

Computing within environmental limits – Energy consumption of HPC

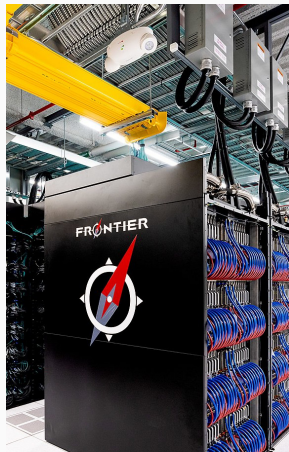
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Université de Versailles, Université Paris-Saclay, Li-PaRAD

Introduction

- **Major ecological crisis:** French roadmap targets carbon neutrality in 2050 (Stratégie Nationale Bas Carbone).
- Requires a **40% energy consumption reduction.**
- HPC **part of the solution:** modeling and improving complex systems
- HPC **part of the problem:** Frontier system at ORNL
 - More than 10^{18} floating point operations per second
 - Consumes **21MW**: the energy of a small town (16 000 french houses)



Environmental impact of computation

- The ICT sector consumes $\approx 5\%$ of the energy worldwide
- It accounts for 1.8% - 2.8% of emitted GHG [Freitag, 2021] :
 - Accounts for embodied emissions.
 - Shadow energy during the whole life-cycle: mining, fabrication, transportation, recycling.
- GHG emissions are only one of the sustainability issues
 - rare-earth mining and waste disposal (eg. Agbogbloshie).
 - human-right abuses, health issues, pollution.
- This presentation focus on energy consumption of HPC

What about renewable energies?

- Low-carbon electricity is a **limited resource**
- Decarbonation → huge increase in electricity demand
 - Heating, Transportation, Industry
 - Computing will compete for low-carbon electricity.

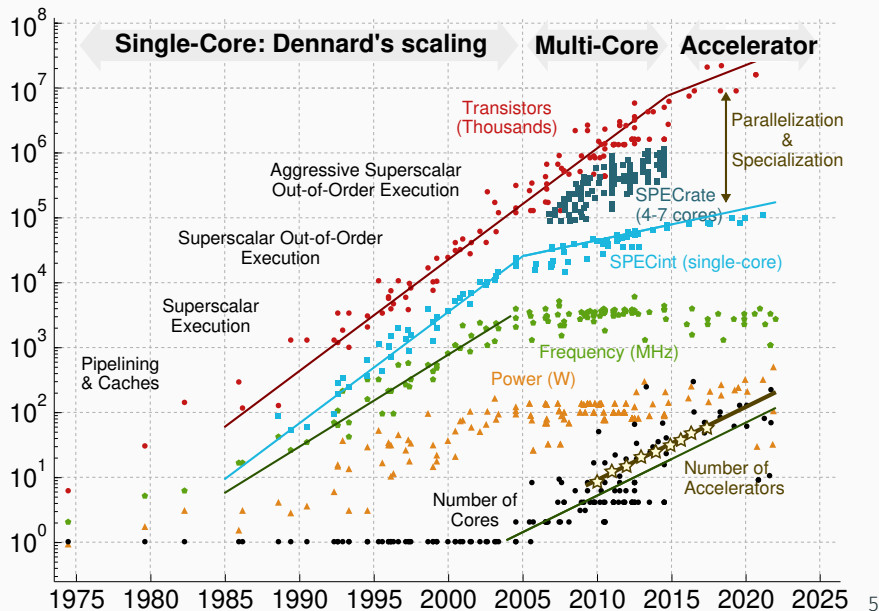
Energy consumption of HPC

AI energy and computation costs

More frugal computing?

