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A Study on Cutting-Edge Techniques for Large-Scale Production Scheduling

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Abstract*: Production scheduling is complicated and recorded. The sector-neutral starting stream fixes scheduling. The second stream adds realistic features like process overlaps or sequence dependent setup periods to traditional models to work on less generic scheduling algorithms for industrial settings. Different techniques have different limitations and issue sizes. Industry 4.0 has improved data collection for complex models. Industrial use cases may include thousands of operations on several devices, unlike benchmark examples of a few hundred. Identify and prioritize Industry 4.0 scheduling techniques to solve concerns and complications. Application scenarios and real-world scheduling issue literature are collected in this study. The publications found that machine learning, constraint programming, and metaheuristics solve large-scale scheduling problems. We found few contributions that address (extremely) large-scale challenges, requiring future investigation. Finding powerful metaheuristics via genetic algorithms and tabu search is exciting. Constrained programming and issue decomposition are also considered for problem-solving..*

Keywords: Large-Scale Optimization, Complex Constraints

I. INTRODUCTION

Scheduling allocates resources and tasks. Manufacturers often strive to maximize resource use, decrease delays, and save prices. These goals need efficient production scheduling. Chemical, textile, steel, and electronics industries schedule production. Fuchigami and Rangel examine industrial scheduling practices [10].

Business 4.0 and new technologies like cloud computing and the internet of things effect production planning and scheduling. Digitization, automation, and networking of manufacturing floor equipment have accelerated data collecting. Complex production relationships may be mapped to larger models with various restrictions using real-time data. Studying these subjects is important due to Industry 4.0's significant scheduling issues.

Constraint programming, mathematical programming, and heuristics have been intensively researched for problem formulation and solution. Hauristics and metaheuristics provide excellent solutions in realistic computation durations, whereas mathematical programming optimizes scheduling. Domain reduction, constraint propagation, and specialized heuristics minimize search space in constraint programming. Recently, machine learning has been applied for scheduling.

Many efforts have been made to improve mathematical models to bridge "academic" scheduling difficulties with real-world application scenarios. Literature accomplishes this broadly, adapting to many situations, or specifically, addressing a real-world theme. Real issues might include tens or hundreds of thousands of processes, whereas academic benchmark problems normally involve a few hundred.

Finding suitable solutions may take time due to the large literature and various real-world features and instance size challenges studied. This article reviews numerous cutting-edge scheduling approaches and their limitations to assist solve real-world scheduling problems. This poll focuses on scheduling problem size. It shows real-world problem-solving effectiveness of certain strategies.

Strategic scheduling literature comprises two streams. The first surveys include general expansions of classical scheduling issues. The non-permutation flow shop scheduling issue, flexible job shop scheduling, resource-constrained project scheduling, and assembly flow shop scheduling are reviewed [5, 15, 17]. Industry-driven problem-solving adaptations are reviewed in the second stream. Reviewing real-world applications summarizes chemical production

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scheduling research. The remaining paper is organized. After discussing manufacturers' primary issues in Section 2, the structured literature review study technique is described in Section 3, the examined articles are grouped by solution methodologies and instance size constraints in Section 4, and the main results are reported in Section 5.

II. INDUSTRIAL SCHEDULING PROBLEMS

Allocating activities to appropriate resources and ordering their processing are common scheduling difficulties. To maximize makespan or delay, these jobs must be planned to fulfill requirements. Scheduling constraints vary widely and represent real-world situations.

Classic academic scheduling issues like the job shop scheduling problem (JSSP) have few constraints: Setting up a shop requires m machines to process n tasks with fixed timeframes. Sequence of machines to visit depends on task, but is predefined. After processing on the previous computer is complete and preemption is outlawed, the next machine may start. While the work shop problem is tough to optimize, real-world issues may need extra limitations. Changing machine setup between tasks takes time and may depend on processing order. Machines may process at different speeds or use numerous resources.

As discussed below, expansions can provide scheduling issues. Resource quality, work order, complex task relationships, and time restrictions.

Work may be done in many ways using common resources. Production workers and machines are impacted. Since workers' experience and talent vary, processing durations depend on resources. Technological differences may explain this machine mismatch. Provide many suitable resources for each activity and processing time. To accommodate this more practical feature, the flexible job shop scheduling problem (FJSSP) lets the processing machine be selected from a list of suitable machines. Kress et al. [18] include machine- and operator-dependent processing times for different machine operator certifications. Real-world use cases classify resources. A resource can handle one job at a time under classical scheduling. This may apply to personnel and tools. Shared workspaces may be scaled up or down depending on the workforce, and there may be unlimited resources, such as an outside area to dry newly painted surfaces [4]. Certain specialist equipment, such injection molding machine left and right components, may make two items simultaneously. This drives scheduling models to include batch production constraints, which restrict simultaneous operations. Ham examines parallel batch processing-compatible FJSSP work families [12]. For instance, explains the flexible assembly job shop problem with sequence-dependent setup periods and component sharing, while Mahmoodjanloo et al. presents FJSSP reconfigurable machine tools.

Gathering resources is required for processing. This might be tank cleaning or machine tool attachment. Resource action sequence affects production job setup time in several cases. Cleaning the device and replacing the cartridge for different colors might take several minutes for a machine that colors product components, however two processes using the same color may take less time. This information is important for production scheduling. Shen et al. establish a tabu search metaheuristic for sequence-dependent setup times flexible job shop scheduling.

