Energy measurement as first step for power-aware application optimization

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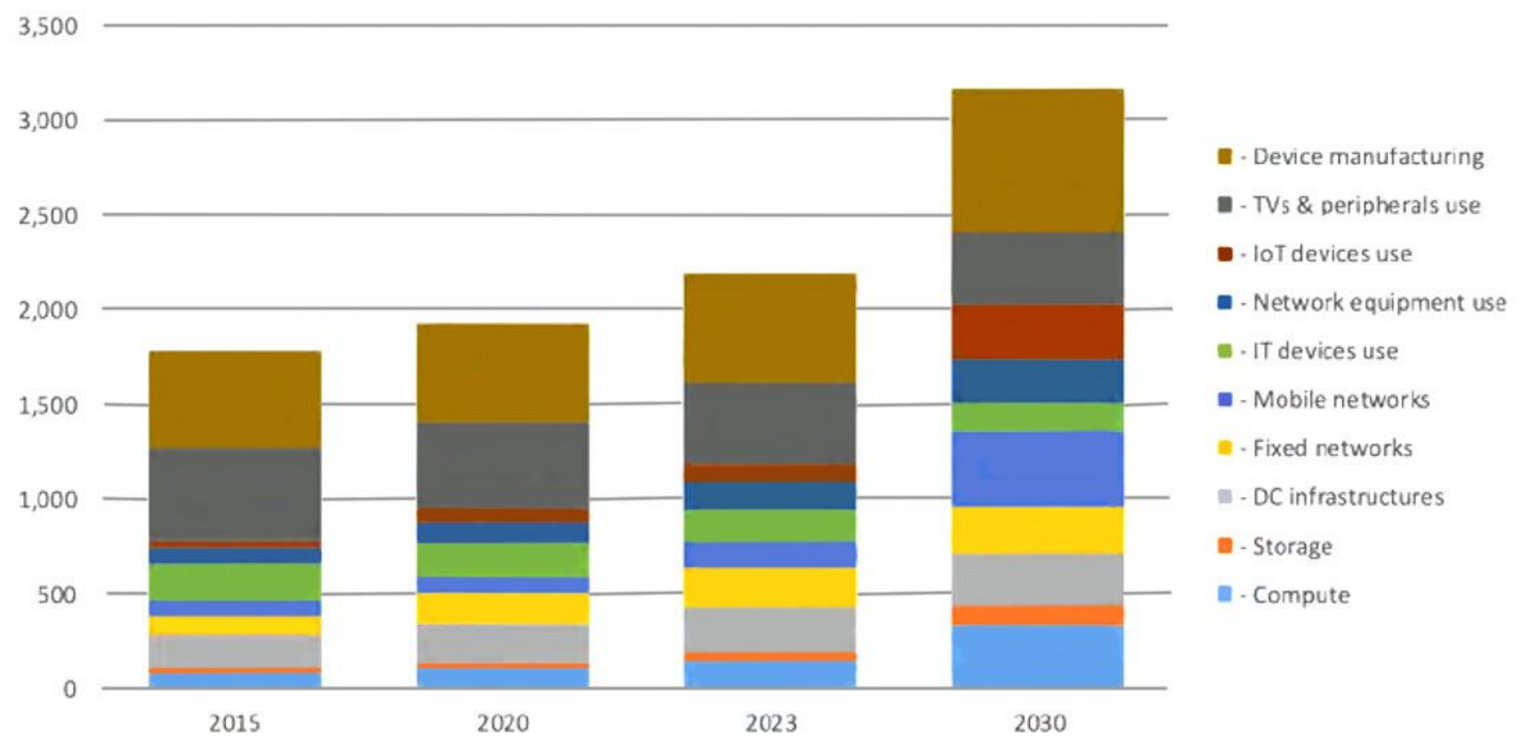
Outline

Evolution of IT energy demand (in TWh)



Schneider Electric estimates that IT sector electricity demand will grow by 50 percent by 2030, reaching 3,200TWh, equivalent to 5 percent Compound Annual Growth Rate (CAGR) over the next decade. | © Image: Schneider Electric

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ELECTRICITY COST PER HOUR FOR THE TOP FIVE SUPERCOMPUTERS.

