626	10^{-5}×4626/2.88=0.016	0.016×8760=140
2030	231	$10^{-2.5}$×231/2.88=0.25	2221
2040	174	10^{-2}×174/2.88=0.6	5292
2050	2.88	10^{0}×2.88/2.88=1	8760
2050	10	10^{0}×10/2.88=3.47	30416
2050	0.182	10^{0}×0.182/2.88=0.063	553
2050	0.003	10^{0}×0.003/2.88=0.001	9.1

III.3 Overall combined results for computing primary energy

Fig. 4 shows the best case for primary energy consumption for computing in relation to the global use.

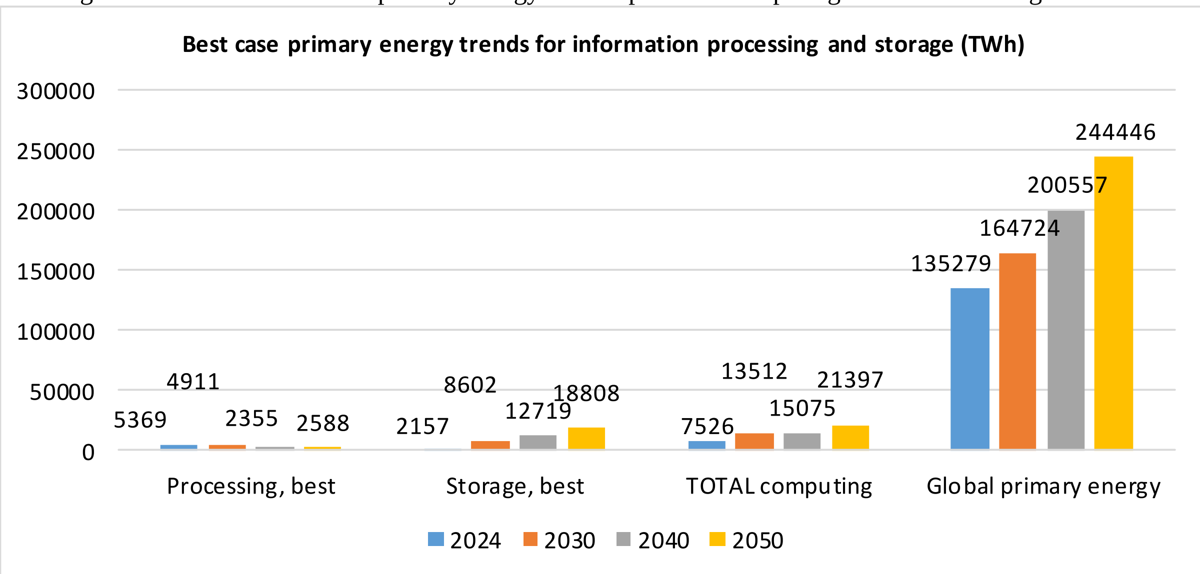

Figure 4. Primary energy trends 2024, 2030, 2040 and 2050 in a best case scenario.

The share of global primary energy will rise from 6% to 9%.

Fig. 5 shows the worst case for primary energy consumption for computing in relation to the global use.

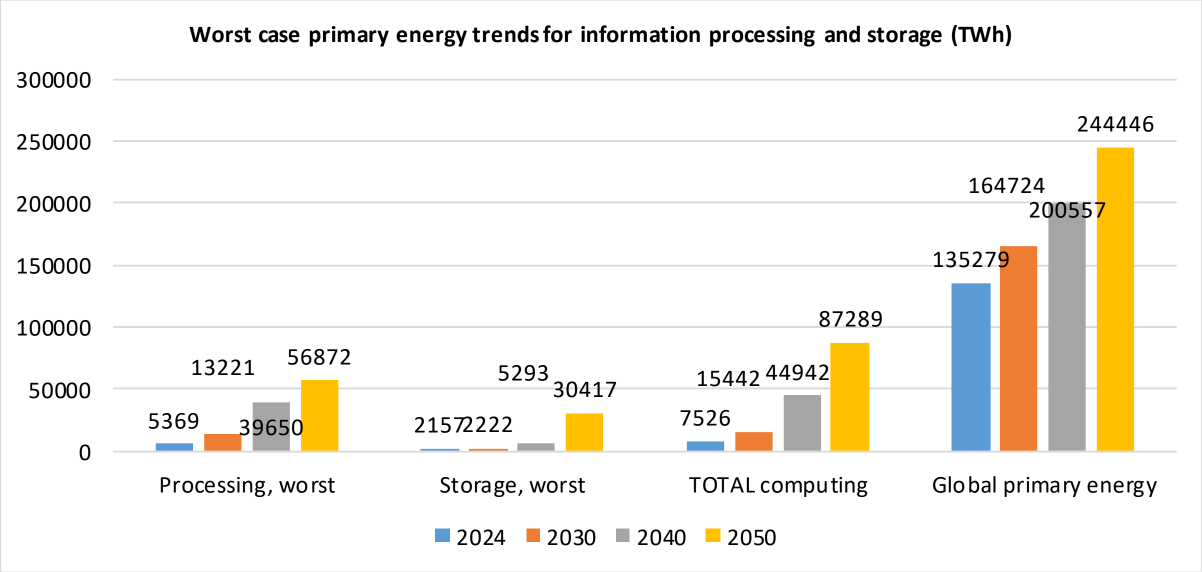

Figure 5. Primary energy trends 2024, 2030, 2040 and 2050 in a worst case scenario.