Energy consumption of HPC

Evolution of processing units [Batten, 2023]



Dennard's scaling 1970-2005

CMOS Power

$$P = \underbrace{1/2 \cdot C \cdot V^2 \cdot f}_{P_{\text{dynamic}}} + \underbrace{V \cdot I_{\text{leak}}}_{P_{\text{static}}}$$

For each generation, transistors dimensions reduced by 30%,

- Voltage and capacitance reduced by 30%
- Frequency increases: $\times 1.4 \approx 1/0.7$
- Surface halved: $0.5 \approx 0.7 \times 0.7$
- Power halved: $\Delta P = 0.7 \times 0.7^2 \times 1/0.7 \approx 0.5$

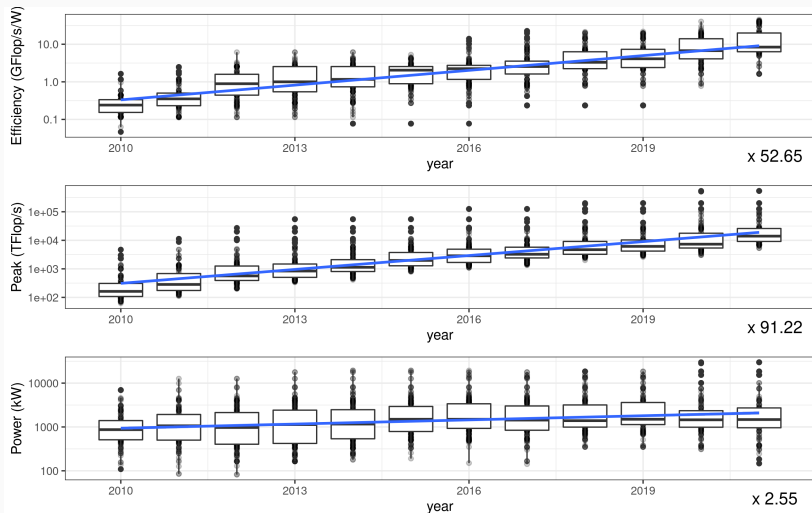
Power per surface unit remains constant but manufacturers double number of transistors and frequency increases:

- Power efficiency doubles every 1.57 years
- Total power increases

- At current scale, leak currents start increasing ($P_{\text{static}} \nearrow$).
Power wall slows Dennard's scaling.
- Computing demand $\rightarrow$ parallelism and specialization.
- Number of cores increases exponentially since 2005.
- Power efficiency still improving:
 - selectively turning-off inactive transistors;
 - architecture design optimizations;
 - software optimizations.

- For domain specific applications, such as AI, specialized accelerators are used
 - Memory and compute units tuned for a specific problem (matrix multiplication) ;
 - Faster and better power efficiency: GPU, TPU, FPGA, ASIC.

Analysis of TOP-100 HPC systems



Efficiency and Peak computation exponential increase.

Rebound effects

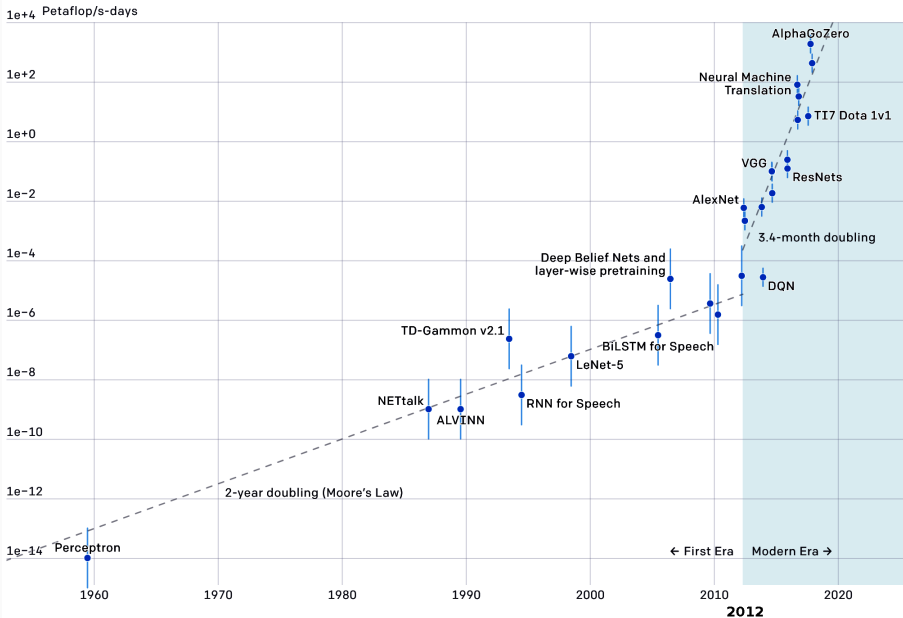
- In 1865, Jevons shows that steam engine improvements translate into increased coal consumption.
- In HPC, efficiency gains contribute to the rising computation demand.
 - net increase of the total power consumption.
- Rebound effects for data-centers [Masanet, 2020]
 - 6% increase in energy consumption from 2010 to 2018 (255 % increase in nodes).
- Indirect rebound effects: computation advances can contribute to the acceleration of other fields.