Machine	Peak Perf.	Power	$/KWh	Total(K$)
FRONTIER	1.685 EFLOPS	21.1MW	0.150	3.165
FUGAKU	537.2 PFLOPS	29.9MW	0.219	6.548
LUMI	428.7 PFLOPS	6.02MW	0.198	1.192
LEONARDO	255.7 PFLOPS	5.61MW	0.561	3.147
SUMMIT	200.8 PFLOPS	10.1MW	0.150	1.515

CO_2 PER HOUR FOR THE TOP FIVE SUPERCOMPUTERS.

Machine	Peak Perf.	Power	Kg(CO_2)/KWh	Kg(CO_2)
FRONTIER	1.685 EFLOPS	21.1MW	0.379	7 997
FUGAKU	537.2 PFLOPS	29.9MW	0.479	14 322
LUMI	428.7 PFLOPS	6.02MW	0.132	795
LEONARDO	255.7 PFLOPS	5.61MW	0.372	2 087
SUMMIT	200.8 PFLOPS	10.1MW	0.379	3 828

Problem ?

- Computer activities uses more energy to provide more computation power
- Carbon is the consequence of energy consumption
  - Computer use energy and not carbon
  - Carbon footprint = Energy x Carbon Intensity
- Optimizing energy use and production is the way to reduce carbon footprint

Goal of optimization : Best trade-off between *“Energy-Time-Memory”*

➔ 3-Dimensional optimization schema

➔ Main constraint for energy production : The source *(low-carbon sources)*

➔ Main constraint for energy use : The quantity *(should be minimized)*

Taxonomy of energy activities in computer

1 → METRICS DEFINITION

Simples metrics : watt, joule, watt-hour, time, FLOPS, kilogram, etc.
Advanced metrics: FLOPS/watt, operation/watt, SWaP, DCIE, etc.

2 → MESUREMENT & PROFILING

Out-band : wattmeters, multimeters, wattproff, HDEEM, DiG, etc.
In-bound : Integrated sensors (Intel's RAPL, NVIDIA-SMI), MSR registry, etc.

3 → PREDICTION

Analytical Models (combinational techniques, instructions power consumption, etc.)
Machine learning based models prediction.

4 → OPTIMIZATION

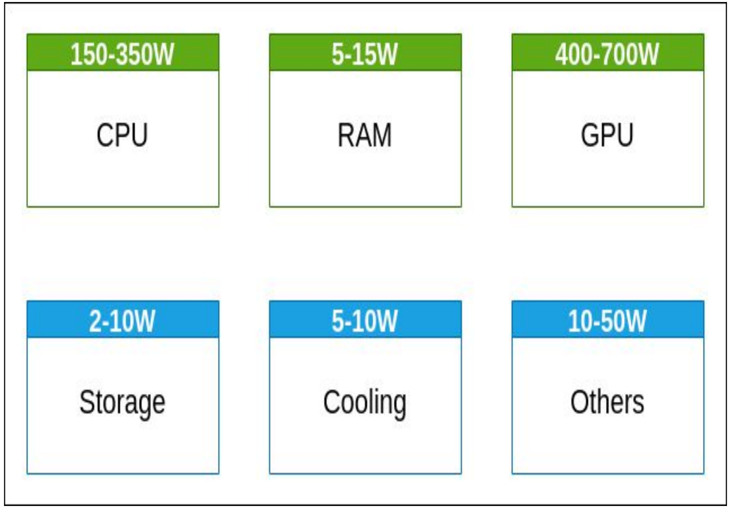
Static approachs : System design, code optimization, etc.
Dynamic approachs : DVFS, Processors states, Dynamic adaptation, etc.

5 EVALUATION & COMPARISON

Evaluate predictions : Compare predicted to measured values
Compare optimization techniques : for different optimizations methods, differents architectures, etc.

Motivations for software profiling

- Energy can be measured through Power Meters or sensors
- The most accurate way, but less helpful for optimization
- We need fine grained measurements to understand the behavior devices and then optimize accordingly
- We can also optimize programs



Mains energy hungry part within a modern computer server

News devices provide integrated sensors for fine grained energy/power measurements

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SOTA Energy measurement tools