The share of global primary energy rise from 6% to 36%.

Fig.5 implies that the improvement of the average J/computation for processing is highly important for the total energy use. Improvement rate from 2020 to 2024 continuing to 2050 is not enough.

IV. DISCUSSION

An intense discussion is ongoing about the future energy use of computing.

For processing, the growth rate for computations/s (56% per year) seems likely to continue between 2024 and 2050. For storage, the growth rate (40% per year) for accumulated bits seems likely to continue between 2024 and 2050.

A computational primary energy use under control in 2030 may require 0.2 pJ/computation (5 Terraoperations/s/W) with $A_{computations}$ = 2.54 Yottacomputations/s.

A computational primary energy use under control in 2040 may require 0.00032 pJ/computation (3125 Terraoperations/s/W) with $A_{computations}$ = 159 Yottacomputations/s.

A computational primary energy use under control in 2050 may require 0.05 fJ/computation (20000 Terraoperations/s/W) with $A_{computations}$ = 10091 Yottacomputations/s. 0.05 fJ/bit is below plasmoid graphene technology in optical and similar to superconducting computing 0.024 fJ/bit.

Superconducting values for $E_{tr} \approx$ 0.003 zJ/transistor will be enough to guarantee a reduction of $E_{computing}$.

If the reduction trend between 2020 and 2024 continues (21.6% per year) until 2050 for $E_{computation}$ the computing energy use for processing will increase 190 times in 2050 compared to 2024.

If the reduction trend between 2020 and 2024 continues (21.6% per year) until 2040 for $E_{computation}$ the computing energy use for processing will increase 35 times in 2040 compared to 2024.

This implies that the average J/computation needs to be improved around 35% per year instead of 21% between 2024 and 2050.

From [3], for computing energy use for storage, it is clear that reversible and superconducting are so far the only identified technologies identified in the present study which can keep the energy consumption in check.

If the 2020 to 2024 trend continues reversible computing will be achieved in the 2050s, i.e. $E_{tr} \approx 0.182$ zJ/transistor, >10 times below the SNL limit.

Bitcoin could be a considerable user of computing energy at 2700 TWh in 2035 with 20% to sustain the network and 80% to mine the coins.

At the end of the day, it will be the physical properties of the microchips that will determine the primary energy consumption trend and eco-effectiveness of computing. This may be true even if hardware improvements cannot explain why the overall power consumption is increasing. The reason is that the total number of computations is dependent on programming language. More use of energy efficient programming languages [26],[27] like C - compared to JavaScript - may lead to fewer overall global computations and smaller energy consumption.

Current solutions are not enough to keep computing electricity under control until 2050 with 10 Ronnacomputations/s. However, the reduction trend keeps on going, and there are promising new technologies capable in theory of delivering a silver lining [28].

V. CONCLUSION

The J/computation performance of proposed technologies are probably enough to keep the power consumption of computing under control until 2030. Moreover, for 2040 and 2050 reversible computing and superconducting computing will be required. The preferable comparison metrics in between generation of chips ought to be more discussed.

REFERENCES

[1]. A.S.G Andrae, and T. Edler, On global electricity usage of communication technology: trends to 2030, *Challenges, 6(1)*, 2015, 117-157.

[2]. A.S.G Andrae, New perspectives on internet electricity use in 2030, *Engineering and Applied Science Letters, 3(2)*, 2020, 19-31. DOI: 10.30538/psrp-easl2020.0038

[3]. M.M. Vopson, The information catastrophe, *AIP Advances*, *10(8)*, 2020

[4]. A.S.G Andrae, Internet's handprint, *Engineering and Applied Science Letters*, *4(1)*, 2021, 80-97.

[5]. P. Wang, P. Zhong, M. Yu, Y. Pu, S. Zhang, and P. Yu, Trends in energy consumption under the multi-stage development of ICT: Evidence in China from 2001 to 2030. *Energy Reports*, *8*, 2022, 8981-8995.

[6]. S. Das, and E. Mao, The global energy footprint of information and communication technology electronics in connected Internet-of-Things devices, *Sustainable Energy, Grids and Networks*, 24, 2020 100408.

[7]. T. Tabata, and T.Y. Wang, Life Cycle Assessment of CO2 Emissions of Online Music and Videos Streaming in Japan, *Applied Sciences, 11(9)*, 2021, 3992.

