# TOWARDS ZERO-WASTE COMPUTING

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This project has received funding from the European Union's Horizon Research and Innovation Actions under Grant Agreement № 101093202.

## TOWARDS ZERO-WASTE COMPUTING

#### Ana-Lucia Varbanescu

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Work & results with Nick Breed, Quincy Bakker, Duncan Bart, Jeffrey Spaan, Jelle van Dijk.



a.l.va

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## Computing is everywhere ... and it's not free!

- Top 10 videos on YouTube<sup>\*</sup> consumed as much as 600-700 EU persons per year (or about 400 North America persons)
- Training Alpha-Zero for a new game consumes as much as 100 EU persons per year
- A mid-size datacenter alone consumes as much energy as a small town
  - And that is not considering purchasing and secondary operational costs (e.g., cooling)
- In 2019 Dutch datacenters combined consumed 3-times more energy than the national railways
  - And consumption increased by 80% in 3 years
- The ICT sector is predicted to reach 21% of the global energy consumption by 2030

\*https://en.wikipedia.org/wiki/List\_of\_most-viewed\_YouTube\_videos#Top\_videos

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 In 201 nation
 And
 The energy consumption of computing is substantial and constantly increasing!
 The ICT sector is predicted to reach 21% of the global energy consumption by 2030

\*https://en.wikipedia.org/wiki/List\_of\_most-viewed\_YouTube\_videos#Top\_videos

## Three types of stakeholders



#### **Developers and users**

**Improve** the energy efficiency of their own codes, making use of algorithmic, programming, and hardware tools

**Design and implement** applications able to adapt to the available system resources



#### System operators

#### Ensure efficient scheduling

of workloads on system resources.

Harvest energy where resources/systems are massively underutilized.



#### **System integrators**

**Offer** the right mix of resources for the application developers and system operators.

**Include efficient hardware** to enable different application mixes.

# Systems

- On-premise hardware
  - Flexible, yet often limited in resources
  - Good for development
  - Limited value for production
- Supercomputers
  - Massive machinery, high-performance
  - Partially shared
  - Less flexible in terms of infra and programming
- Datacenters & Cloud computing
  - Scale-by-credit card
  - Excellent efficiency
  - Possible limitations in terms of performance (SLA)
- Computing continuum
  - New development in distributed computing
  - Unclear for scientific computing
  - Relevant for complete data analysis (sensor-to-result)





# Supercomputing/Data-centers



- Supercomputing is extremely high in carbon emissions, mainly due to scale.
- Embodied carbon\*: Indirect emissions, e.g., production, shipping, and disposal of system components.
- Operational carbon: Electricity, heating, cooling, etc. for the site operation.



Fugaku 0.44Exa @30MW



Frontier 1.2Exa @23MW



Aurora 2Exa? @60MW?

\*Data and tools: <u>https://boavizta.org/en</u>

# Sustainable acquisition

- We need new lifecycle assessment & procurement procedures
- Current Goal: Maximize Throughput (Workloads)
- Constraints:
  - Budget = Machine Cost + Electricity;
  - System Footprint/Weight; Cooling Capacity; Power Supply; …
- New Constraint: Carbon Budget



## Extend lifetime

- We need to Extend Lifetime, Reuse, and Recycle
- System Lifetime: Typically 4-6 years
  - Extended lifetime => embodied carbon reduction.
- Reuse & Recycle: Reduce carbon emissions caused by disposal & production
  - Reuse: e.g., LRZ offers decommissioned machines for free.
  - Recycling: accelerators, DRAM chips, heat pipes, cooling infra, ...



Courtesy of: Carsten Trinitis, TUM - at Sustainability Day @DATE, March 26, 2024, Valencia, Spain

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# New scheduling & RM opportunities

- Efficient operation
  - Schedulers
  - Automated tools
  - Support/education for users

- Additional opportunities
  - Shared resources
  - Location shifting
  - Time/Peak shifting

BDB ANDERSON

"Multitask?! I barely have cia, Spain time to task!"

