Enea Vincenzo Napolitano

Measuring and Mitigating the Environmental Impact of Artificial Intelligence

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Cycle: XXXVIII

Year: Third

Candidate’s information

- MSc degree in Data Science @ Federico II
- DIETI Research group/laboratory: PICUSlab
- PhD start date: January 1, 2023
- Scholarship type: RESTART
- Period abroad: May 1, 2024 – October 31, 2024 @ BDS LAB - University of Houston, Houston (USA)

Summary of study activities

- Smart Environments & Digital Public Services (trajectory mining, indoor–outdoor mobility, justice digitalization)
- Computational Optimization (sparse matrix analytics, transitive closure, SQL vs Python paradigms, HPC)
- Sustainability of AI (CO_2 estimation models, awareness assessment, hybrid metrics)

Research area(s)

Central Research Problem
How to make digital systems, AI solutions, and data-intensive infrastructures **more efficient and environmentally sustainable** while supporting modern smart environments (cities, logistics, healthcare, public services).

- **Urban & Public Service Intelligence**
  Problem: improve mobility, decision flows, and public office efficiency in digital ecosystems.

- **Computational Efficiency in Large-Scale Data Processing**
  Problem: traditional computation (e.g., graph closure, sparse data) struggles when data grows.

- **Environmental Sustainability of AI & Digital Technologies**
  Problem: AI adoption increases energy consumption and CO_2 emissions, but the community lacks shared standards for impact reporting.

Research results

- **AI-driven decision support for urban mobility and digital public services (non-thesis, research line result)**
  Showed that AI classification and trajectory analysis can support improved workflow optimization and mobility evaluation.

- **Digital transformation contribution for justice sector workflows (non-thesis, societal impact result)**
  Demonstrated that document classification and process analysis can reduce manual bottlenecks and improve case-flow management.

- **Optimized transitive closure algorithm for high-performance workloads (thesis side result)**
  Demonstrated substantial performance improvements over widely used graph-processing libraries, especially for large adjacency matrices.

- **Proof that Python-based sparse analytics can outperform DBMS logic when carefully optimized (thesis side result)**
  Showed that SQL-like logic replicated in Python achieves superior computation on sparse matrices under controlled benchmarks.

- **Hybrid metric for AI environmental impact (core thesis result)**
  Developed a unified model to estimate CO_2e emissions of AI tasks, integrating hardware, runtime, energy source and deployment paradigm.

- **Large-scale empirical assessment of sustainability awareness in ML research (core thesis result)**
  Conducted a systematic study revealing that most ML works do not report environmental footprint, highlighting a structural lack of sustainability disclosure.

Research products I

[P1]	Borraccia, Salvatore, Elio Masciari, and Enea Vincenzo Napolitano. "Green metrics for AI: A hybrid strategy for environmental impact assessment." *Array* (2025): 100528.
[P2]	Masciari, Elio, and Enea Vincenzo Napolitano. "Assessing awareness of environmental sustainability in machine learning research." *World Wide Web* 28.4 (2025): 43.
[P3]	Masciari, Elio, and Enea Vincenzo Napolitano. "An effective measure for evaluating the environmental impact of AI tasks: E. Masciari, EV Napolitano." *Computing* 107.7 (2025): 153.
[P4]	Indrio, Flavia, et al. "Functional gastrointestinal disorders predictors in neonates and toddlers: A machine learning approach to risk assessment." *Heliyon* 11.1 (2025).
[P5]	di Torrepadula, Franca Rocco, et al. "Machine learning for public transportation demand prediction: A systematic literature review." *Engineering Applications of Artificial Intelligence* 137 (2024): 109166.
[P6]	Anniciello, Arianna, Simona Fioretto, Elio Masciari, and Enea Vincenzo Napolitano. "Human-in-the-Loop Generative AI for Explainable Insurance Decision." *Advances in Mobile Computing and Multimedia Intelligence: 23rd International Conference, MoMM 2025, Matsue, Japan, December 8–10, 2025, Proceedings*. Springer Nature, 2025.

