Integrating machine learning and operations research methods for scheduling problems: a bibliometric analysis and literature review

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Abstract: Operations research (OR) techniques have been widely used for optimizing problems, such as manufacturing scheduling, supply chain optimization, and resource allocation. Despite its effectiveness, traditional OR, especially exact methods, often struggle with scalability, computational efficiency, and adaptability to the dynamic and uncertain environments of Industry 4.0. While machine learning (ML) advancements provide novel approaches for addressing these challenges, they also present limitations, such as the lack of guaranteeing exact solutions and the need of relevant data. Therefore, the integration of OR and ML offers a balanced solution, leveraging ML's capability to extract patterns from large datasets and making predictive decisions and OR's precision to enhance decision-making processes, especially in scheduling tasks withing the context of Industry 4.0. This combination not only improves solution robustness and efficiency but also mitigates individual limitations of both fields. and make predictive decisions under uncertainty complements the decision-making process of OR. This paper aims to conduct a bibliometric analysis and a brief literature review on the integration of ML and OR, focusing on their application in scheduling problems.

Keywords: Industry 4.0, Scheduling, Operation Research, Machine Learning

1. INTRODUCTION

The scheduling domain involves complex decision-making including NP-hard scenarios like job shop scheduling (Pinedo, M. 2016). The complexity of these problems has motivated researchers tackling scheduling challenges. Traditional Operations Research (OR), particularly Mixed-Integer Linear Programming (MILP), are used to solve such problems due to their optimality in well-defined scenarios (Ku and Beck, 2016). However, the utility of operations research is often limited by the difficulty in handling uncertainty and dynamic changes in the environment (Yahouni et al., 2019), as well as the prohibitive computational cost associated with solving large-scale problems (Georghiou *et al.*, 2019).

Advancements in artificial intelligence (AI), particularly in machine learning (ML), have introduced powerful tools capable of learning from data to make predictions or decisions without being explicitly programmed for specific tasks (Alpaydin, 2020) (Seeger et al. 2022). Despite these advancements, ML techniques come with their own set of limitations. They often lack the ability to provide guaranteed exact solutions and require substantial amounts of relevant data to train effective models. These constraints highlight the importance of integrating ML with OR techniques. This complementary relationship addresses the scalability, computational efficiency, and adaptability challenges faced by traditional OR methods, especially in the dynamic and uncertain environments of Industry 4.0.
Since the 1990s, there has been an interest in integrating Machine Learning (ML) with Operations Research (OR) to tackle scheduling problems, as evidenced by early efforts (Brown and White, 1991), (Smith *et al.*, 1996). Initially, these attempts primarily focused on enhancing heuristic methods with neural network algorithms. However, these early integrations did not yield significant improvements at the time. With the recent advancements in AI, particularly in reinforcement learning and deep learning, a renewed effort has emerged to accelerate exact methods, such as branch and bound (Parjadis *et al.*, 2021), and to refine metaheuristic approaches (Chen and Wang, 2024).

Recent reviews have explored various ways to integrate OR and ML. (Bengio *et al.*, 2021) focused on solving combinatorial optimization problems, highlighting the significant role of imitation learning in accelerating learning processes in reinforcement learning, without delving into specifics regarding scheduling or other problem types. Similarly, (Lodi, and Zarpellon, 2017) demonstrated the use of ML for branching strategies in solving MILP problems, presenting methods employing supervised learning algorithms (such as Decision Tree and Support Vector Machine (SVM)) to learn branching strategies within the branch and bound algorithm and comparing results using random MILP instances from the literature. Another review by Smith, and Jones (2023) introduced ML to solve Combinatorial Optimization problems, with a focus on MILPs, especially the branch and bound and some heuristic algorithms, and how ML can be integrated with them. This review, however, did not extensively cover scheduling problems, and many papers in this area remained unmentioned.

This gap in the literature motivates our bibliometric analysis, which specifically addresses the integration of OR and ML for scheduling problems. A subject not exhaustively explored to our knowledge. Scheduling problems continue to be among the most studied in combinatorial optimization. Hence, we have chosen to focus exclusively on scheduling problems, delving into detail on ML and OR can be integrated in solving these challenges efficiently. The structure of this paper is as follows: Section 2 outlines the research methodology, detailing the processes of keyword extraction, paper filtration, and bibliometric analysis. Section 3 presents the content analysis, where we will explore the various AI and OR methods used to solve scheduling problems. Finally, the conclusion will synthesize these ideas and discuss their implications for future research in this interdisciplinary field.