Courtesy of: Carsten Trinitis, TUM - at Sustainability Day @DATE, March 26, 2024, Valencia, Spain time to tas

@ MARK ANDERSON, WWW.ANDERTOONS.COM

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## **Developers & users**

- Measure/Quantify
- Select the right systems
- Select the right implementation tools
- Select the right algorithms
- Tweak and tune ... and iterate

#### Non-trivial! But we must start somewhere ...

# Agenda

- Stakeholders & actions
- Different views on performance
  - Zero-waste computing
- 2.5 case-studies
- (re)Defining systems codesign
- Take home message



"Larry, do you remember where we buried our hidden agenda?"



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#### Assumptions

- Modern (and future) systems are parallel and heterogeneous
  - In many dimensions
- Systems are characterized by peak performance (with various "roofs")
- All applications want more performance
  - Applications must enable parallelism
- One Application => n algorithms => n\*m implementations
  - Algorithms: characterized by complexity
  - Algorithms/implementations: characterized by arithmetic/operation intensity ops/byte

#### Some relevant performance metrics\*

• Speed-up: how much faster do we get with new machines, algorithms, ...

```
S(workload) = Perf(Old)/Perf(New)
```

• Efficiency: how efficient are we in getting performance

```
E(workload) = Perf / Resources
```

• Energy efficiency: how energy efficient are we in getting performance

```
EE(workload) = Perf / Energy
```

• Utilization: how efficient are we utilizing our resources

```
U(resource) = Achieved / Peak
```

High-performance computing

High-efficiency computing

\*please accept the naïve notation and pseudo-definitions

#### Waste in computing

Unneccesary time (or energy) spent in (inefficient) computing is compute waste.

To reduce compute waste, we must focus on efficiency-to-solution

#### Detecting waste [1]

- We assume computing waste is a consequence of underutilized resources.
- Informally, assume:
  - <mark>P1</mark> = performance(algorithm, workload, <mark>system1</mark>)
  - P0 = idealPerformance(algorithm, workload, system1)



Ideal performance is non-trivial to quantify.

\*performance is not necessarily runtime.

# Detecting waste [2]

- We assume computing waste is a consequence of underutilized resources.
- Informally, assume:

system1 > system2

- P1 = performance(algorithm, workload,
  - 2 = performance(algorithm, workload,

<mark>system1</mark>) <mark>system2</mark>)

• "Strict" definition:

if (<mark>P1 == P2</mark>) => waste in <mark>P1</mark>

• "Relaxed" definition: if ( abs (P1 - P2) > T ) => waste in P1 with T = threshold for performance loss

quantification and improvement. \*performance is not necessarily runtime.

Challenges in both

efficiency

#### Reducing waste in computing



# Systems at hand & efficiency knobs

## Cores, power, energy...

#### Multi-core CPU

- Multi-core energy consumption != N \* energy/core
  - Complex architecture, different clocks, shared resources
- Various ways to implements DVFS + power reduction techniques
- Non-trivial correlation with performance

#### • GPU

- Power is significantly impacted by the type of workload and occupancy
- Always check the power cap, too!
- Heterogeneous & multi-node computing
  - Sum of energy by components
  - Networking energy lacking



# **CPU** example

- AMD EPYC CPU
- Running SGEMM
  - Different frequencies



Courtesy of Benjamin Czaja, SURF, NL

## **GPU** example

GPU	SMs	Cores/SM	Total Cores	Max Power [W]	Idle Power [W]
A4000	48	128	6144	140	39.5
A6000	84	128	10572	300	71.5
A2	10	128	1280	60	18.1
A100	108	64	6912	250	37.9



# GPU example (cont'd)

- Caching patterns make a significant difference
- Compute vs memory intensive – mem consumes more.
- Memory coalescing, negligible
- Data types & instruction mix show some differences



## Performance vs. energy

- Low performance → waste in computing
  - We power resources that are not needed
- High performance  $\rightarrow$  faster execution  $\rightarrow$  less energy consumed
  - - Strong assumption that power is constant

In the context of multi-core and heterogeneous systems, minimizing execution time might not guarantee lowest energy consumption.