Research products II

[P7]	Borraccia, Salvatore, Elio Masciari, and Enea Vincenzo Napolitano. "A Hybrid Approach to Estimating AI Carbon Emissions." *International Conference on Database and Expert Systems Applications*. Cham: Springer Nature Switzerland, 2025.
[P8]	Masciari, Elio, and Enea Vincenzo Napolitano. "Optimizing Transitive Closure Computation for High Performance Computing and Security." *2025 33rd Euromicro International Conference on Parallel, Distributed, and Network-Based Processing (PDP)*. IEEE, 2025.
[P9]	Conza, Maria Luisa, et al. "Enhancing Employee Health Through an Experimental Diet: Insights from Machine Learning Analysis." *2025 33rd Euromicro International Conference on Parallel, Distributed, and Network-Based Processing (PDP)*. IEEE, 2025.
[P10]	Napolitano, Enea Vincenzo, Elio Masciari, and Carlos Ordonez. "Integrating flow and structure in diagrams for data science." *2024 IEEE International Conference on Big Data (BigData)*. IEEE, 2024.
[P11]	Masciari, Elio, and Enea Vincenzo Napolitano. "Environmental sustainability of ai: Estimating co 2 e emissions across cloud, edge, and fog paradigms." *International conference on web information systems engineering*. Singapore: Springer Nature Singapore, 2024.

Research products III

[P12]	Masciari, Elio, and Enea Vincenzo Napolitano. "Sustainability and High Performance Computing." *International Conference on Information Integration and Web Intelligence*. Cham: Springer Nature Switzerland, 2024.
[P13]	Masciari, Elio, and Enea Vincenzo Napolitano. "The environmental cost of high performance computing system simulation." *2024 32nd Euromicro International Conference on Parallel, Distributed and Network-Based Processing (PDP)*. IEEE, 2024.
[P14]	Indrio, Flavia, et al. "Infantile Predictors of Functional Gastrointestinal Disorders: A Machine Learning Approach to Risk Assessment." (2024). SEBD 2024.
[P15]	Fioretto, Simona, Elio Masciari, and Enea Napolitano. "Machine Learning for KPI Development in Public Administration." *Proceedings of the 13th International Conference on Data Science, Technology and Applications, DATA 2024*. SciTePress, 2024.
[P16]	Benfenati, Domenico, et al. "AI in Medicine: Activities of the CINI-AIIS Lab at University of Naples Federico II." *CEUR WORKSHOP PROCEEDINGS*. Vol. 3762. CEUR-WS, 2024.
[P17]	Napolitano, Enea Vincenzo. "Intelligent technologies for urban progress: exploring the role of ai and advanced telecommunications in smart city evolution." *European Conference on Advances in Databases and Information Systems*. Cham: Springer Nature Switzerland, 2023.

Research products IV

[P18]	Amato, Flora, et al. "Evolving justice sector: An innovative proposal for introducing ai-based techniques in court offices." *International Conference on Electronic Government and the Information Systems Perspective*. Cham: Springer Nature Switzerland, 2023.
[P19]	Fioretto, Simona, Elio Masciari, and Enea Vincenzo Napolitano. "Dossier classification to support workflow management optimization." *International Conference on Numerical Computations: Theory and Algorithms*. Cham: Springer Nature Switzerland, 2023.
[P20]	Napolitano, Enea Vincenzo, et al. "How pandemic affected the adoption of e-health systems." *Proceedings of the 27th International Database Engineered Applications Symposium*. 2023.
[P21]	Anniciello, Arianna, et al. "Digital Twins for Traffic Congestion in Smart Cities: A Novel Solution Using Data Mining Techniques." *KMIS*. 2023.
[P22]	Fioretto, Simona, Elio Masciari, and Enea Vincenzo Napolitano. "Can the Study of Trajectories Help to Extract Information from Business Processes?." *PMAI@ IJCAI*. 2023.

Research products V

[P23]	Fioretto, Simona, Elio Masciari, and Enea Vincenzo Napolitano. "A Joint Analysis of Trajectory Mining and Process Mining for Smartphone User Behaviour." *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*. Cham: Springer Nature Switzerland, 2023.
[P24]	Napolitano, Enea Vincenzo. "Trajectory Mining for Smart Cities: A Focus on Indoor Localization using 5G Technology." *SEBD*. 2023.
[P25]	Amato, Flora, et al. "Introducing AI-Based Techniques in the Justice Sector: A Proposal for Digital Transformation of Court Offices." *SEBD*. 2023.
[P26]	Anniciello, Arianna, et al. "Covid-19 impact on health information technology: the rapid rise of e-Health and Big Data driven innovation of healthcare processes." *2022 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*. IEEE, 2022.

