Learning-based Approaches for Parallel Machine Scheduling with Energy Considerations

Porteur : Taha ARBAOUI
Partenaires : (si applicable)
Laboratoire : DISP
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Résumé : (200 mots)
Machine learning approaches have drawn a lot of attention in recent years. Thanks to their efficiency on some real-world problems, their use has seen a sharp increase in several domains like computer vision, natural language processing, etc. However, many other fields that, for the moment, lack the necessary amount of data to run these approaches did not see any development. With the 4th industrial revolution, companies will gather more data on their logistic and production operations. It becomes then necessary and important to exploit the generated data to improve the optimization approaches used to manage the operations.
The goal of this project is to investigate the use of machine learning to improve existing optimization techniques. The proposed approaches will be tested on parallel machine scheduling problems, as they represent one of the hardest and most treated problems in combinatorial optimization. The expected outcome of the project is a set of machine-learning-based optimization approaches that outperform existing heuristic and exact approaches in terms of speed and solutions' quality. The selected students will start by reviewing existing parallel machine scheduling approaches [1] and whether successful application of machine learning for scheduling has been done [2]. The second phase will concern investigating which machine learning methods are to be combined with combinatorial optimization techniques.

Sujet développé :

The rapid rise of machine learning (ML) has revolutionized numerous fields such as natural language processing, computer vision, and intelligent automation. Its success is largely driven by the availability of large datasets and the ability of ML models to learn complex patterns and make near-optimal decisions. However, traditional industrial optimization problems, particularly those in production and logistics, have historically lacked sufficient data for ML integration. With the onset of the Fourth Industrial Revolution and the increasing adoption of smart manufacturing systems, organizations are now collecting substantial data on machine performance, energy usage, and scheduling outcomes. This creates a timely opportunity to redefine classical optimization techniques through data-driven machine learning approaches.

One of the most critical domains for such innovation is parallel machine scheduling, which plays a central role in modern manufacturing systems. Traditionally, this problem focuses on minimizing makespan (Cmax), which corresponds to the completion time of the last job. However, due to increasing environmental concerns and rising energy costs, energy efficiency has emerged as an equally important objective. Energy consumption in manufacturing environments is heavily influenced by scheduling decisions, machine idle times, and load distributions. As a result, the parallel machine scheduling problem has evolved into a bi-objective optimization challenge, where both makespan and energy consumption must be simultaneously minimized.

In this project, the goal is to develop new optimization approaches that leverage machine learning to improve the trade-off between production efficiency and energy usage. By incorporating ML into optimization frameworks, the project aims to intelligently learn scheduling policies that reduce peak energy demands and optimize machine utilization, without compromising solution quality or computational performance. Machine learning models can be used to predict energy consumption patterns, adaptively select scheduling rules, and guide search algorithms toward low-energy, low-makespan regions of the solution space.

The project will begin with a thorough review of existing approaches for parallel machine scheduling, with a special focus on energy-aware and bi-objective optimization methods. In addition, the student will explore emerging research on the integration of machine learning into combinatorial optimization, including reinforcement learning, graph-based learning, and surrogate modeling. The second phase will focus on designing hybrid algorithms that combine ML with traditional optimization techniques such as heuristics, metaheuristics, or exact methods. These hybrid approaches will be tailored to address both objectives simultaneously, ensuring that the resulting schedules strike an optimal balance between production efficiency (Cmax) and energy consumption.

The expected outcome of this project is a suite of innovative machine-learning-driven bi-objective optimization methodologies that outperform existing solutions in terms of speed, adaptability, and quality. By targeting both makespan and energy consumption, the project directly contributes to sustainable manufacturing practices and supports global efforts toward reducing industrial energy usage and carbon emissions.

References

[1] Pinedo, Michael L. Scheduling: theory, algorithms, and systems. Springer, 2016.
[2] Calvet, Laura, et al. "Learnheuristics: hybridizing metaheuristics with machine learning for optimization with dynamic inputs." Open Mathematics 15.1 (2017): 261-280.
[3] Bengio, Yoshua, Andrea Lodi, and Antoine Prouvost. "Machine learning for combinatorial optimization: a methodological tour d'horizon." European Journal of Operational Research (2020).
[4] Talbi, El-Ghazali. "Combining metaheuristics with mathematical programming, constraint programming and machine learning." Annals of Operations Research 240.1 (2016): 171-215.
[5] Karimi-Mamaghan, M., Mohammadi, M., Meyer, P., Karimi-Mamaghan, A. M., & Talbi, E. G. (2021). Machine Learning at the service of Meta-heuristics for solving Combinatorial Optimization Problems: A state-of-the-art. European Journal of Operational Research.
[6] Zhao, F., Jiang, T., & Wang, L. (2022). A reinforcement learning driven cooperative meta-heuristic algorithm for energy-efficient distributed no-wait flow-shop scheduling with sequence-dependent setup time. IEEE Transactions on Industrial Informatics, 19(7), 8427-8440.
[7] Liang, P., Xiao, P., Li, Z., Luo, M., & Zhang, C. (2024). A novel deep reinforcement learning-based algorithm for multi-objective energy-efficient flow-shop scheduling. IET Collaborative Intelligent Manufacturing, 6(4), e12121.