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SCIENCES POUR LA CONCEPTION, L'OPTIMISATION ET LA PRODUCTION

Enhancing Robust Optimization in Industry 4.0 Manufacturing Scheduling by integrating Machine Learning and Traditional Optimization Techniques

Ayoub Ouhadi
PhD student at G-SCOP
DOME2S Team

Under supervision of:
Pr. Maria DI-MASCOLO (Research Director at CNRS)
Dr. Zakaria YAHOUNI (Associate Professor)

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SAGIP Société d'Automatique, de Génie Industriel & de Productique
UMR 5272
GRENOBLE INP UGA
cnrs
UGA Université Grenoble Alpes

Laboratoire des Sciences pour la Conception, l'Optimisation et la production

Motivation

	Pros of ML and OR	Cons of ML and OR
Operations Research	• Crucial for decision-making in Industry 4.0. • Exact methods like MILP provide optimal solutions.	• Struggles with scalability and adaptability in dynamic Industry 4.0. • Computational inefficiency in larger data (especially for exact methods).
Machine Learning	• Learns patterns from large data sets. • Enhances decision-making with robust predictive capabilities.	• Cannot guarantee optimal solutions. • Requires substantial, relevant data to train effectively.

Research Question

How can **machine learning** techniques be effectively **integrated** with traditional **operations research** methods to enhance robust optimization in Industry 4.0 **manufacturing scheduling** ?

Example: How can we accelerate Branch and Bound search using Machine Learning ?

Literature Review

- Using keywords related to "**integration**", "**Machine Learning**", "**Operations Research**", and "**Scheduling**", we initially obtained **829** articles.

- After removing duplicates and manually selecting relevant papers, **110** articles were retained.

- At this stage, we have not included keywords related to robustness. These aspects will be considered in a subsequent analysis