Support	Perun	CodeC	EIT	CTracker	Eco2AI	TraC	PyJoules	Perf	LIKWID	PAPI	IntelPG	Powertop	Score-P	Variorum	CrayPat	DDT-MAP	EA2P
GPU support																	
Nvidia GPU	✓	✓	✓	✓	✓	✓	✓							✓	✓	✓	✓
AMD GPU	✓													✓		✓	✓
Intel GPU														✓			
CPU and RAM supports																	
Intel CPU	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
AMD CPU					✓			✓	✓			✓	✓	✓			✓
RAM	✓	✓	✓	✓	✓	✓			✓					✓			✓
OS support																	
Linux	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓
Windows		✓									✓						✓
Mac OS		✓	✓			✓					✓						
Other important characteristics																	
Documentation	✓	✓	✓			✓	✓	✓	✓	✓	✓	✓	✓	✓			✓
Configurable	✓	✓	✓									✓					✓
Code API	✓	✓	✓	✓	✓	✓	✓		✓	✓							✓
Open Source	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓
Perf oriented								✓	✓	✓			✓		✓	✓	
Energy oriented	✓	✓	✓	✓	✓	✓	✓				✓	✓		✓			✓
Multi-Nodes	✓								✓				✓	✓	✓	✓	✓
Device details																	✓

Reality with existing tools (why a new tool ?)

- Difficult to get, installed (*need for hand configuration*) and run
- Not reliable measurements (provide estimates - inconsistency)
- Lack of flexibility (device dependent - OS dependent)
- Lack of documentation (comprehension of the approach and outputs)

Thus our motivation to design a new energy measurement tool

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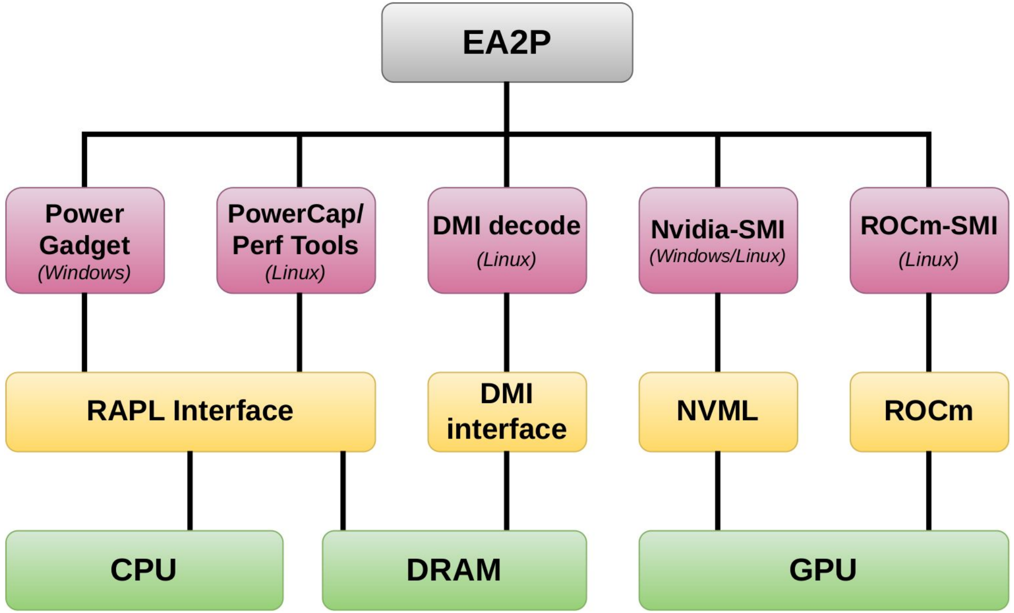
Key characteristics expected from of a profiling tool

- **Programmability**
  Should provides fine-grained control over energy profiling and allows developers to focus on specific parts of the codebase to optimize energy efficiency and performance (instrumentation and APIs)
- **Flexibility**
  To measure specific parts of the computer, allowing configurations, auto target hardware detection, and porting to other architectures.
- **Standalone**
  Easy to install, few dependences on others library and tools, minimum privileged rights for access
- **Portability**
  Compatibility across device generations, even within the same manufacturer (facilitate maintenance)
- **Accuracy**
  The tool does indeed measure the desired behavior and should be consistent across workloads

Design overview : Energy Aware Application Profiler (EA2P)

Open Source available at :
https://github.com/HPC-CRI/EA2P
Documentation at :
https://hpc-cri.github.io/EA2P/



- written in Python
- we retrieve the values of the (power dedicated) registers through medium-level tools
- can be used in a standalone *(external call)* form or through an API for programmability (internal call)
- automatically detects needed subtools for its execution (e.g. perf, PowerCap, …)