#### Auto-tuning, anyone?

Goel and McKee – "A Methodology for Modeling Dynamic and Static Power Consumption for Multicore Processors"



#### Case study #1: Heterogeneous systems

https://gitlab.qub1.com/vrije-universiteit/master-project/thesis https://scripties.uba.uva.nl/search?id=record\_27683

#### Heterogeneous computing

- A heterogeneous platform = a CPU + a GPU (the starting point)
- An application workload = an application + its input dataset
- Workload partitioning = workload distribution among the processing units of a heterogeneous system



# Heterogeneous computing for all??

- Model-based load-balancing for heterogeneous computing
  - Analytical model
  - Empirical calibration
  - Embedded in the Glinda framework
- Challenging programming
  - Leverages performance portable programming models
- Maximizes performance and/or resource utilization => minimizes waste
  - Uses all types of resources in the system
- Driven by performance
  - Could/should be extended for energy efficiency

\*Jie Shen et al., IEEE TPDS. 2015 "Workload partitioning for accelerating applications on heterogeneous platforms"

# Energy improvements

- Basic assumptions
  - Tasks run on different processors
  - Idle processors waste energy
  - Higher/lower operating frequencies
    - => more/less power respectively
    - => reduce or increase runtime respectively

#### Opportunities

- Dynamic Voltage and Frequency Scaling (DVFS)
- Reducing operating frequencies in idle states to save energy
  - No active task => no runtime increase
- Increasing operating frequencies in busy states to save energy
  - Lower runtime => less time to consume energy



# Approach

- Framework to monitor and improve the energy consumption of heterogeneous applications
  - Analyze application at runtime
    - Use live execution data
  - Determine application states
    - CPU/GPU-utilization patterns
  - Apply DVFS for this phases
    - Observe energy changes
  - Design policies to maximize energy consumption
    - What, when, and how to apply DVFS



# **Empirical analysis**

- Workload: 10 different applications from different benchmarking suites
- System: Geforce GTX 960 GPU and an AMD Ryzen 7 3700x CPU.
- Metrics of interest: runtime and energy consumption
- Reference implementation = "do nothing"
  - Gain and/or loss against reference
- Five policies :
  - Maximum Frequency
  - System
  - MinMax
  - Ranked MinMax
  - Scaled MinMax