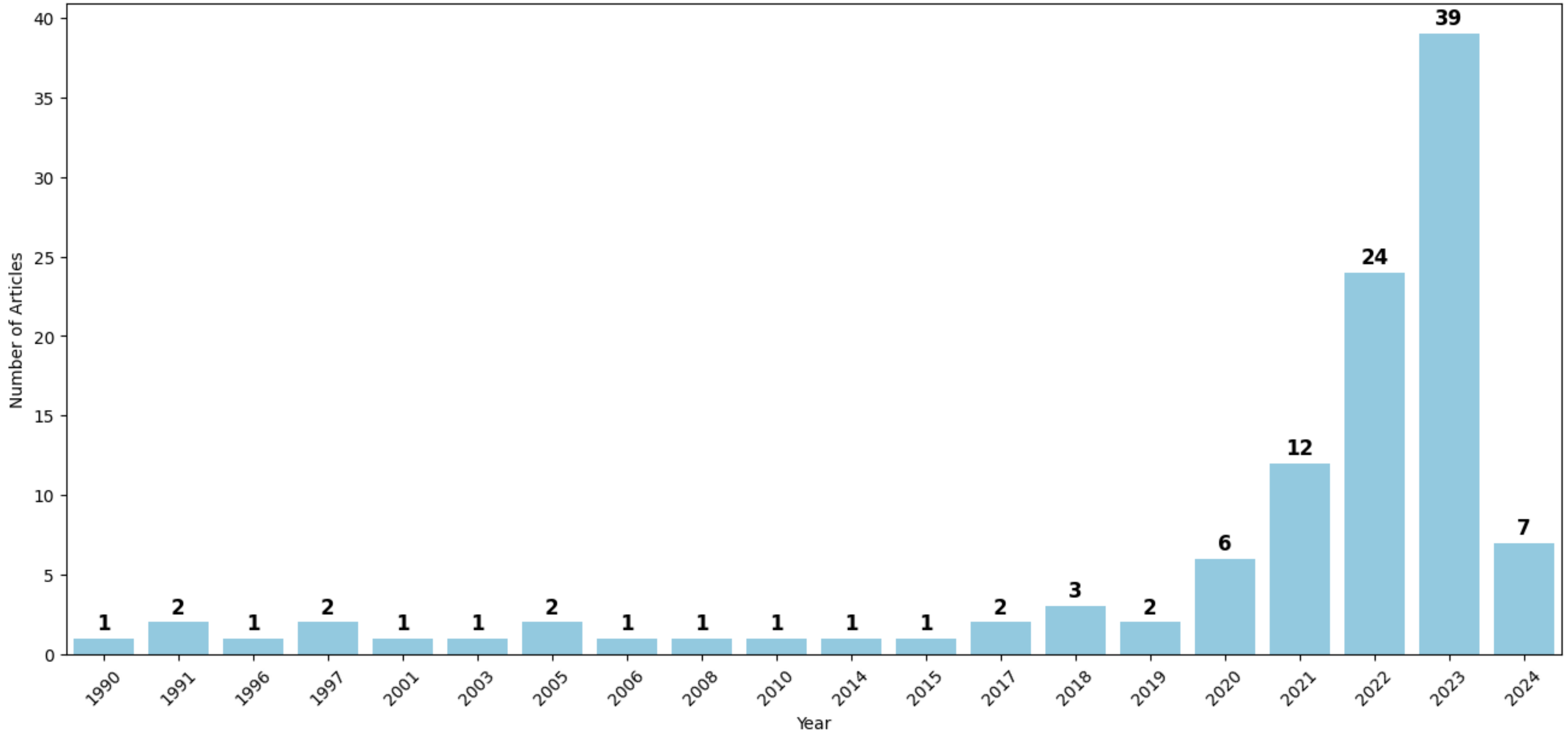
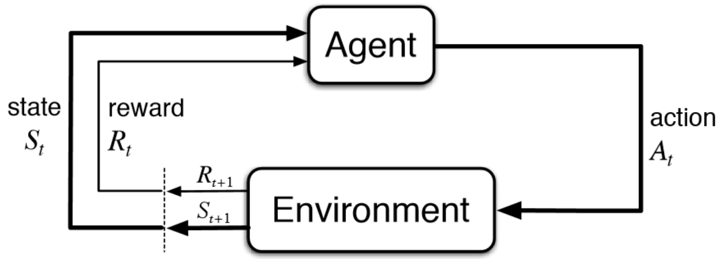
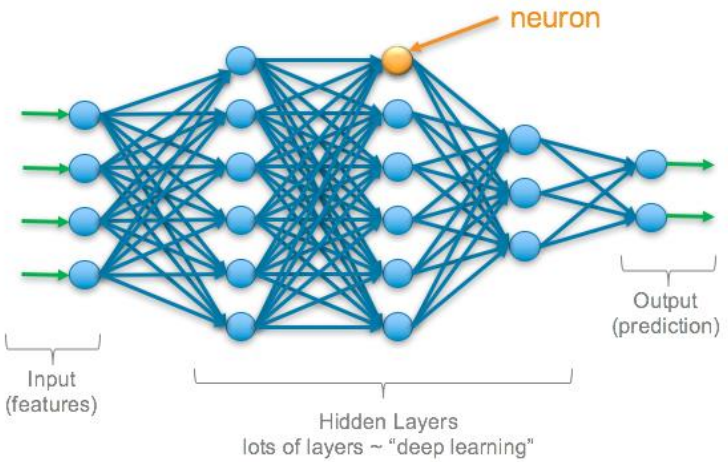


Figure 1: Distribution of articles by year (until Feb 2024)