2. RESEARCH METHODOLOGY

2.1 Defining and combining the relevant keywords

In our research methodology, we prioritize the selection and synthesis of keywords, forming the bedrock of our comprehensive literature review. Our approach begins with a thorough examination of the prevailing keywords in leading academic publications within the fields of ML and OR. Following the strategy outlined in relevant references, we selectively review the top journals in these fields as identified by recognized academic rankings. Our core interest lies in the integration of ML techniques with traditional OR methods to solve manufacturing scheduling problems.

To capture the essence of our research, we identified a set of primary keywords related to “integration”: ("integrat*" OR "combinat*" OR "synergy" OR "confluence" OR "fusion"). Next, we selected keywords to capture the most important subfields of ML and OR: (“operations research” OR “combinatorial optimization” OR “mathematical optimization” OR “linear programming” OR “nonlinear programming” OR “integer programming” OR “mixed-integer programming” OR “Exact method”) AND (“Machine learning” OR “artificial intelligence” OR “deep learning” OR “Neural Networks” OR “supervised learning” OR “unsupervised learning” OR “reinforcement learning”). Finally, we included keywords related to scheduling: (“scheduling” OR “production Planning” OR “smart manufacturing” OR “robust scheduling”).

Utilizing a logical combination of these keywords through the use of 'AND' and 'OR' operators, we create various keyword strings to explore the intersection of ML and OR. This approach facilitates a targeted yet extensive examination of how ML methodologies can be integrated with OR to enhance problem-solving capabilities, optimize algorithms, and introduce innovative computational strategies.

2.2 Research database

There are many resources to find relevant articles. Since the search is automatic and produces a large number of articles, we selected for retention only those sources (shown in Table 1) that allow us to filter titles, keywords and abstracts.

Table 1. Results of the sources

Sources	Filters	
	Title or Abstract	Full text
Web of Science	281	579
Science Direct	353	4098
IEEE *(ieeexplore.ieee.org)*	78	577
ArXiv *(https://arxiv.org/)*	117	312

2.3 Defining filters

We make use of the filters listed in Table 2 to locate pertinent articles for this literature review. In fact, we start by taking all the papers that are relevant to our topic and that contain at least one of the combined keywords in either their titles or abstracts. We then gradually apply exclusion and inclusion criteria to these papers. Second, we eliminate every duplicate and manually select articles discussing the integration of ML and OR (for scheduling problems), yielding 110 articles as shown in Table 2.

Table 2. Use of criteria to filter the articles

N°	Scope	Criteria	Results (articles)
1	Research question	Inclusion: Finding the combined keywords in the title or abstract or article keywords	829
2	Filtering	Exclusion: Duplicated papers	769
3	Relevance and Focus	Inclusion: Integration AI -OR for scheduling	110

3. RESULTS OF BIBLIOMETRIC ANALYSIS

As shown in Figure 1, the 110 articles under investigation, were written between 1990 and 2024. The first wave of articles addressing AI's application to scheduling issues appears in the first period, which spans 1990 to 2019. The first articles that mentions the integrations of AI and OR for Scheduling problems were trying to integrate Neural Networks with heuristic algorithm (e.g. Lee, 1990 and Glover and Laguna, 1991). However, the density of publications during this time was very low. The second wave, which spans 2020 to 2024, is distinguished by a rise in publications that use ML techniques combined with OR to address scheduling issues.

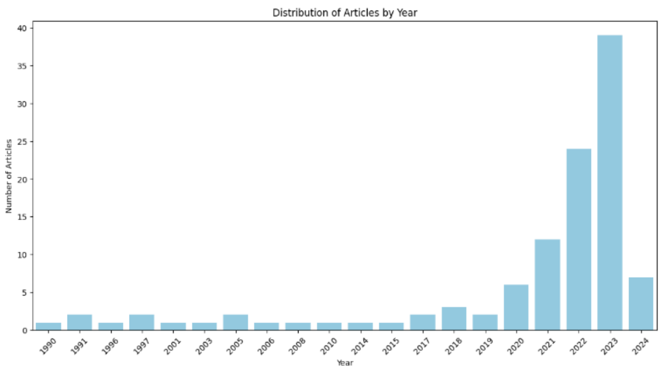

Fig. 1. **Evolution of the articles through years (until end of January 2024)**

Figure 2 introduces the top platforms (journals) of publication. we can notice that "Computers & Operations Research" emerges as the top journal with 9 publications, followed closely by the "European Journal of Operational Research" with 8 publications. This shows their importance in this research subject of integrating ML and OR for Scheduling problems. In addition, "Expert Systems with Applications" maintains a significant presence with 5 publications.