PhD thesis overview

In recent years, discussions have begun on how to reconcile the aspect of accuracy with that of energy, and in particular on how to make artificial intelligence tasks improve from the point of view of energy consumption, while sacrificing a small percentage of accuracy, which does not affect the overall result.

PhD thesis

The main factors influencing emissions for Artificial Intelligence systems can be identified in the following points:

- Model size
- Algorithms used
- Supported hardware infrastructure
- Training time
- Geographical location of the data centre

Carbon measurement tools for Artificial Intelligence algorithms

- CodeCarbon (Lottick et al., 2019)
- MLCO2 (Lacoste et al., 2019)
- Experiment-Impact-Tracker (EIT) (Henderson et al., 2020)
- CarbonTracker (Anthony et al., 2020)
- Cumulator (Trebaol et al., 2020)
- Eco2AI (Budennyy et al., 2022)
- Green Algorithms (Lannelongue et al., 2020)
- LLMCarbon (Faiz et al., 2023)
- OpenCarbonEval (Yu et al., 2024)
- Cloud instances (Dodge et al., 2022)

Proposed equation

$$P = \text{Core Count} \times \text{Clock Speed (GHz)} \times \text{Operations per Clock Cycle} \qquad (1)$$

$$C = \frac{\text{Geographical Dependence Factor (Provider, Location)}}{\text{Consumption (HW, Provider)} \times \text{Usage Time}} \qquad (2)$$

$$\eta = \frac{\text{Useful Output (FLOPS)}}{\text{HW Consumption (kWh)} + \text{Cooling Consumption (kWh)}} \qquad (3)$$

Dimension Analysis

- **Relationship between P and η**: Considering that P is measured in FLOPS and η in FLOPS/kWh, we can consider the total energy consumption as ηP, which dimensionally is expressed in kWh.

- **Influence of C**: As C is measured in $kgCO_2e/kWh$, we can examine its impact on the total CO_2e emissions by including it in our equations, multiplying it by ηP, thus obtaining a $kgCO_2e$ value.

AI emission equation

$$E = \left(\frac{P(H, N, A) \times C(S, L, H, T)}{\eta(H, R)} \right) + \lambda(L_c, O, D) \tag{4}$$

Case Study

Setup Description

EHBDA Cluster (University of Naples Federico II):

- H: Nvidia DGX A100, 312 teraFLOPS
- L: Naples, Italy
- P: 312 teraFLOPS
- C: 0.209 kgCO2e/kWh
- η: 51 GFLOPS/kWh
- R: Air conditioners (0.5 kWh)
- S: Mix of non-renewable (49%) and renewable energy sources (51%) as provided by our energy provider

Emissions

Algorithm	Time (hours)	Parameters (M)	E (kg CO_2e) (Our Method)	MLCO2 (kg CO_2e)
U-Net Medical	0.1	30	0.13	0.01
DLRM	0.27	25	0.35	0.05
MosaicBERT	2.6	137	3.32	0.28
BERT-Base	3.6	110	4.60	0.37
ResNet50	4.1	25	5.24	0.38
TacoTron2	4.2	13	5.37	0.39

Table 5 Environmental impact of AI models trained on EHBDA, comparing our method with MLCO2 estimates.

Hybrid Method estimation

Considering the 10 trackers seen before:

- Introduction of the Weighted Average of the results of the 10 most popular tools, identified in the previous slides.
- Introduction of a dynamic methodology for the recognition of the type of algorithm/model, related to a specific Artificial Intelligence architecture, and consequent assignment to the corresponding framework.

WEIGHTED AVERAGE OF THE SELECTED TRACKERS

The following steps are used to calculate the weighted value:

1) Determination of the weights to be assigned to each tracker based on certain criteria, namely: Authority, Accuracy, Completeness, Availability of real-time data, Ease of implementation and Accessibility to results.

2) Calculation of the weighted average of carbon emissions.