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Analytical Models

$$Power\_RAM = Power\_base \times nb\_slots \times mem\_use \quad (1)$$

$$Energy\_RAM = (\sum_{i=1}^{N} Power\_RAM) \times interval, \quad (2)$$

- Power_base is the TDP like value (or nominal power) associated to each memory type and capacity.
- nb_slots is the total number of memory slots within the entire motherboard
- mem_use is the percentage (i.e. footprint)

$$Energy_{GPU} = \sum_{i=1}^{N} P_i \times \Delta T_i, \quad (3)$$

where Pi (resp. ∆Ti) is the power value of the GPU (resp. the ith time interval during which we assume a constant power Pi) at measurement step i

$$\begin{aligned}
&E_{CPU_{dom}} = 0\\
&e_{current} = 0\\
&\textbf{if } (E_i > e_{current})\\
&\qquad E_{CPU_{dom}} = E_{CPU_{dom}} + (E_i - e_{current})\\
&e_{current} = E_i
\end{aligned}$$

Update of the overall CPU energy for Intel RAPL. For AMD CPU, we use perf as wrapper.

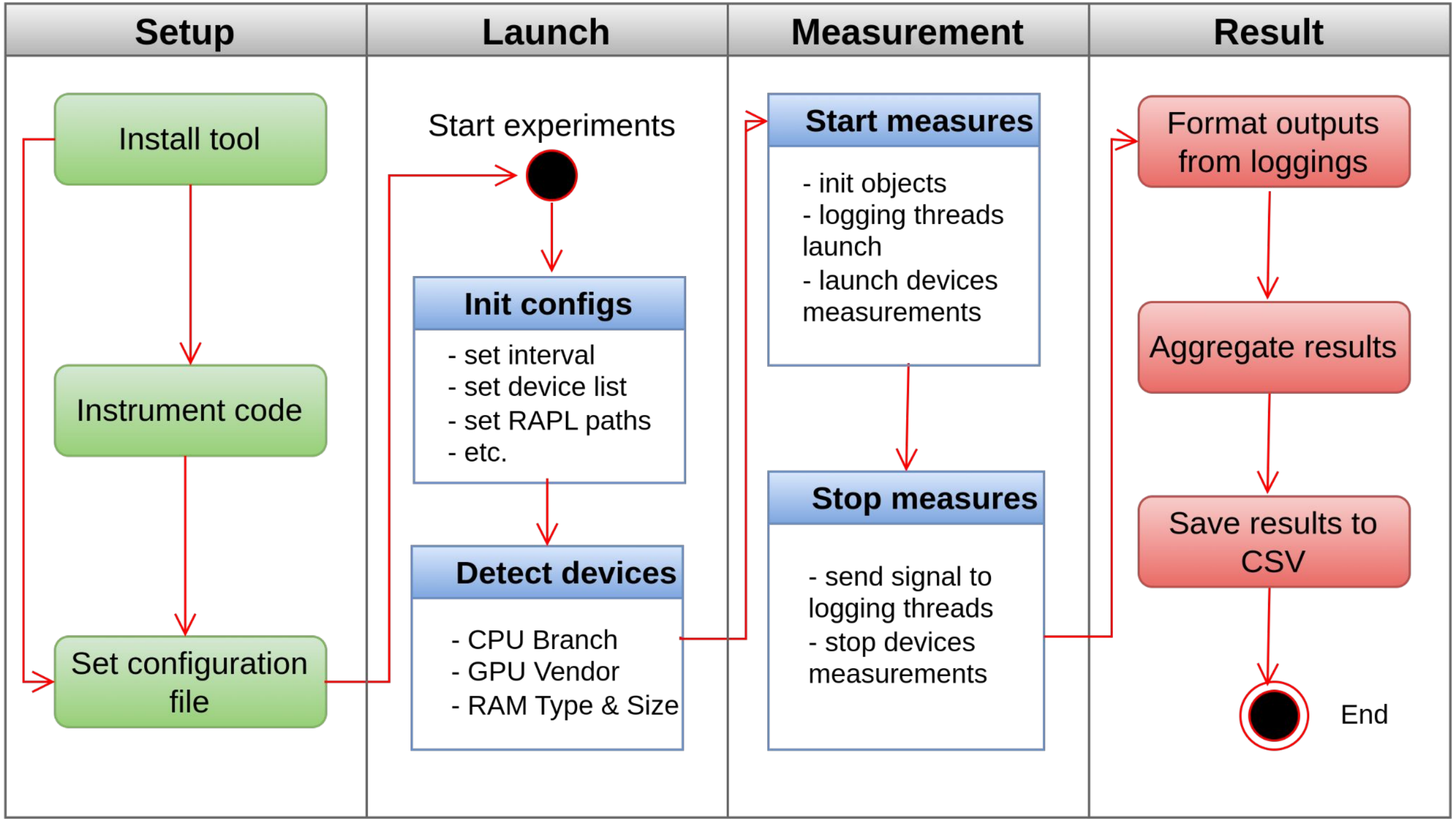
Sample instrumentation

- VGG16 fine tuning (just train the last layer)
- Example of annotation for power measurement
- Main call for training

```python
def build_model(num_classes):
    inputs = tf.keras.layers.Input(shape=(IMG_SIZE, IMG_SIZE, 3))
    model = VGG16(include_top=False, input_tensor=inputs, weights="imagenet")

    # Freeze the pretrained weights
    model.trainable = False

    # Rebuild top
    x = tf.keras.layers.GlobalAveragePooling2D(name="avg_pool")(model.output)
    x = tf.keras.layers.BatchNormalization()(x)

    top_dropout_rate = 0.2
    x = tf.keras.layers.Dropout(top_dropout_rate, name="top_dropout")(x)
    outputs = tf.keras.layers.Dense(num_classes, activation="softmax", name="pred")(x)

    # Compile
    model = tf.keras.Model(inputs, outputs, name="VGG16")
    optimizer = tf.keras.optimizers.Adam(learning_rate=1e-2)
    model.compile(
        optimizer=optimizer, loss="categorical_crossentropy", metrics=["accuracy"]
    )
    return model
```

```python
model = build_model(num_classes=NUM_CLASSES)