Literature Review: Analysis of OR and ML methods

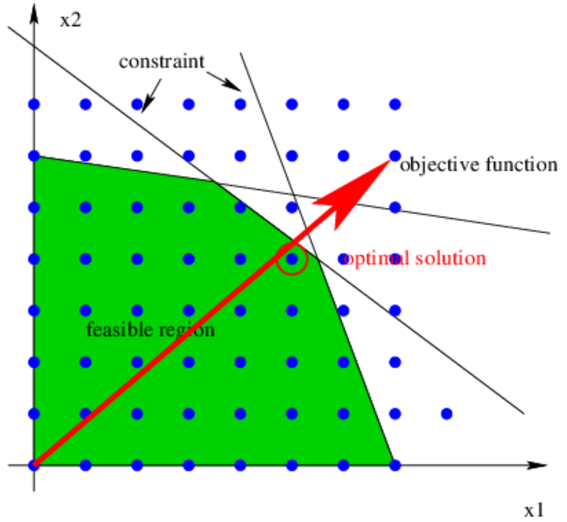


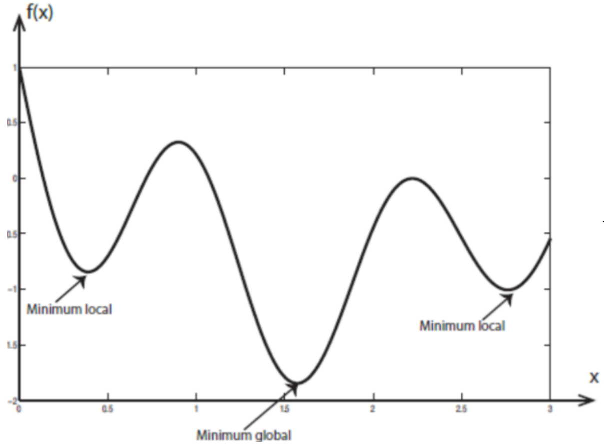


Category	Algorithm	Occurrences
Reinforcement Learning	Q-learning	13
	Proximal Policy Optimization (PPO)	9
	Deep Q-Network	5
	Policy Gradient	3
	Actor–Critic (A2C)	2
	Dueling DQN	2
	Imitation Learning	2
	...	5
Total		**41**
Deep Learning	Neural Networks (NN)	8
	Deep Neural Networks (DNNs)	7
	Recurrent Neural Networks (RNNs)	3
	Long Short-Term Memory (LSTM)	3
	Augmented Neural Networks (AugNN)	2
	...	8
Total		**31**
Traditional ML	Random Forests	2
	...	11
Total		**13**
Grand Total		**85**

Table 1 : Categorization and Occurrences of Machine Learning Algorithms

Literature Review: Analysis of OR and ML methods





Category	Method	Occurrences
Exact Methods	Mixed Integer Linear Programming (MILP)	13
	Column Generation	3
	Integer Linear Programming (ILP)	3
	Branch-and-Price	3
	Two-Stage Stochastic Programming (2SP)	2
	Constraint Programming (CP)	2
	Mixed Integer Programming (MIP)	2
	Stochastic Mixed-Integer Programming	2
	...	4
Total		**34**
Heuristic and Metaheuristic Methods	Genetic Algorithm (GA)	11
	Heuristic Approaches	7
	Simulated Annealing (SA)	4
	Particle Swarm Optimization (PSO)	3
	Tabu Search	3
	Cooperative Scatter Search (SS)	2
	Variable Neighborhood Search (VNS)	2
	...	19
Total		**51**
Grand Total		**85**

Table 2 : Categorization and Occurrences of Operations Research Methods

Literature Review: Analysis of OR and ML combinations

Classe ML	Exact Methods	Heuristics and Metaheuristics
Deep Learning (Neural Networks)	10	22
Reinforcement Learning (RL)	15	26
Traditional ML	9	3

Table 3 : Cross-Tabulation between ML and OR Class of Methods

Combination of Methods		Count
Neural Networks (NN)	Mixed Integer Linear Programming (MILP)	4
Q-learning	Genetic Algorithm (GA)	3
Deep Neural Networks (DNNs)	Mixed Integer Linear Programming (MILP)	2
Deep Q-Network	Mixed Integer Linear Programming (MILP)	2
Q-learning	Cooperative Scatter Search (SS)	2

Table 4 : Most Common Combinations of ML and OR Methods

Most common integration types

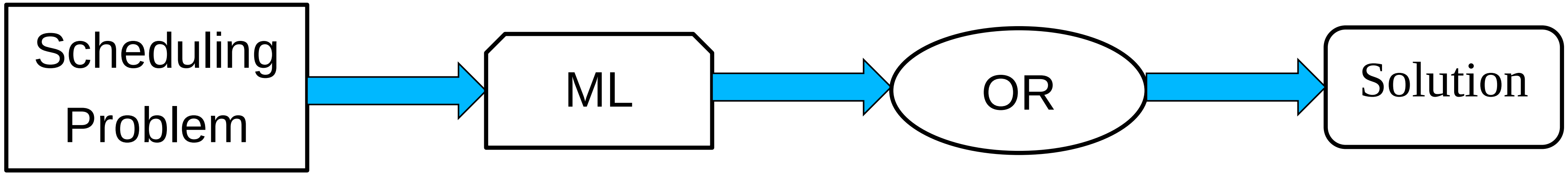
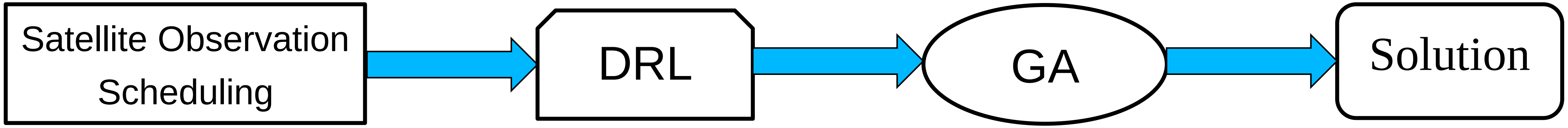