[8]. M. Koot, and F. Wijnhoven, Usage impact on data center electricity needs: A system dynamic forecasting model. *Applied Energy, 291*, 2021, 116798.

[9]. R. Madlener, S. Sheykhha, W. Briglauer, The electricity-and CO2-saving potentials offered by regulation of European video-streaming services, *Energy Policy*, *161*, 2022, 112716.

[10]. J.M.M. Aliaga, A. Cheptsov, and A. Hervás, Towards Energy Efficient Computing Based on the Estimation of Energy Consumption. *Sustained Simulation Performance 2019 and 2020: Proc. Joint Workshop on Sustained Simulation Performance*, University of Stuttgart (HLRS) and Tohoku University, 2019 and 2020, 2021, 21-33.

[11]. M. Matuszewski, A. Opala, and R. Mirek, et al., Energy-Efficient Neural Network Inference with Microcavity Exciton Polaritons, *Physical Review Applied, 16,* 2021, 024045. DOI: 10.1103/PhysRevApplied.16.024045C.L. Ayala, T.

[12]. Tanaka, R. Saito, M. Nozoe, N. Takeuchi, and N. Yoshikawa, MANA: A monolithic adiabatic iNtegration architecture microprocessor using 1.4-zJ/op unshunted superconductor josephson junction devices, *IEEE Journal of Solid-State Circuits*, *56*, 2020, 1152-1165.
[13]. B. Prieto, J.J. Escobar, J.C. Gómez-López, A.F. Díaz, and T. Lampert, Energy Efficiency of Personal Computers: A Comparative Analysis. *Sustainability*, *14(19)*, 2022, 12829
[14]. S. Dago, J. Pereda, N. Barros, S. Ciliberto, and L. Bellon, Information and thermodynamics: Fast and precise approach to landauer's bound in an underdamped micromechanical oscillator. *Physical Review Letters*, *126*, 2021, 170601.
[15]. A.S.G. Andrae, Prediction studies of the electricity use of global computing in 2030. *International Journal of Science and Engineering Investigations, 8(86)*, 2019, 27-33.
[16]. Y. Lee, S. Kim, and H.I. Lee, et al., Demonstration of Anti-ambipolar Switch and Its Applications for Extremely Low Power Ternary Logic Circuits. *ACS Nano,16(7)*, 2022, 10994-11003.
[17]. M. Zahedinejad, H. Fulara, and R. Khymyn, et al., Memristive control of mutual spin Hall nano-oscillator synchronization for neuromorphic computing. *Nature Materials, 21*, 2022, 81–87.
[18]. S. Jiang, Y. Li, Q. Lu, Y. Hong, D. Guan, Y. Xiong, and S. Wang, Policy assessments for the carbon emission flows and sustainability of Bitcoin blockchain operation in China. *Nature communications, 12, 2021,* 1-10.
[19]. A. De Vries, Bitcoin's growing energy problem, *Joule, 2(5)*, 2018, 801-805.
[20]. V.B. Suresh, C.S. Katta, and S. Rajagopalan, et al., Bonanza Mine: An Ultra-Low-Voltage Energy-Efficient Bitcoin Mining ASIC, *Proc. IEEE International Solid-State Circuits Conference, San Francisco, CA, USA*, 2022.
[21]. A.S.G. Andrae, Hypotheses for primary energy use, electricity use and CO2 emissions of global computing and its shares of the total between 2020 and 2030, *WSEAS Transactions on Power Systems, 15,* 2020, 50-59.
[22]. A.S.G. Andrae, Comparison of Several Simplistic High-Level Approaches for Estimating the Global Energy and Electricity Use of ICT Networks and Data Centers, *International Journal of Green Technology, 5,* 2019, 51-66.
[23]. Z.W. Xu, Cloud-sea computing systems: Towards thousand-fold improvement in performance per watt for the coming zettabyte era, *Journal Computer Science and Technology, 29,* 2014, 177181.
[24]. A.M. Ionescu, Energy efficient computing and sensing in the Zettabyte era: From silicon to the cloud. *Proc. IEEE International Electron Devices Meeting (IEDM), San Francisco, CA*, 2017, 1-2.
[25]. W. Van Heddeghem, S. Lambert, B. Lannoo, D. Colle, M. Pickavet, and P. Demeester, Trends in worldwide ICT electricity consumption from 2007 to 2012, *Computer Communications, 50,* 2014, 64-76.
[26]. R. Pereira, M. Couto, F. Ribeiro, R. Rua, J. Cunha, J.P. Fernandes and J. Saraiva, Ranking programming languages by energy efficiency. *Science of Computer Programming*, *205*, 2021, 102609.
[27]. J. Manner, Black software-the energy unsustainability of software systems in the 21st Century. *Oxford Open Energy, 2,* 2023, oiac011. https://doi.org/10.1093/ooenergy/oiac011
[28]. M.P. Frank, and K. Shukla, Quantum foundations of Classical Reversible Computing, *Entropy, 23(6),* 2021, 701.