@power_meter.measure_power(
    package="tensorflow",
    algorithm="VGG16",
    data_type="images",
    data_shape="(32,32,60000)",
    algorithm_params="batch_size=64,epochs=10,optimizer=Adam,loss='categorical_crossentropy'"
)
def train_model():
    model.fit(ds_train, epochs=epochs, batch_size=batch_size, validation_data=ds_test)

if __name__ == '__main__':
    train_model()
```

Functional overview of EA2P



Experimental validation: The testbed used

Platforms :

name	Intel-1	AMD-1	AMD-2	Intel-2
CPU name	i9 12950HX	EPYC 7452	EPYC 7513	E5-2698v4
GPU name	RTX 3080Ti	A100 SXM4	A100 SXM4	Tesla V100
CPU TDP	55W	155W (x2)	200W(x1)	135W (x2)
GPU TDP	150W	400W (x2)	400W (x4)	300W (x8)
CPU threads	24	64 (x2)	64 (x1)	40 (x2)
GPU VRAM	16GB	40GB (x2)	40GB (x4)	32GB (x8)
CPU RAM	32 GB	128 GB	512 GB	512 GB
Multi-SoC	No	Yes	No	Yes

Applications:

- System sleep test
- VGG16 with cifar10 TensorFlow dataset
- VGG16 with Stanford dogs TensorFlow dataset
- Parallel OpenMP multiplication with matrix size 8000x8000, varying number of threads
- Parallel OpenMP Streaming vector TRIAD, varying data size (for RAM model validation)

Energy reported values

- **psys :** Energy of the system on chip *(motherboard energy like in BMC counters with IPMI tools)*
- **package :** The CPU domain *(the CPU chip energy)*
- **uncore :** The integrated GPU energy of the package
- **cores :** The total consumption of all CPU cores of the package
- **gpu :** The consumption of GPU devices *(like Nvidia, AMD, ..)*
- **ram :** The energy of RAM domains
- **time :** The CPU elapsed time of application or instrumented code

Experimental validation : measurements overhead EA2P vs perf

Application	tool	Pkg (std)	RAM (std)	time(s) (std)
sleep	perf	2.254(0.004)	1.290(0.002)	183.508(0.02)
	EA2P	2.181(0.02)	1.270(0.001)	180.272(0.002)
	gap (perf-EA2P)	**0.073**	**0.02**	**3.236**
CIFAR-CPU	perf	28.592(0.32)	4.899(0.10)	445.236(5.36)
	EA2P	28.252(0.40)	4.825(0.12)	438.33(6.81)
	gap (perf-EA2P)	**0.34**	**0.074**	**6.906**