Example of weight calculation

Framework	Authority	Precision	Completeness	Real-time	Ease	Accessibility	Fi Total
CodeCarbon	0.90	0.90	0.80	0.70	0.80	0.80	**4.9**
$MLCO_2$	0.70	0.80	0.20	0.90	0.90	0.90	**4.4**
EIT	0.70	0.70	0.80	0.20	0.40	0.50	**3.3**
CarbonTracker	1	0.70	0.70	0.60	0.80	0.70	**4.5**
Cumulator	0.70	0.70	0.20	0.50	0.50	0.50	**3.1**
Eco2AI	0.70	0.70	0.50	0.50	0.50	0.50	**3.4**
Green Algorithms	0.80	0.80	1	0.80	0.90	0.80	**5.1**
LLMCarbon	0.20	0.70	0.10	0.10	0.20	0.20	**1.5**
OpenCarbonEval	0.10	0.70	0.10	0.10	0.20	0.20	**1.4**
Istanze Cloud	0.70	0.70	0.40	0.20	0.40	0.40	**2.8**

Application

GTX TITAN, CPU Intel Core i9-9900, RAM 32 GB, Runtime:100 h, Region: Europa (Paris)		
Tracker	Pesi ($\boldsymbol{\omega_i}$)	Emissioni(kgCO2e) ($\boldsymbol{e_{ico2e}}$)
CodeCarbon	0.142	2.54
$\mathbf{MLCO_2}$	0.128	2.50
Experiment Impact Tracker	0.096	2.09
CarbonTracker	0.131	2.80
Cumulator	0.090	1.40
Eco2AI	0.099	1.94
Green Algorithms	0,148	2.04
LLMCarbon	0.044	2.12
OpenCarbonEval	0.041	5.51
Istanze Cloud	0.081	2.10

E_{CO2e}(kgCO2e)
2.36

DYNAMIC TOOL FOR AI ALGORITHM/MODEL RECOGNITION

In order to guarantee the characteristic of dynamism/adaptability of the framework, it is first of all necessary to define examples of algorithms that work on the main areas of artificial intelligence, namely:

1) Machine Learning (ML)

1) Deep Learning (DL)

2) Natural Language Processing, NLP

3) Large Language Model, LLM

DYNAMIC TOOL FOR AI ALGORITHM/MODEL RECOGNITION

Application of algorithms to related AI fields						
Framework	Machine Learning	Deep Learning	NLP	LLM	Cloud	GPU multiple
CodeCarbon	Specific	Yes	Adaptable	Adaptable	Yes	Adaptable
MLCO2	Specific	Yes	No	No	Yes	No
EIT	Specific	Yes	Adaptable	Adaptable	No	Yes
CarbonTracker	Yes	Specific	Adaptable	Adaptable	No	No
Cumulator	Specific	Yes	No	No	No	No
Eco2AI	Yes	Specific	Yes	Specific	No	Yes
Green Algorithms	Yes	Yes	Yes	No	Yes	Yes
LLMCarbon	No	No	Yes	Specific	Yes	Yes
OpenCarbonEval	No	No	Adaptable	Specific	Yes	Yes
Cloud Instances	Specific	Yes	Specific	No	Specific	No

Example

BERT-base. Given its characteristics:

- 110 million parametersù
- Trained on a specific dataset called "IMDB dataset»
- Cloud Facility with Google Cloud Platform Provider
- NVIDIA A100 GPU hardware infrastructure with about 80 GB of memory and a TDP between 300-400W

Considering that it is a large NLP model, supported by a cloud infrastructure, following the association rules set out in the previous table, it will be assigned to the Green Algorithms framework, as the latter is suitable for working with NLP tasks, with NVIDIA GPUs, efficient on the IBDM dataset, and also takes into account the energy consumption of the cloud infrastructure.