AI energy and computation costs

Artificial Intelligence

- 2012: **AI renaissance** brought by increased data availability and computation resources
 - breakthroughs in multiple domains
 - many innovations : algorithms, specialized processors, optimizations
- Most systems use **neural networks** :
 - Training (stochastic gradient descent + backpropagation)
 - Inference (forward pass)
- For both, **the bottleneck is matrix multiplication**

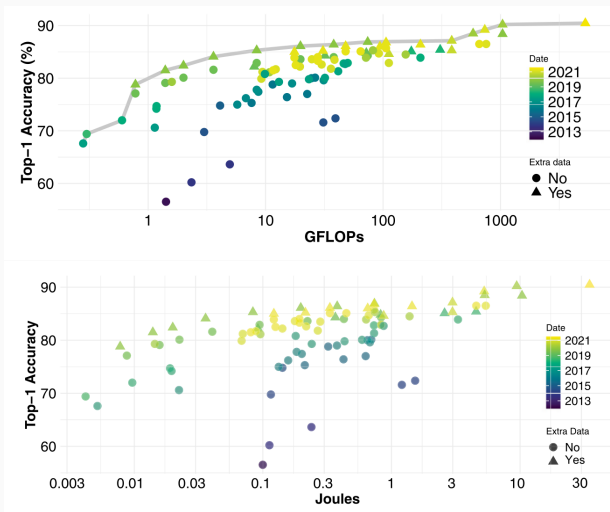
Training cost doubles every 3.4 months [OpenAI, 2020]



Should we study training or inference?

- **Training:** huge cost but done once
 - GPT3, 175 billion parameters, ≈ 314 ZettaFLOP
 - GPT4, 1.7 trillion parameters
- **Inference:** millions of users and requests
 - 80-90% cost of a deployed AI system is spend on inference [NVIDIA, 2019]

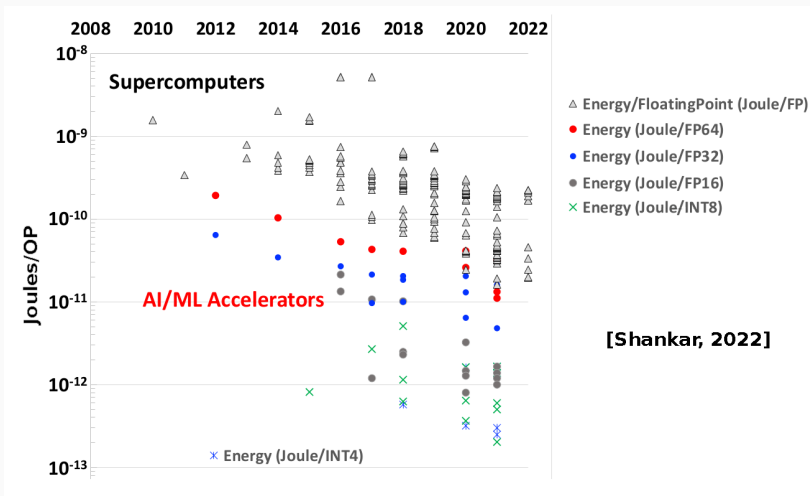
Inference cost - Diminishing returns for computer vision



Exponential increase in compute for linear accuracy gain
[Desislavov, 2023 / Schwartz, 2019]

More frugal computing?

Smaller precision / Smaller models for AI



LLM **success of smaller models** (Llama, Chinchilla) fine-tuned for specific tasks with LoRA.