Figure 1 : ML used to provide OR method with initial settings (parameters) or initial solutions

Most common integration types



Predicts initial job sequences and parameters for the Genetic Algorithm (GA)

Uses the initial parameters to optimize the scheduling

Song, Y., Ou, J., Pedrycz, W., Suganthan, P. N., Wang, X., Xing, L., & Zhang, Y. (2024). Generalized Model and Deep Reinforcement Learning-Based Evolutionary Method for Multitype Satellite Observation Scheduling. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*.

Most common integration types

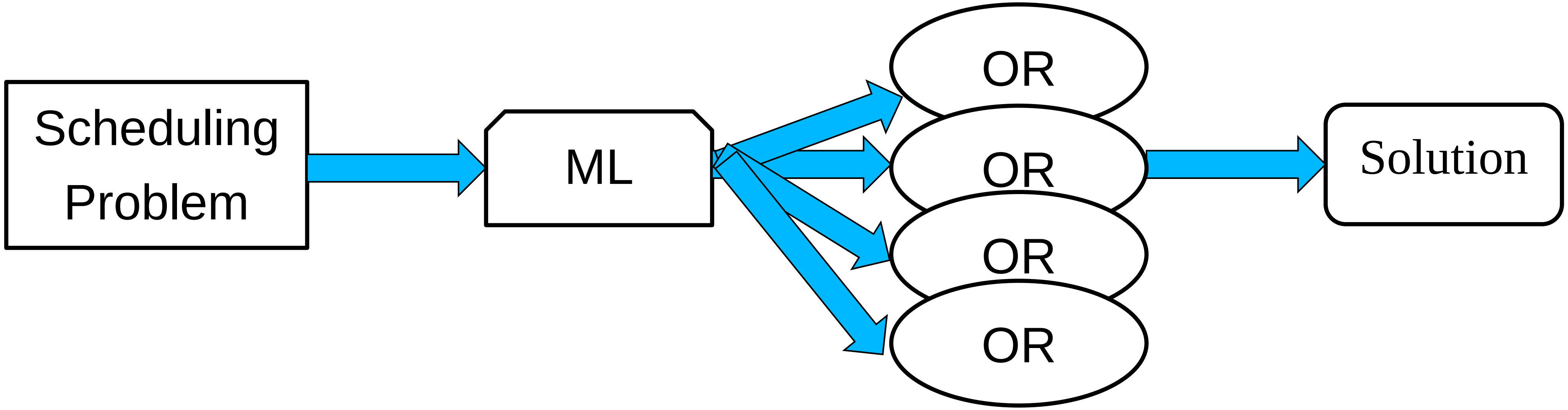
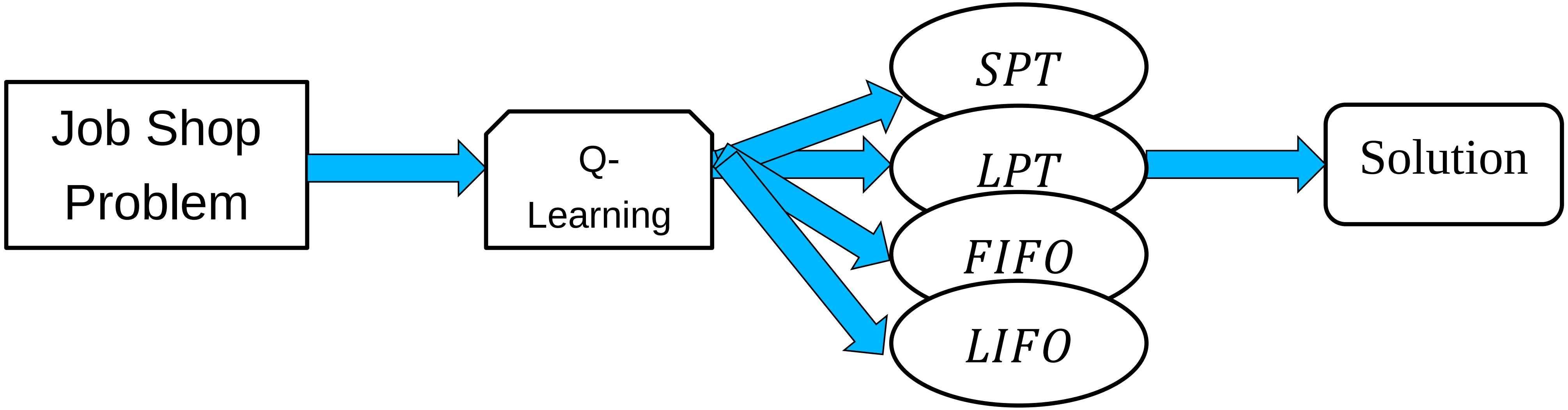