#### Results

	Policy											
Applications	No Action		MinMax		$\operatorname{System}$		Maximum frequency		Ranked MinMax		Scaled MinMax	
	Energy	Time	Energy	Time	Energy	Time	Energy	Time	Energy	Time	Energy	Time
BFS	5248.7 J	$60.5 \mathrm{s}$	6499.7 J	$70.6 \mathrm{\ s}$	5669.3 J	$69.7~\mathrm{s}$	6276.2 J	60.2 s	5294.3 J	$61.2 \mathrm{~s}$	5496.3 J	$70.8 \mathrm{~s}$
			(23.8%)	(16.7%)	(8.0%)	(15.2%)	(19.6%)	(-0.5%)	(0.9%)	(1.2%)	(4.7%)	(17.0%)
Myocyte												
LavaMD	7454.3 J	52.1 s	6962.4 J	$52.6 \mathrm{~s}$	7024.6 J	$52.3~\mathrm{s}$	7473.5 J	51.0  s	$6951.1 \ { m J}$	$52.9 \mathrm{~s}$	7125.0 J	$53.8 \ s$
			(- <mark>6.6</mark> %)	(1.0%)	(-5.8%)	(0.4%)	(0.3%)	(-2.1%)	(-6.8%)	(1.5%)	(-4.4%)	(3.3%)
NW	6103.3 J	$64.9 \mathrm{\ s}$	6465.5 J	$77.0 \mathrm{\ s}$	7132.7 J	$74.1 \mathrm{s}$	7787.6 J	$70.4 \mathrm{~s}$	$5619.0 \ { m J}$	$78.5 \mathrm{s}$	5635.6 J	$82.5 \mathrm{s}$
			(5.9%)	(18.6%)	(16.9%)	(14.2%)	(27.6%)	(8.5%)	(-7.9%)	(21.0%)	(-7.7%)	(27.1%)
Particlefilter-float	8540.8	$89.5 \mathrm{s}$	9245.1 J	$99.6 \ s$	10028.8 J	$96.9~\mathrm{s}$	10301.2 J	91.5  s	7666.4 J	$102.8 \mathrm{~s}$	7578.4 J	$107.6 \mathrm{~s}$
	0040.0		(8.2%)	(11.3%)	(17.4%)	(8.3%)	(20.6%)	(2.2%)	(-10.2%)	(14.8%)	(-11.3%)	(20.2%)
Kmeans	5729.4 J	$66.2 \ s$	6248.0 J	$77.0 \mathrm{\ s}$	6303.4 J	$74.4 \mathrm{~s}$	6633.3 J	$66.5 \mathrm{s}$	$5514.4 \; J$	68.9 s	5932.2 J	$77.9 \mathrm{\ s}$
			(9.1%)	(16.3%)	(10.0%)	(12.4%)	(15.8%)	(0.5%)	(-3.8%)	(4.1%)	(3.5%)	(17.7%)
Bandwidth	6337.7 J	$50.4 \mathrm{~s}$	5957.7 J	$54.0 \mathrm{~s}$	$6128.0 \ { m J}$	$52.3~\mathrm{s}$	$6165.4 \; { m J}$	$51.0 \mathrm{~s}$	$6029.5 \ { m J}$	$53.5 \ s$	6004.9 J	$54.7~\mathrm{s}$
			(- <mark>6</mark> .0%)	(7.1%)	(-3.3%)	(3.8%)	(-2.7%)	(1.2%)	(-4.9%)	(6.2%)	(-5.3%)	(8.5%)
UnifiedMemoryPerf	33188.3 J	$266.1~{\rm s}$	28612.8 J	$263.1~{\rm s}$	32491.1 J	$257.5 \mathrm{\ s}$	$34542.5 \ { m J}$	$258.4 \mathrm{\ s}$	$27956.7 \; J$	$262.5 \mathrm{\ s}$	27810.9 J	$258.6~{\rm s}$
			(-13.7%)	(-1.1%)	(-2.1%)	(-3.2%)	(4.1%)	(-2.9%)	(-15.8%)	(-1.4%)	(-16.2%)	(-2.8%)
matrixMul	9295.6 J	66.6 s	$10442.3 { m J}$	$67.6 \ s$	$10962.8 \ { m J}$	$67.0 \ { m s}$	$10086.7 \; J$	$66.5 \ s$	$10913.3 \; { m J}$	$67.5 \ s$	$10264.3 \ { m J}$	$68.0 \mathrm{~s}$
			(12.3%)	(1.5%)	(17.9%)	(0.6%)	(8.5%)	(-0.2%)	(17.4%)	(1.4%)	(10.4%)	(2.1%)
Jacobi unoptimized	10980.4 J	118.1 s	7802.1 J	$124.6 \mathrm{\ s}$	8192.6 J	$128.0 \mathrm{\ s}$	8039.1 J	$109.0 \mathrm{\ s}$	8958.9 J	$109.3 \mathrm{\ s}$	8440.3 J	$124.8 \mathrm{\ s}$
			(-28.9%)	(5.5%)	(-25.4%)	(8.4%)	(-26.8%)	(-7.7%)	(-18.4%)	(-7.5%)	(-23.1%)	(5.7%)
Jacobi optimized	7697.2 J	$95.3 \mathrm{~s}$	$5467.1 \; { m J}$	$101.9 \mathrm{~s}$	$5280.8 \; { m J}$	$101.4 \mathrm{~s}$	5021.9 J	$85.8 \mathrm{~s}$	6090.9 J	86.6 s	$5400.4 \; { m J}$	$102.1 \mathrm{~s}$
			(-29.0%)	(6.9%)	(-31.4%)	(6.4%)	(-34.8%)	(-10.0%)	(-20.9%)	(-9.1%)	(-29.8%)	(7.1%)