Tradeoff: Model complexity - Cost - Explainability

- Inference cost grows with model complexity
- Simpler models are often more interpretable
 - Traditional science also prefers simpler models
- DNN not necessary for all tasks

Two case-studies in HPC

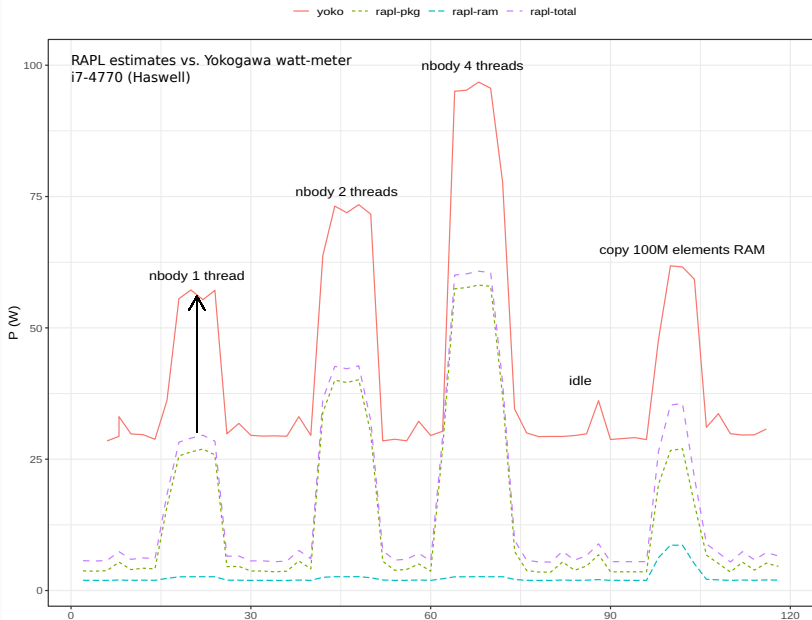
- **Computing slower:** DVFS for LU decomposition in KNM architectures
- **Computing less precisely:** mixed precision in YALES2 solver

Measuring the energy?

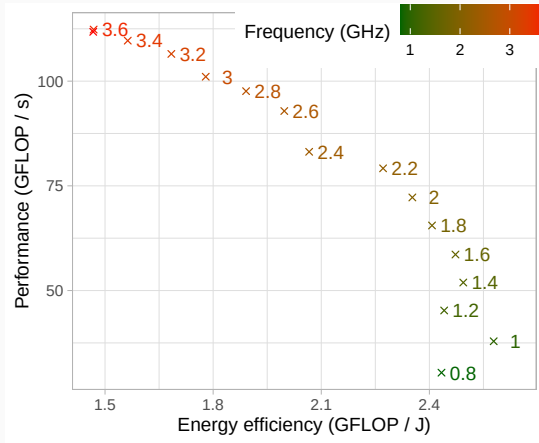
- Wall watt-meters
 - precisely measure the total consumption
 - slow sampling resolution ($\approx 1s$)
 - hard to use within a super-computer
- Manufacturers energy-counters (rapl, nvml, ...)
 - easy to access and high sampling rate
 - do not capture the whole system consumption
 - use power estimate models



RAPL vs. Yokogawa watt-meter



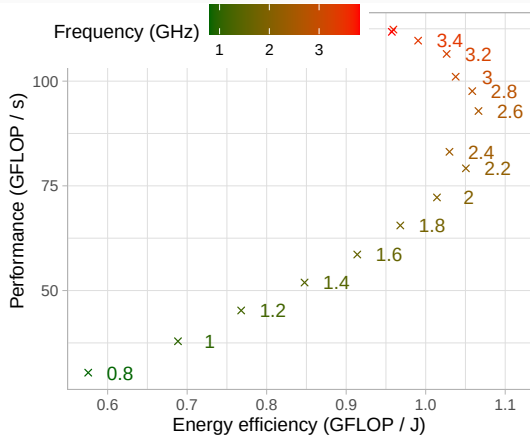
DVFS study of LU decomposition



- Knights Mill 72 cores
- Intel MKL dgetrf
- $n \in [1000, 3000]$
- RAPL estimation

