Annotated Bibliography

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References

[1] Vasileios Alevizos, Nikitas Gerolimos, Eleni Aikaterini Leligkou, Giorgos Hompis, Georgios Priniotakis, and George A. Papakostas. Sustainable swarm intelligence: Assessing carbon-aware optimization in high-performance ai systems. *Technologies*, 13(10), 2025.

This 2025 peer-reviewed article from the journal Technologies evaluates the carbon footprint of swarm-based optimization algorithms within High-Performance Computing (HPC) environments. The authors introduce a "Emission Impact Metric" that links algorithmic behavior to real-time power consumption and grid-intensity data. By analyzing 41 different algorithms across 480 experimental runs, the study highlights a significant efficiency gap; for instance, Particle Swarm Optimization emitted only 24.9 g of CO_2 per optimum compared to 61.3 g for standard Grid Search. The researchers propose a framework for auditable runtime controls that can throttle or release AI processes based on carbon objectives without sacrificing the quality of the solution. Seeing students working with Swarm Intelligence concepts for their Independent Study at Wooster got me thinkning about how I could apply these concepts to something I'm passionate about. I think this is one such study.

[2] Thomas H. Cormen, Charles E. Leiserson, Ronald L. Rivest, and Clifford Stein. *Introduction to Algorithms, Third Edition*. The MIT Press, 3rd edition, 2009.

This is a popular algorithms textbook which is well-cited. In particular, Part VI on graph algorithms will be of interest. Chapter 26 discusses flow networks and introduces commonly used notation. It formally describes the problem of obtaining a maximum flow and its equivalence to obtaining a minimum cut. The classical method of Ford and Fulkerson's algorithm for finding a maximum flow is described, and it includes several examples. Additional methods for obtaining a maximum flow, including the push-relabel method, are also described. The chapter notes include additional references to specific articles which may be helpful, such as those of historical interest (the article in which an algorithm was originally proposed) as well as state-of-the-art improvements (more recent articles to improve the approach).

[3] Sarah Hug and Mark McKay. Problematizing AI literacy access - understanding student AI literacy from student voices. In *Proceedings of the 2025 Conference on Research on Equitable and Sustained Participation in Engineering, Computing, and Technology*, RESPECT 2025, page 339–342, New York, NY, USA, 2025. Association for Computing Machinery.

[4] Aparna Vinayan Kozhipuram, Samar Shailendra, and Rajan Kadel. Retrieval-augmented generation vs. baseline llms: A multi-metric evaluation for knowledge-intensive content. *Information*, 16(9), 2025.

This paper compared four LLMs (from 1.1 Billion parameters to 13 Billion parameters), to see if Retrieval Augmented Generation (RAG) helps smaller models catch up to big ones. The models used were TinlyLlama 1.1B, Mistral 7B, Llama 3.1 8B and Llama 1 13 B. RAG is an AI architecture that optimizes the performance of models by allowing them to access external knowledge bases, enabling them to generate responses based on real, up-to-date data rather than solely relying on their training data. Unlike LLMs that rely on static training data, RAG pulls relevant text from databases, uploaded documents, or web sources. The researchers used a "multi -metric" approach using seven lexical and semantic scores to evaluate the performance gains of RAG LLM's over baseline LLMs. This is a 2025 peer reviewed article from the Information Journal, published by MDPI. Since I am interested in Environmental Studies and Data Science, one area of research for me could be looking into how RAG models might be more sustainable or cheaper to run compared to massive models.