Fig. 2. **The most cited journals with OR-ML integration**

The analysis of publications by country (see Figure 3) showcases China as the leading contributor with 37 publications, followed by the USA with 22. The United Kingdom, Canada, Netherlands, Spain, Germany, Iran, France and Japan also make notable contributions. Collaborations between countries, such as those between China and Belgium, the United Kingdom and Spain, and the USA and Iran, highlight the importance of international partnerships in advancing research. This global distribution and collaboration underscore the widespread interest and collective effort in this fields, reflecting a rich contribution from across the world.

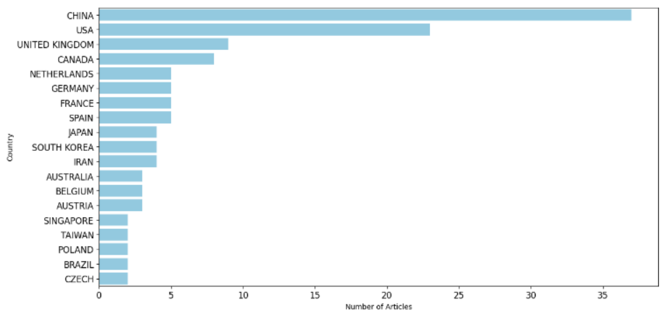

Fig. 3. **Distribution of articles by country**

4. RESULTS OF CONTENT ANALYSIS

In this analysis, our aim is not to conduct an exhaustive state-of-the-art review of the literature. Instead, we provide an overview that captures the most used ML and OR techniques. This approach allows us to identify the most utilized strategies and frameworks in the field, offering a broad perspective on the current research landscape.

In the content analysis of the selected articles, a focused examination of the most utilized Machine Learning (ML) methods reveals a distinct preference for specific algorithms. Reinforcement Learning (RL), including its various forms such as Q-Learning, Deep Q-Learning, and Proximal Policy Optimization (PPO), is the most prominently featured ML algorithm, cited in 37 articles. This high frequency shows the increasing interest of RL for addressing complex and dynamic challenges, particularly following the apparition of advanced techniques like PPO, introduced by OpenAI in 2017 (Schulman et al., 2017). Deep Learning (Neural Networks) is also notable with 28 mentions, showcasing its profound impact on research progress due to its proficiency in modeling non-linear relationships and processing large datasets. Notably, Deep Learning is often employed in conjunction with RL algorithms, a combination that leverages the strengths of both approaches to enhance problem-solving capabilities.

Other ML algorithms (in 12 articles) like Bayesian Optimization (Mei et al., 2021), Decision Tree (Gumuskaya et al., 2021), Random Forest (Wang et al., 2022 and Sugisha et al., 2024), Adversarial ML (Xu et al., 2023), Robust Kernel Density Estimation (RKDE) (Mohseni et al., 2023), Boosting Algorithm (Václavík et al., 2018), Online regression model (Vaclavik et al., 2018), and ARIMA (Limmer and Einecke, 2022) are each mentioned once (except for random forests, used in two articles). Although less frequently cited, their inclusion shows the diversity of ML methods being explored in this research. The numbers mentioned in tables are for articles not methods, some articles use more than one integration, so the total number of ML methods is 85 in 77 articles. The rest of articles are mainly state of the art or do not explicitly mention methods integrated to solve scheduling but still important for our global research. For furthers analysis, we will use the 77 articles.