Overhead validation on intel client "Laptop" (Intel Core i9 12950 HX)

- *Each of the experiments was repeated 5 times to assess the consistency through the standard deviation which turned to be tiny.*
- *For simplicity, we only report the average values of the 5 runs and we report standard deviation to illustrate the variability which is due to the operating system and the machine state.*

Experimental validation : EA2P VS CodeCarbon and multiGPU report

Application	tool	CPU (Wh)	GPU (Wh)	time(sec)
sleep	CodeCarbon	0.30538	0.98752	181.931
	EA2P	0.20417	0.82411	180.706
VGG16 CIFAR-GPU	CodeCarbon	0.22944	2.07726	67.993
	EA2P	0.23011	2.04792	67.757

GPU validation on Nvidia ("Laptop"). *CPU is the energy of package domain*

Appli	pkgs(Wh)	ram (Wh)	GPU0 (Wh)	GPU1 (Wh)	GPU2 (Wh)	GPU3 (Wh)	GPU4 (Wh)	GPU5 (Wh)	GPU6 (Wh)	GPU7 (Wh)	time (sec)
Sleep	2.19481	1.33308	2.17964	2.10399	2.12799	2.10432	2.10385	2.12957	2.10584	2.14317	181.038
VGG16 DOG-CPU	**28.52879**	5.4077	5.63378	5.41911	5.50514	5.41387	5.39961	5.49029	5.41896	5.52412	495.096
VGG16 DOG-GPU	1.21921	0.38869	**2.51989**	0.81177	0.81666	0.80432	0.81027	0.81626	0.80222	0.81376	52.459

Multi GPU systems energy report "gemini" EA2P

Fine tuning VGG16 with Stanford dog dataset consume a total of more than 77 Wh for more than 9 minutes running on 80 threads Intel Xeon server with 8 Nvidia V100 GPU mounted.
The same program using GPU computing consume around 10 Wh for less than a minute of execution on the same machine. So 10x faster and 8x energy efficient