Figure 2 : ML is trained on historical data to recognize patterns and chooses the suited OR method to find the best possible solution.

Most common integration types



Belmamoune, M. A., Ghomri, L., & Yahouni, Z. (2022, September). Solving a job shop scheduling problem using q-learning algorithm. In *International Workshop on Service Orientation in Holonic and Multi-Agent Manufacturing* (pp. 196-209). Cham: Springer International Publishing.

Most common integration types

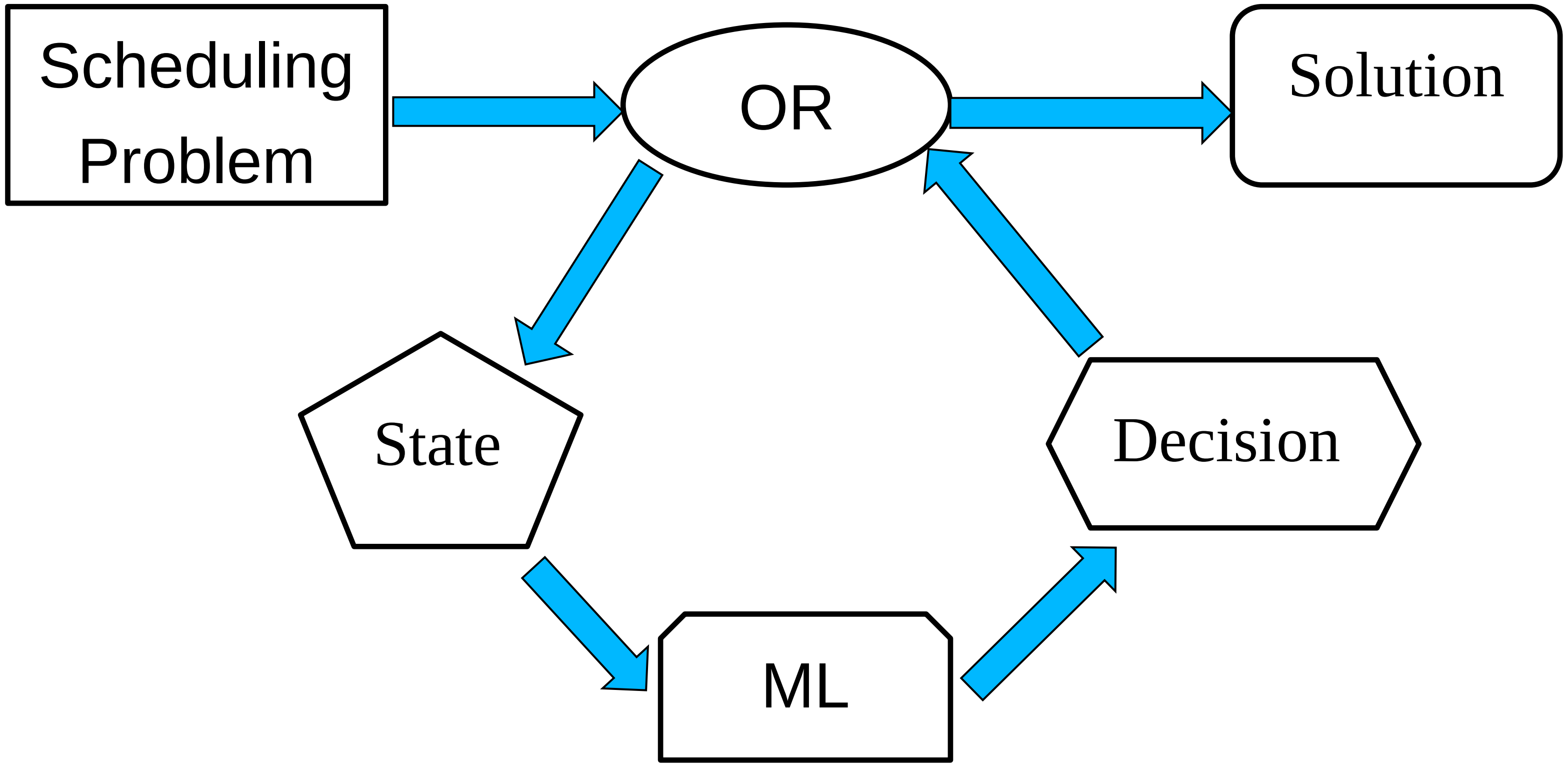
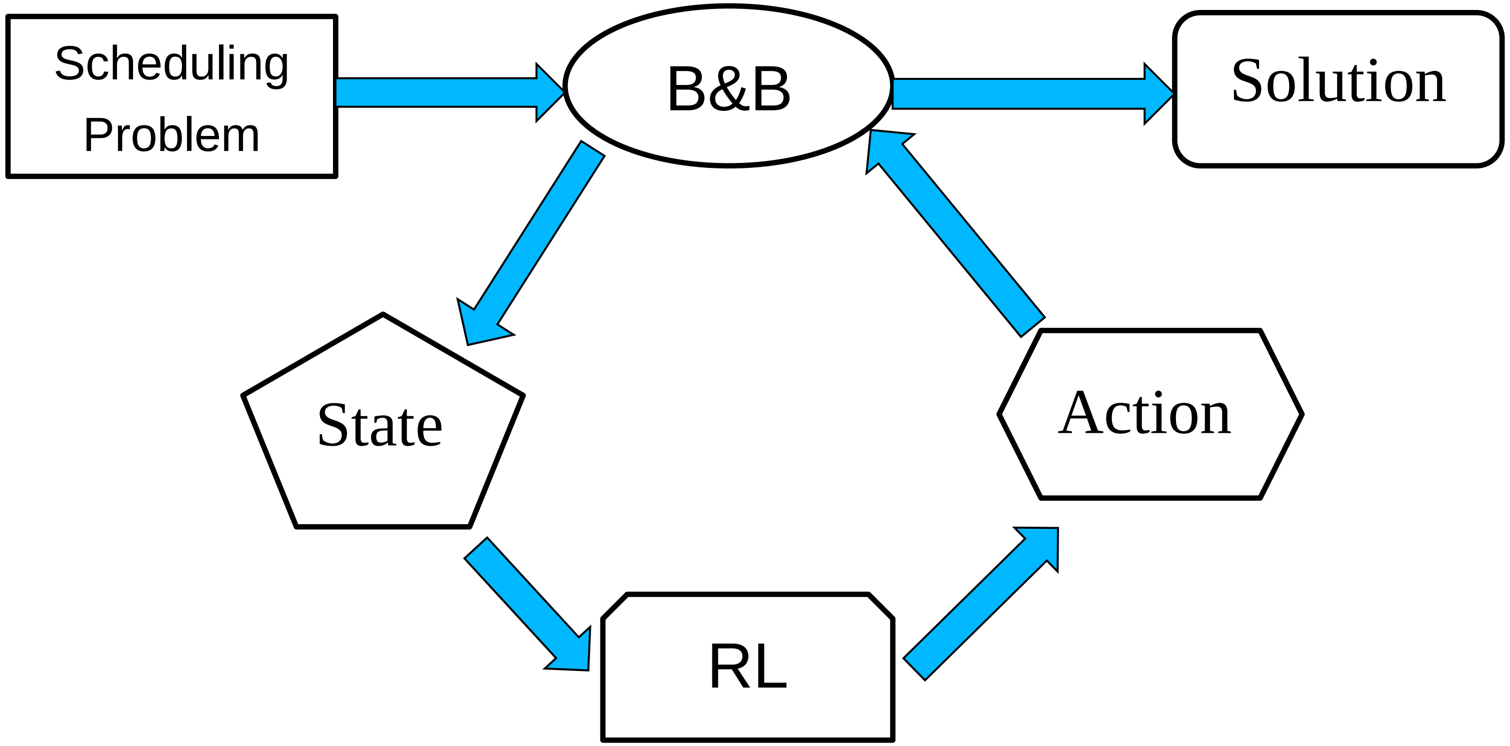
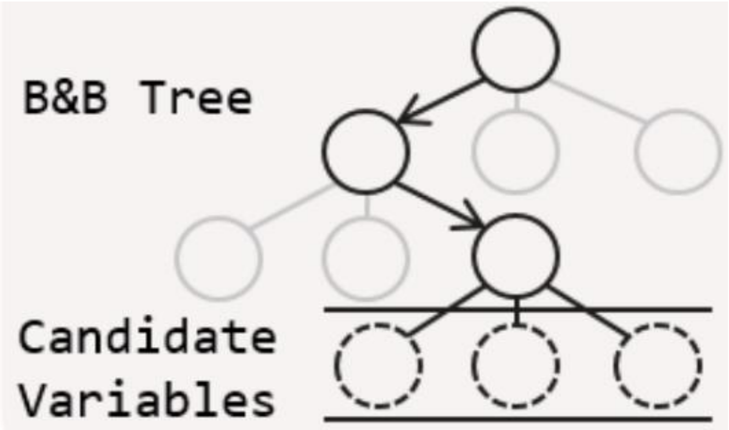