Table 3. Most used ML methods

ML methods	Articles	Total Number
Reinforcement Learning (RL)	(Dos Santos et al., 2014), (Ahmadi et al., 2018), (Tang et al., 2020), (Shahmardan & Sajadieh, 2020), (Wang et al., 2021), (de Mars & O'Sullivan, 2021), (Brammer et al., 2021), (Chen et al., 2022), (Ahmadi et al., 2022), (Du et al., 2022), (Kenworthy et al., 2022), (Hu et al., 2022), (Paranjape et al., 2022), (Köksal et al., 2022), (Brammer et al., 2021, 2022), (Bao et al., 2023), (Zhao et al., 2023), (Kallestad et al., 2023), (Yin & Yu, 2023), (Wang et al., 2023), (Chen et al., 2023a), (Tassel et al., 2023), (Xu et al., 2023), (Zeng et al., 2023), (Sun et al., 2023), (Yaakoubi & Dimitrakopoulos, 2023), (Karimi-Mamaghan et al., 2023), (Ying & Lin, 2023), (Shengren et al., 2023), (Jia et al., 2023), (O'Malley et al., 2023), (Song et al., 2023), (Ding et al., 2023), (Chen & Wang, 2024), (Song et al., 2024), (Cui & Yuan, 2024).	37
Deep Learning (Neural Networks)	(Abada et al., 1997), (Zhu & Padman, 1997), (Yang & Wang, 2001), (Salcedo-Sanz et al., 2003), (Agarwal et al., 2006), (Liu et al., 2008), (Agarwal et al., 2010), (Yang, 2018), (Gao et al., 2020a), (Gao et al., 2020b), (Xu et al., 2020), (Yin & Ming, 2021), (Schiele et al., 2021), (Tahsien & Defersha, 2022), (Chen et al., 2022), (Corsini et al., 2022), (Kotary et al., 2022), (Chen et al., 2022), (Kim et al., 2022), (Hashemi et al., 2023), (Huy et al., 2023), (Liu et al., 2023), (Rigo et al., 2023), (Morinaga et al., 2023), (Uzunoglu et al., 2023), (Chen et al., 2023), (Khandoker et al., 2023), (Xu et al., 2024).	28

In the other hand, Operations Research (OR) methods used in the articles showcases a diverse range of algorithms (Table 4). Mixed Integer Linear Programming (MILP) stands out with 12 mentions, underscoring its fundamental role in solving a wide array of optimization problems through mathematical modeling especially scheduling problems. Followed by Genetic Algorithm with 11 citations, then Heuristic

Approaches are each cited in 7 articles, reflecting their importance in solving complex scheduling problems that are too difficult for traditional exact methods. Genetic Algorithms (GA) are particularly noted for their ability to find high-quality solutions in large search spaces, while Heuristic Approaches are valued for their problem-specific strategies that offer practical, often near-optimal solutions. Simulated Annealing and Lagrangian Relaxation, each mentioned respectively in 4 and 3 articles, highlight their utility in tackling problems where traditional optimization methods falter. Lagrangian Relaxation is recognized for its ability to decompose complex problems into simpler sub-problems, whereas Simulated Annealing is appreciated for its heuristic search capabilities that mimic the process of annealing.

Table 4. Most used OR methods

OR Algorithm	Articles	Total Number
MILP	(Gao et al., 2020), (Hu et al., 2022), (Paranjape et al., 2022), (Limmer & Einecke, 2022), (Morinaga et al., 2023), (Chen et al., 2023), (Sun et al., 2023), (Ying & Lin, 2023), (Rigo et al., 2023), (Huy et al., 2023), (Xu et al., 2024), (Pang et al., 2024).	12
Genetic Algorithm	(Salcedo-Sanz et al., 2003), (Agarwal, Colak, & Deane, 2010), (Ahmadi et al., 2018), (Yang, 2018), (Schiele, Koperna, & Brunner, 2021), (Tahsien & Defersha, 2022), (Köksal Ahmed et al., 2022), (Zeng et al., 2023), (Song et al., 2023), (Cui & Yuan, 2024), (Song et al., 2024).	11
Heuristic approach	(Zhu and Padman, 1997), (Yang and Wang, 2001), (Agarwal et al., 2006), (Wang et al., 2021), (Chen et al., 2022), (J. Chen et al., 2022), (Chen et al., 2023)	7
Simulated annealing	(Abada et al., 1997), (Shahmardan and Sajadieh, 2020), (Khandoker et al., 2023), (Yaakoubi and Dimitrakopoulos, 2023)	4
Lagrangian Relaxation	(Liu et al., 2008), (Kotary et al., 2022), (Liu et al., 2023)	3
Column generation	(Beulen et al., 2020), (Sugishita et al., 2021), (Xu et al., 2023)	3
Integer Linear Programming	(Yin et al., 2021), (Kenworthy et al., 2022), (Yin & Yu, 2023)	3

In addition, we can find other methods like Variable Neighborhood Search (VNS) (Santos *et al.*, 2014), (Ding *et al.*, 2023), Constraint Programming (CP) (Tassel *et al.*, 2023), (Xu *et al.*, 2023), Stochastic Programming (Gumuskaya *et al.*, 2021), (Hashemi *et al.*, 2023), and Local Search Algorithm (Brammer *et al.*, 2022), (H. Chen *et al.*, 2022), each noted in 2 articles. This diversity of methods gives us different choices to integrate an ML method with an OR algorithm (Table 5).