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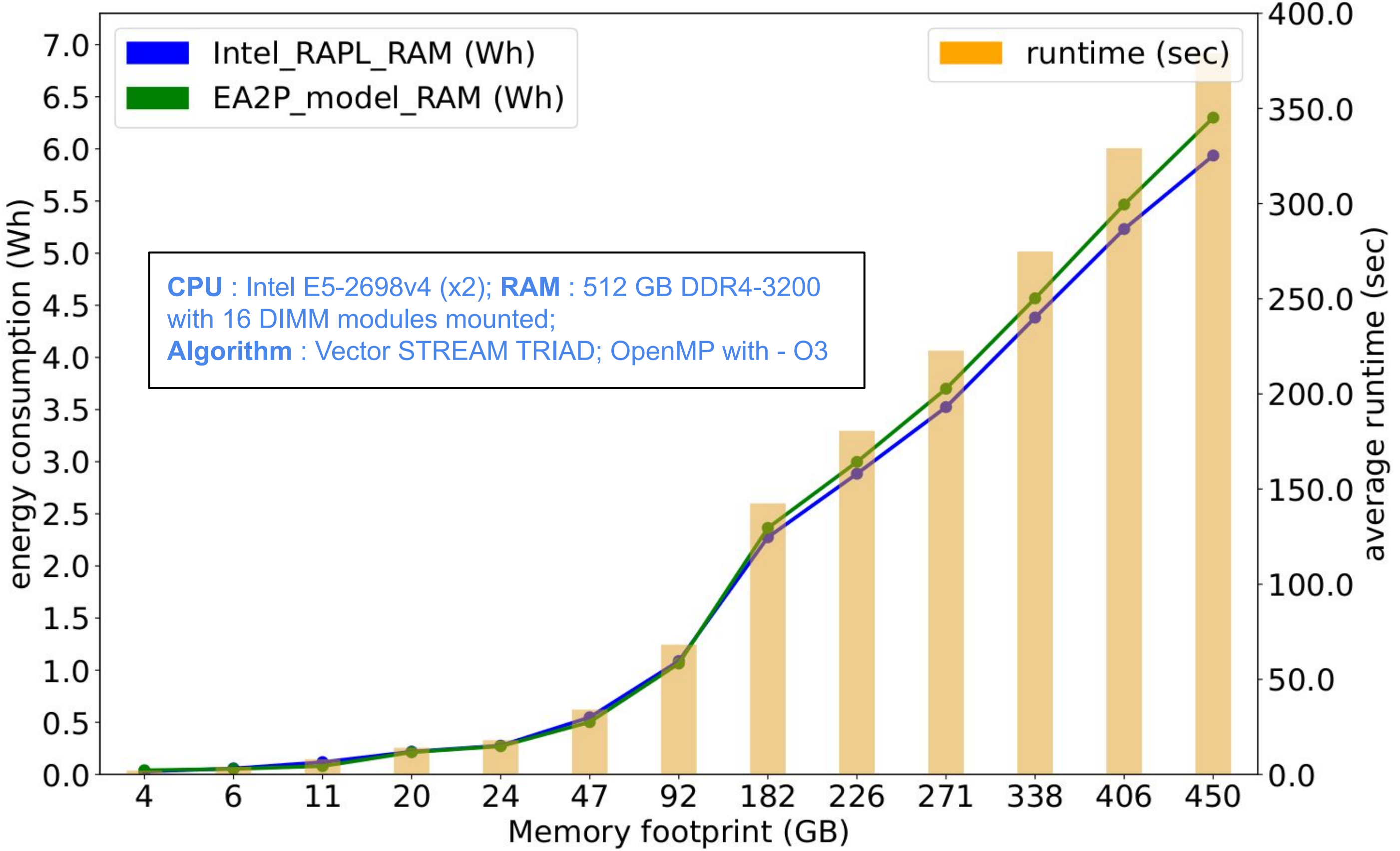
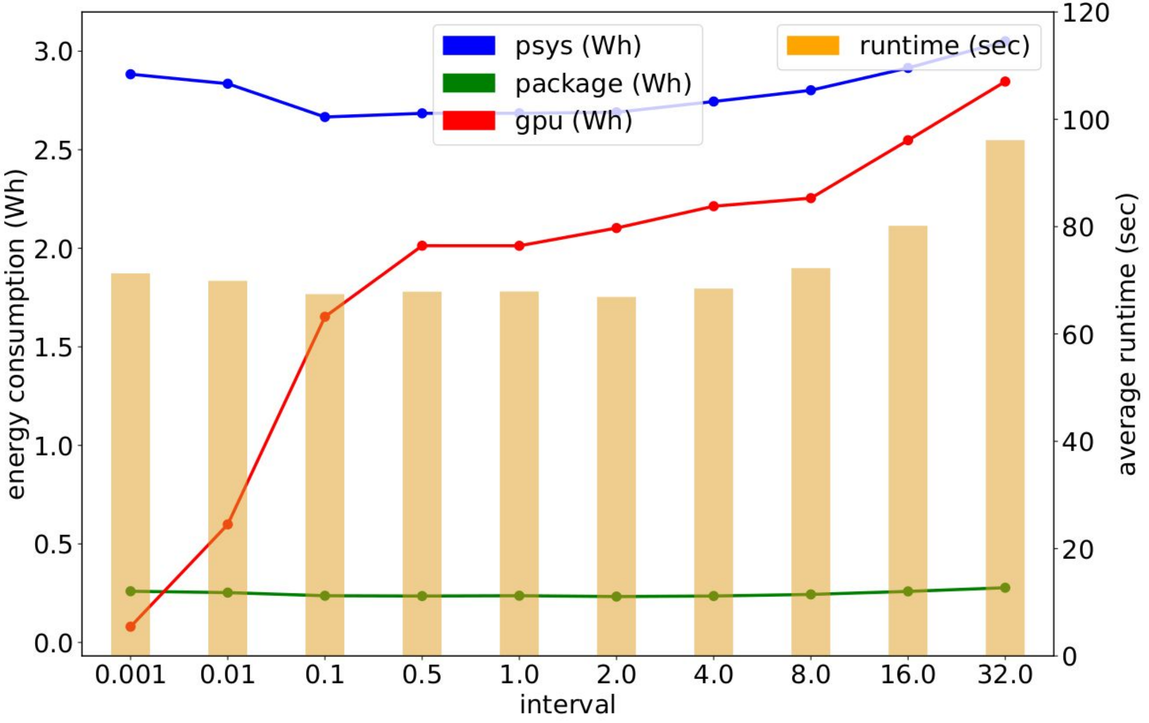
Experimental validation : RAM Model validation through intel RAPL