## Results

	Best Policy							
Applications	Sin	gle Core		Multi Core				
	Name	Energy	Time	Name	Energy	Time		
BFS	Scaled MinMax	-0.5%	0.2%	Ranked MinMax	0.9%	1.2%		
LavaMD	Maximum Frequency	-0.7%	-0.1%	MinMax	-6.6%	1.0%		
NW	Ranked MinMax	4.8%	4.4%	Ranked MinMax	-7.9%	21.0%		
Particlefilter-float	Ranked MinMax	-0.0	1.5%	Ranked * MinMax	-10.2%	14.8%		
Kmeans	Ranked MinMax	3.7%	0.6%	Ranked MinMax	-3.8%	4.1%		
Bandwidth	Maximum Frequency	-2.3%	0.1%	Maximum <sub>*</sub> Frequency	-2.7%	1.2%		
UnifiedMemoryPerf	MinMax	-1.5%	-3.8%	Scaled MinMax	-16.2%	-2.8%		
matrixMul	Maximum Frequency	3.5%	-0.0%	Maximum Frequency	8.5%	-0.2%		
Jacobi unoptimized	MinMax	-3.5%	-7.4%	Maximum Frequency	-26.8%	-7.7%		
Jacobi optimized	MinMax	-2.7%	-9.4%	Maximum Frequency	-34.8%	-10.0%		

#### Lessons learned

- Heterogeneous computing => high performance, high energy consumption
- Energy harvesting can work
  - Depends a lot on the implementation
- There is a broader question: how can we explore trade-offs between energy and performance ?
  - Harvesting = how to keep performance fixed
  - Energy budgets = how to maximize performance

Git repository:

https://gitlab.qub1.com/vrije-universiteit/master-project/energymanager

Thesis:

https://gitlab.qub1.com/vrije-universiteit/master-project/thesis

#### Lessons learned

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- Energy harvesting can work
  - Depends a lot on the implementation
- There is a broader question: how can we explore trade-offs between energy and performance ?
  - Harvesting = how to keep performance fixed
- Heterogeneous systems require heterogeneous applications
- Not using the CPU/GPU is by definition wasteful

Reduced waste by frequency scaling.

https://gitlab.qub1.com/vrije-universiteit/master-project/energymanager

Thesis:

https://gitlab.qub1.com/vrije-universiteit/master-project/thesis


### Case study #2: Shrinking the platform

### Possible workflow to identify waste

- 1. Pick a workload
- 2. Pick a baseline platform
- 3. Reduce resources
- 4. Measure performance
- 5. **Compare** performance

No difference or better performance? Found waste and/or a better system.

How to reduce resources? How to measure performance? How to compare?

The devil is in

the details.

# Measuring Predicting performance

Benchmarking

Impossible

Co-location

Difficult to setup

- Simultaneous execution with a (specific) resource-consuming application
- Partitioning

Not available on many systems

- Partitions with isolated GPU resources
- Analytical modelling
- Statistical modelling
- Simulation

Not sufficiently accurate

best option (currently)

#### Proposed workflow



### **Experimental setup**

Applications:

- 5 Rodinia kernels:
  - Compute-bound: hotspot, k-means (2)
  - Memory-bound: k-means (1)

backpropagation (1), backpropagation (2)

Systems:

- Baseline: RTX 2060 Super
- Variables:
  - **SMs**: 25, 30, ...., 40
  - **Core clock**: 1000, 1150, ...., 1900
  - **Memory clock**: 800, 1250, ..., 3500

Simulation run-time ≈ 24-40 hours

#### Simulated with:



https://github.com/romnn/gpucachesim

## Varying SMs

#### Compute-bound:

- Hotspot
- K-means (2)

#### Memory-bound:

- K-means (1) •
- Backprop (1)
- Backprop (2)

More resources ≠ better performance





--- Hotspot (1)

K-means (1) — Backpropagation (1)

### Core clock

#### Compute-bound:

- Hotspot
- K-means (2)

#### Memory-bound:

- K-means (1) •
- Backprop (1)
- Backprop (2)





## Memory clock

#### Compute-bound:

- Hotspot
- K-means (2)

#### Memory-bound:

- K-means (1)
- Backprop (1)
- Backprop (2)





#### SMs: BFS

BFS is memory bound.

Is the strict definition reasonable? Should we use the relaxed definition?



--- Breadth first search (1)

#### Memory clock: BFS

As BFS is memory bound, we do expect to see performance gain when the memory clock speed increases.



---- Breadth first search (1)

#### Lessons learned

- We demonstrated waste at resource-level can be significant
- We demonstrated it is possible\* (in simulation) to update platforms
- New opportunities for ...
  - Partitioning
  - Scheduling
  - Runtime systems
- Waste can (/should?) be investigated per resource.
- Difficult to model, trivial (but sloooow) to simulate.