Table 5. Most used combination ML-OR for scheduling

ML method	OR method	Number of occurrences
Reinforcement Learning	Genetic Algorithm	6
Deep Learning	Genetic Algorithm	5
Deep Learning	MILP	5
Reinforcement Learning	MILP	5
Deep Learning	Heuristic Algorithms	4
Reinforcement Learning	Heuristic Algorithms	3
Other Traditional ML	Branch and bound	2

The analysis of combinations of ML and OR for scheduling problems reveals a strong preference for integrating Reinforcement Learning and Deep Learning with Genetic Algorithms, indicating a trend towards adaptive decision-making strategies in complex scheduling environments. The frequent pairing of Deep Learning and RL with "MILP" (Mixed Integer Linear Programming) suggests an effective synergy between predictive modeling and precise optimization, commonly applied in logistics and scheduling. The variety of OR methods, such as Heuristics and Branch and bound, paired with different ML techniques, underscores the interdisciplinary nature of current research, aiming to leverage the predictive power of ML to enhance traditional OR solutions. Unique combinations, like "ARIMA with MILP" or "Boosting Algorithm with Tabu Search", highlight some applications where the specific problem characteristics guide the choice of methods. As we said before, some articles use more than one integration, therefore, the number of cited methods is greater than the number of articles.

In our bibliometric analysis, we have cataloged the diverse application fields and specific types of scheduling challenges addressed through the integration of machine learning and operations research. This integration is particularly prominent in sectors such as **aerospace**, where it tackles complex scheduling scenarios ranging from agile satellite observations (Chen et al., 2022) to resource-constrained project scheduling (Rigo et al., 2023), reflecting the high stakes and dynamic demands of the field. In the **energy** sector, the focus shifts towards optimizing operations under stringent constraints and uncertainties, with notable applications in unit commitment (O'Malley et al., 2023) and demand response scheduling (Gao et al., 2020), which are critical for modern smart grids and energy systems management. **Healthcare** scheduling also benefits significantly, with the integration applied to the nurse rostering problem (Khandoker et al., 2023) and flexible physician scheduling (Wang et al., 2022), directly impacting service quality and operational efficiency. **Manufacturing**, with the most cited articles, takes a central role, where diverse scheduling types such as job shop (Tassel et al., 2023), flow shop (Tahsien et al., 2022), and Permutation flow shop (Karimi-Mamaghan et al., 2023) are optimized to enhance production efficiency and adaptability. Lastly, the **transportation** and **logistics** sector employ these integrated techniques to improve robustness and efficiency in vehicle routing, airline crew rostering (Kenworthy et al., 2022), and dynamic scheduling for cargo handling. Each of these applications not only underscores the adaptability and effectiveness of combining ML with OR but also highlights the specific challenges and innovations driven by this interdisciplinary approach in managing complex, real-world problems across various industries.

Integrating ML and OR enhances operational efficiencies and sustainability across sectors. In manufacturing, optimized scheduling reduces waste and energy consumption, promoting sustainable practices. In energy systems, intelligent scheduling supports demand response management and integrates renewable energy sources, conserving energy and reducing fossil fuel dependence. In healthcare, efficient scheduling optimizes medical resource use, minimizing energy and waste while enhancing patient care services.

5.CONCLUSION

In this bibliometric study, we have shown the integration of Machine Learning and Operations Research within the context of Industry 4.0 scheduling. Our findings show the important roles of Reinforcement Learning and Deep Learning. These methods demonstrated significant potential in enhancing dynamic and complex scheduling tasks. Early efforts primarily enhanced heuristic methods with ML, whereas recent trends emphasize exact OR methods to ensure optimal solutions, particularly in job shop and flow shop scheduling.

Recognizing the critical need for exact solutions in improving operational efficiency, our future research will explore how ML, especially RL, can be efficiently integrated with OR methods such as branch and bound. Such integrations promise to merge OR's optimality with ML's adaptive and predictive prowess. Despite notable advancements, our review has identified key gaps including the need for advanced data management strategies that ensure data quality without compromising privacy and the agility required in ML-OR integrations for real-time decision-making. These gaps are especially pronounced in dynamic sectors like transportation logistics and emergency healthcare. Moreover, the sustainability impacts of these integrations remain underexplored and represent a vital area for future inquiry.

To address these challenges, we aim to deepen our exploration of the types of scheduling problems tackled, assessing which ML-OR methods are most effectively employed for each. This nuanced analysis will not only clarify the current state of research but also guide future studies towards innovative solutions that enhance both the sustainability and operational resilience of Industry 4.0.

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