Experimental validation : Sampling frequency influence

Application : VGG16 training on CIFAR10 with TensorFlow with batch size 64 and 10 epochs
CPU : Intel Core i9 12950HX (24 Threads)
RAM : 32 GB DDR5-4800
GPU : RTX 3080Ti, 16GB, GDDR6

psys	package	gpu	time	interval
2.88300	0.25986	0.08007	71.28928	0.001
2.83491	0.25284	0.59910	69.90146	0.010
2.66597	0.23706	1.65259	67.43378	0.100
2.68465	0.23551	2.01294	67.88068	0.500
2.68499	0.23720	2.01260	67.91608	1.000
2.69010	0.23293	2.10269	66.90635	2.000
2.74465	0.23574	2.21340	68.46401	4.000
2.80177	0.24374	2.25440	72.26552	8.000
2.91496	0.25907	2.54813	80.16185	16.000
3.05029	0.27769	2.84596	96.12139	32.000



- Sampling frequency is the time between two query of energy values
- CPU (psys and package) energy and time are more correlated with sampling interval
- Normally, psys >= package+gpu since it's the entire board value
- GPU depend on Nvidia-smi which report the power and not the energy. So we notice consistency problem with low sampling intervals.
- Threads join from logging process is the problem of time overhead for big intervals

Multi-nodes measurement *(Numpy Matmul)*

MEASUREMENTS ON AMD-2 WITH 10240 × 10240 MATRICES, using send-Receive communication (2 first nodes compute)

Node	Pkg(J)	GPU 0 (J)	GPU 1 (J)	GPU 2 (J)	GPU 3 (J)	RAM (J)	Time (s)
0	536.67	255.75	261.8	258.92	271.46	75.6	4.34
1	555.88	380.09	344.25	331.31	357.12	100.8	5.85
2	94.84	113.97	123.36	128.24	134.06	33.6	1.24
3	94.09	112.98	121.65	135.57	147.30	33.6	1.24
Total	1281.48	862.78	851.09	854.02	909.93	243.6	12.67

MEASUREMENTS ON AMD-2 WITH $2^{14} \times 2^{14}$ MATRICES, using broadcast (all nodes compute)

Node	Pkg(J)	GPU 0 (J)	GPU 1 (J)	GPU 2 (J)	GPU 3 (J)	RAM (J)	Time (s)
0	1493.59	648.52	680.59	649.10	666.36	201.6	13.25
1	1419.99	714.36	633.82	625.94	670.95	193.2	12.54
2	1457.43	664.03	666.67	652.40	719.44	201.6	13.03
3	1472.65	667.21	653.88	659.93	689.50	201.0	13.11
Total	5843.66	2694.11	2634.95	2587.35	2746.25	596.4	51.93

MEASUREMENTS ON AMD-2 WITH $2^{15} \times 2^{15}$ MATRICES, using broadcast (all nodes compute)

Node	Pkg(J)	GPU 0 (J)	GPU 1 (J)	GPU 2 (J)	GPU 3 (J)	RAM (J)	Time (s)
0	9109.88	3374.76	3530.46	3319.83	3425.45	1058.4	74.66
1	8777.08	3674.04	3255.40	3208.25	3430.79	999.6	70.65
2	9012.43	3353.60	3363.65	3291.97	3638.53	1041.6	73.26
3	9090.88	3408.30	3347.95	3435.98	3442.57	1058.4	74.43
Total	35990.27	13810.70	13497.44	13256.03	13937.32	4158.0	293.00

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Conclusion and future works

- Conclusion:
  - EA2P provide fine grained results per device & power domains (Intel) Measurement for RAM, AMD GPU & CPU, Nvidia GPU, and Intel CPU
  - Benchmarking underscores the complex relationship between performance, power consumption, and energy efficiency across different architectures and workloads
- Future works
  - Implement robust error handling mechanisms and logging functionalities to help handling troubleshooting in EA2P
  - Apply system power management techniques to study best energy/performance strategies
  - Design power management techniques by deeply investigating all hardware power-saving features for energy-aware programming and scheduling

Thank you for your Attention !

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