**Reconfiguring** the system can reduce compute waste.



### Case study #3: Embracing load imbalance

## HemoCell – coupled simulation

- Simulated blood flow using ...
  - Fluid simulation
  - Particle simulation
- Aims for high-performance
  - Using distributed processing & MPI
- Observations:
  - Load imbalance is difficult to fix
  - ... but can be easier to detect
  - Adapting the frequency of nodes to their load can lead to energy savings!
- Technique: DVFS per node.



https://hemocell.eu/

#### Load imbalance



C1: Fluid imbalance.



C2: Particle Imbalance.



C3: Fluid and particle imbalance

### **Empirical analysis**

- 16 node experiment (DAS6 machine)
  - 1,2 have higher workloads
  - 3,6 have "normal" workloads
- 3 DVFS strategies
  - Reduce the frequency of the underutilized nodes

	Nodes	
Strategy	1-2	3-16
S1	$2.8\mathrm{GHz}$	$1.5\mathrm{GHz}$
S2	$2.8\mathrm{GHz}$	$2.4\mathrm{GHz}$
S3	$2.4\mathrm{GHz}$	$1.5\mathrm{GHz}$

Energy savings [C1, C2]



#### Energy savings [C3]



#### Lessons learned

- We demonstrated **waste due to load imbalance**
- We demonstrated it is possible\* to make use of load imbalance to reduce energy consumption
- New opportunities for …
  - Runtime systems
  - Scheduling
- Key challenge: can we automate the process?
  - Detect load imbalance
  - Select correct frequencies
  - Apply DVFS

#### Lessons learned

- We demonstrated waste due to load imbalance
- We demonstrated it is possible\* to make use of load imbalance to reduce energy consumption
- New opportunities for ...
  - Runtime systems
  - Scheduling

- Waste due to load imbalance does happen

- Difficult to re-balance, easier to save energy

**DVFS** remains is a valid approach, when permitted.

## Co-designing systems and applications

Can we co-design?

### Co-design

"Co-design is the process of involving multiple stakeholders in the design and development of products, services, or systems with the goal of creating solutions that are more relevant, effective, and satisfying to the people who will use them." [1]

"Hardware/Software Codesign is the design of cooperating hardware components and software components in a single design effort." [2]

"Co-design: to design (something) by working with one or more others : to design (something) jointly" [3]

[1] https://www.mural.co/blog/co-design-method [2] Patrick R. Schaumont, "A Practical Introduction to Hardware/Software Codesign"

[3] https://www.merriam-webster.com/dictionary/codesign

#### Today's approach to high-performance





## **Open questions**

- What is the right abstraction for the input?
- How do we split the workload in "basic units"?
- How do we build "basic units" performance models?
- How do we prune the search space?
- How do we do code building and tuning?
- What about the data?

•



## In summary ...

#### Take borne message to-the-office



- High-efficiency computing is needed to avoid a (computing) energy crisis
  - Zero-waste computing is a strong motivating example ...
  - ... but we need tools and methods for it.
- Reduce waste in computing is within reach
  - Improve applications and improve systems
- Tempting to co-design applications and systems
  - Performance engineering to the rescue
    - Many practical questions still arise …
- We propose a co-design approach in Graph-Massivizer



### **Towards Zero-waste Computing**



- Awareness: utilizing computing resources with little efficiency is equivalent to wasting computing.
- **Performance and efficiency**: non-functional properties, such as performance and efficiency, are essential to understand computing waste.
- Design-time: performance/efficiency must be essential concerns, like functionality
- Stakeholders: domain-specialists/application owners must (also) take responsibility in reducing waste in computing.

## To do: Zero-waste computing

#### Design and development:

"Build the right computing system for the job at hand"

- Better hardware
  - Design and modeling to build the right infrastructure
- Better software
  - Performance and energy analysis is essential to improve efficiency
- Better tools
  - For design, analysis, and modeling

#### Awareness:

"Acknowledge and improve the efficiency of 'generic' systems"

- Better metrics
  - To demonstrate the waste in computing
- Better methods
  - To analyse the complex tradeoffs between performance, energy, QoS, ...