Save energy by computing slower: 1GHz

When accounting for the whole system



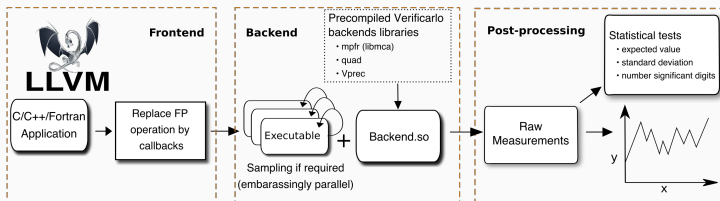
- Model : RAPL + 40W

- Optimal 2.6 GHz : compute faster and turn off machine
- Saves idle power (race to idle)



verificarlo github.com/verificarlo/verificarlo

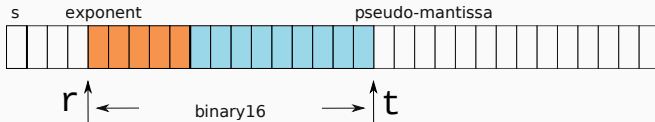
- Based on the LLVM compiler
- Active open source project with 15 contributors
- Backends: debugging (MCA, Cancellation) + mixed-precision (Vprec)
- MCA overhead from $\times 6$ (binary32) to $\times 160$ (binary64).



Verificarlo: Checking Floating Point Accuracy through Monte Carlo Arithmetic.

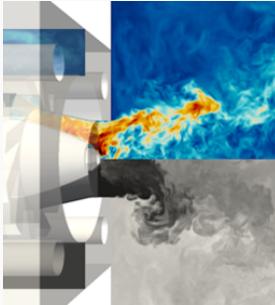
VPREC for mixed precision

- Estimate numerical effect of bfloat16, tensorflow32, fp24 on standard IEEE-754 hardware (before paying the porting cost)
- VPREC emulates any range and precision fitting in original type
 - Uses native types for storage and intermediate computations
 - Handle overflows, underflows, denormals, NaN, $\pm\infty$
 - Rounding to nearest (faithful)
 - Fast: $\times 2.6$ to $\times 16.8$ overhead



YALES2 application

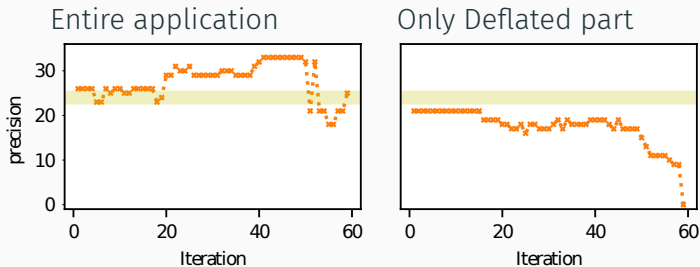
- Computational Fluid Dynamics solver from Coria-CNRS
 - Deflated Preconditioned Conjugate Gradient
 - CG iterations alternate between a:
 - Deflated coarse grid
 - Fine grid



VPREC: Find minimal precision over iterations that preserves convergence (dichotomic exploration)

Automatic exploration of reduced floating-point representations in iterative methods. Chatelain, Petit, de Oliveira Castro, Lartigue, Defour. Euro-Par 2019

Mixed-precision on Yales2



Minimal precision that preserves convergence.

Energy	16% gain on the deflated part
Communication	28% gain on communication volume
Time	10% speedup on CRIANN cluster (560 nodes)

Need for an interdisciplinary discussion

- AI / HPC can contribute towards sustainability (eg. acceleration of weather forecast models)
... but its energy cost must be reduced
- Efficiency:
 - Improve hardware and software
 - Use smaller models / smaller precision... subject to rebound effects
- Frugality in computing:
 - Balance computation cost vs. outcomes for each task
 - Choose the right sized model
 - Assess the environmental impact

Exemple: e-health solution in Tanzania [d'Acremont, 2021]

Treatment of febrile children illnesses in dispensaries.

- **IMCI**: Paper-based decision tree WHO
- **e-POCT** CART tree tailored to real data on a standalone tablet
 - Final CART tree easy to interpret and manually checked
 - Randomized-trial → better clinical outcomes and antibiotic prescription reduction
- Sophisticated AI that continuously collects patient data and adapts the algorithm ?
 - Increase in hardware and computation costs.
 - Loss in explainability and verification of the algorithm.

D'Acremont presentation: https://youtu.be/oKcy_cY0Q0w