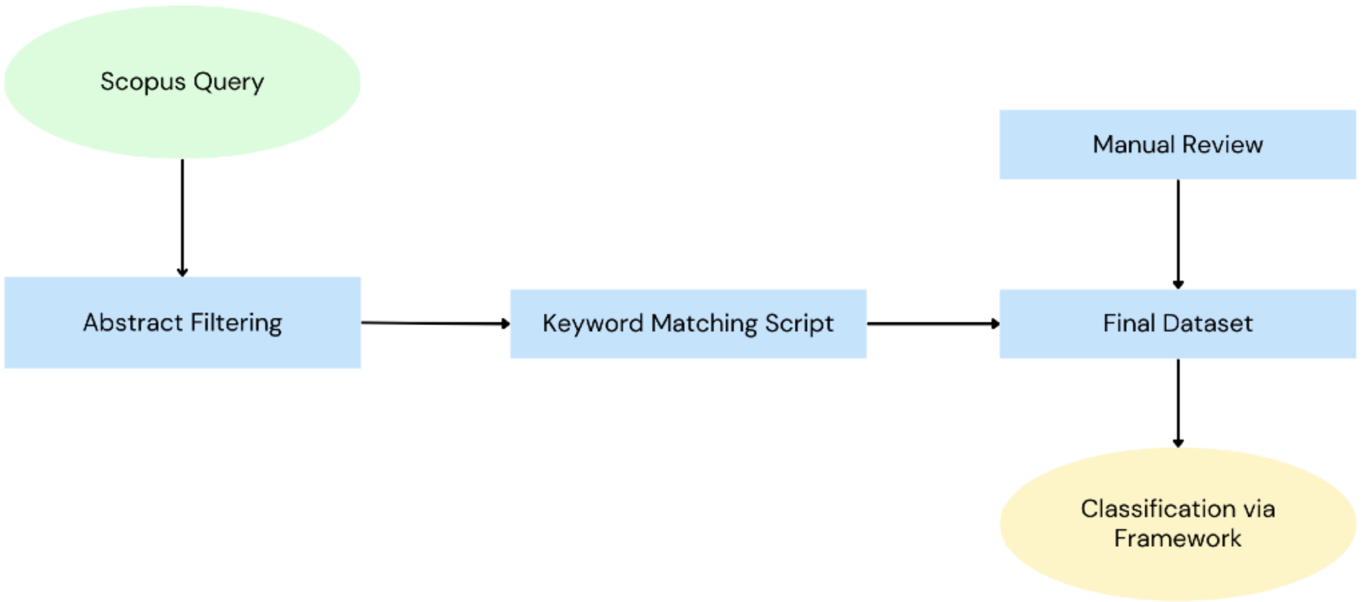
ML Awareness

- Systematically assess how much and how the ML research community considers environmental sustainability in top-tier publications (2021–2024)
- Dataset: over ~1,100 papers from NeurIPS, ICML, ICLR, AAAI, IJCAI, and ECML-PKDD; sampling and filtering performed via structured queries and Python scripts
- Main findings: rare environmental mentions; CO_2e values almost never reported; lack of transparency regarding hardware, cloud usage, and iteration counts.

Contribution

- Classification framework over 18 analytical dimensions (algorithm, hardware, dataset, cloud, optimization, emissions, sustainable proposals, etc.).
- Large-scale analysis (1126 papers) structured into 10 RQ.
- Cross-sectional synthesis: transparency gaps and underreporting of emissions; proposed guidelines for sustainable ML practices.

Dataflow


Scopus Query
Abstract Filtering
Keyword Matching Script
Manual Review
Final Dataset
Classification via
Framework

RQ	% with data	% missing	Insight (1–10)
RQ1 Algorithms	95.0	5.0	9
RQ2 HW & Dataset	40.0	60.0	4
RQ3 Cloud vs Local	25.0	75.0	3
RQ4 Optimization	15.0	85.0	2
RQ5 Emissions	0.3	99.7	1
RQ6 Temporal Trends	100.0	0.0	10
RQ7 Mitigation	1.0	99.0	1
RQ8 Conferences	100.0	0.0	10
RQ9 Sectors	100.0	0.0	10
RQ10 Complexity vs Impact	100.0	0.0	10

Indicator	Value
Initial papers (2021–2024)	2,934
Selected (with experimentation)	1,272
Final dataset	**1,126**
Environmental mentions	29
Actual CO_2e measurements	3
No cloud specification	823
Explicit local	281
Explicit cloud	23
HW and dataset unspecified	157
Dataset specified, HW missing	679

Results

- Transparency issues: HW, cloud usage, and training iterations frequently omitted, hindering reproducibility and impact estimation.
- Minimal emission reporting: fewer than 0.3% include concrete measurements; mentions remain rare.
- Complexity: larger datasets and iteration counts correlate with higher environmental impact.

Suggestions

- Standardized checklist including: HW specs, PUE/CI, duration, iteration count, emission estimation tools
- Adopt an efficiency-first mindset: pruning, quantization, distillation, ecc.
- Prefer low-carbon regions and schedule experiments during low-carbon windows.

Conclusion

Measuring to Mitigate

- One cannot improve what is not measured: the proposed analytical and hybrid strategies enable verifiable, data-driven sustainability in AI. Towards transparent, efficient, and accountable AI systems.
- Future directions: standard benchmarks, lifecycle metrics, and emission-aware AI development.

Thank you for your attention

iteePhD
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