Figure 3 : ML is used to dynamically adjust parameters and strategies within OR methods such as B&B, Genetic Algorithms, simulated annealing, and others, based on real-time feedback, focusing on enhancing the search process.

Most common integration types (for RL-Heuristics)





Parjadis, A., Cappart, Q., Rousseau, L. M., & Bergman, D. (2021). Improving branch-and-bound using decision diagrams and reinforcement learning. In Integration of Constraint Programming, Artificial Intelligence, and Operations Research: 18th International Conference, CPAIOR 2021, Vienna, Austria, July 5–8, 2021, Proceedings 18 (pp. 446-455). Springer International Publishing.

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Conclusion

- **Integration Insights:** Literature review reveals various methods to integrate ML and OR.
- **Rising Trends:** Notable increase in the use of Reinforcement Learning (RL) techniques.
- **Application Domains:** Diverse applications found in manufacturing, healthcare, aerospace, and energy sectors.
- **Sustainability Impact:** Integration of ML and OR contributes to sustainability by optimizing resources and reducing waste.

Perspectives

- Given the emphasis on robustness in our thesis, we are initially focusing on exact methods to ensure we achieve optimal solutions within an acceptable time frame, as opposed to approximate solutions.

- Our research explores how to integrate ML and OR to enhance exact methods like Branch and Bound (B&B) by utilizing Reinforcement Learning (RL) to reduce the search space.

- We aim to apply these methods to real-world scenarios such as:
  - **Operating Room Scheduling**
  - **Manufacturing Scheduling**

References

- Chen, J., Chen, M., Wen, J., He, L., & Liu, X. (2022). A Heuristic Construction Neural Network Method for the Time-Dependent Agile Earth Observation Satellite Scheduling Problem. *Mathematics*, *10*(19), 3498.
- Zeng, D., Zhan, J., Peng, W., & Zeng, Z. (2023). Evolutionary job scheduling with optimized population by deep reinforcement learning. *Engineering Optimization*, *55*(3), 494-509.
- Song, Y., Wei, L., Yang, Q., Wu, J., Xing, L., & Chen, Y. (2023). RL-GA: A reinforcement learning-based genetic algorithm for electromagnetic detection satellite scheduling problem. *Swarm and Evolutionary Computation*, *77*, 101236.
- Parjadis, A., Cappart, Q., Rousseau, L. M., & Bergman, D. (2021). Improving branch-and-bound using decision diagrams and reinforcement learning. In Integration of Constraint Programming, Artificial Intelligence, and Operations Research: 18th International Conference, CPAIOR 2021, Vienna, Austria, July 5–8, 2021, Proceedings 18 (pp. 446-455). Springer International Publishing.
- Václavík, R., Novák, A., Šůcha, P., & Hanzálek, Z. (2018). Accelerating the branch-and-price algorithm using machine learning. European Journal of Operational Research, 271(3), 1055-1069.

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