In many traditional scheduling issues, work begins when its predecessor ends. These connections may have more complicated features that affect operation speed. In steel manufacturing, minimum and maximum overlap durations are important for processing things at certain temperatures. The study examines flexible job shop scheduling overlap. After the predecessor, the successor may need to be done promptly. A "no-wait constraint," as illustrated in [2]. Transit timings may matter. [7] displays multi-objective FJSSP transportation time.

Internal ERP systems communicate industrial scheduling units batch sizes and deadline dates. It often sets deadlines, affecting production schedule. Start and end timings must be followed along with activity sequence. Missing a work deadline frequently incurs a price. Early may be pricey. For these historical eras, see [16, 3].

III. RESEARCH METHODOLOGY: STRUCTURED LITERATURE REVIEW

This article reviews current strategies for handling (extremely) big scheduling problems. For this, a detailed literature research was done. An appropriate search phrase captured key points. Schedule, job, shop, and optimization must be in the title, abstract, or keywords to limit search results to research articles. huge scale or huge size instances must exist to justify the emphasis on really vast difficulties. A Scopus search of 2022–2017 journal and conference proceedings articles found 81. Two manual screenings were done on these publications. To confirm the issue, the documents were

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verified first. Job shop, flexible job shop, open shop, and resource-restricted project scheduling allow several tasks to be handled on different machines in a different order. All are reviewed as industrial scheduling abstractions. Flow shop, hybrid flow shop, parallel machine scheduling, single machine scheduling, and assignment difficulties were excluded. Here, 41 of 81 papers were deleted. Second, humans screened the remaining 40 articles to validate that the issue cases were serious. Large-scale studies included 1000 procedures. After reviewing 26 articles, 14 were published. All 14 referenced articles were filtered to include pre-2017 publications containing big scale instance or large size instance in the title, abstract, or keywords. Twenty additional 2021–2001 items were examined following further screening. Six papers remained after deleting duplicates and repeating the manual two-phase selection. Our 20 systematic literature review articles 14 from the first stage and 6 from the second are included in Table 1. Part 4 examines chosen articles.

A. Solution methods: a state-of-the-art

Advanced solution approaches to solve scheduling problems considering complex real-world constraints fall into four major categories: mixed integer programming, metaheuristics, constraint programming, and machine learning. However, none of the papers found in the performed literature survey used mixed integer programming to problem situations of big size. The papers that were found in the study that addressed large-scale scheduling problems that is, issue occurrences involving at least 1000 operations are summarized below. We go over the scheduling issue under consideration, the method for developing a solution, and the largest problem size that has been solved for each contributor.

B. Constraint programming

Constraint programming (CP) solves combinatorial optimization problems via constraint propagation to decrease variable domains. The scheduling literature has focused on it because it solves large scheduling problems. Da Col and Teppan compare IBM and Google constraint programming leaders [6]. The open-source Google solver solved issues with up to 100,000 operations, whereas the IBM CP Optimizer solved certain situations with up to 1 million operations to optimality. These studies were limited to six hours. The huge number of solved instances encourages a deeper look at these solvers' methodologies. Laborie et al. [20] describe the IBM CP Optimizer's main components. The "Failure directed search" and "Self adapting large neighborhood search" are extended in [19] and.

These two heuristics have different goals. The "self adapting large neighbourhood search" algorithm finds great schedules throughout the solution space by making major schedule adjustments. This is done by adding and removing solution components. Complete the partial schedule to a full solution using one of the completion processes. Iteratively updating completion techniques' performance allows effective ways to be employed more frequently. The second heuristic, "Failure directed search," quickly finds unrealistic solutions to restrict the search field. Branching on variables may provide unrealistic solutions. Due to its early identification of problematic solutions, "Failure directed search," the most successful strategy, tracks and selects choices more frequently in following cycles. When "Self adapting large neighbourhood search" fails, "Failure directed search" helps. IBM CP Optimizer integration of these two search methods with constraint propagation shrinks variable domains to enhance solution process. Another constraint programming solution to a difficult scheduling problem is to extend constraint propagation to other heuristic frameworks to find viable solutions and eliminate neighborhoods that do not improve; scheduling constraints spread well.

The authors propose mixed integer programming models and constraint programming formulations for the online printing shop scheduling problem, a version of the flexible job shop scheduling problem treated in the metaheuristic part. The commercial IBM CP Optimizer, which represents CP, outperformed IBM CPLEX, which represents mixed integer programming. CP Optimizer could handle 1000-operation problem scenarios, but MIP models were restricted to 20.

IV. MACHINE LEARNING

Third-party scheduling problem-solving methods include neural networks and reinforcement learning. Machine learning in industry is growing due to Industry 4.0's objective of automating processes and huge data sets. Though it is the newest solution technique in this sector, the scheduling literature is paying more attention to it, and more is expected.

Machine learning often considers dynamic scheduling contexts where workloads arrive or machines break down often. Reinforcement learning is the most common solution for these problems. Reinforcement learning helps an agent learn a scheduling approach by repeatedly affecting the environment and receiving reward signals. Lei et al. [21] use deep reinforcement learning to flexible job shop scheduling using a deep neural network as the agent. The framework learns machine action and operation rules and provides production schedules for problem instances with up to 2000 activities. The resulting schedules beat human heuristic criteria solutions.

Basic dispatching concepts like the earliest due date or fastest processing time may be used to prioritize and schedule tasks. Zhang et al. applied deep reinforcement learning for conventional job shop priority dispatching. They model the Markov Decision Process and present the scheduling approach using GNNs. GNNs are great at leveraging graph characteristics. As many as 2000 operations are investigated. Han and Yang [13] provide a deep reinforcement learning framework for job shop scheduling. Reinforcement learning and deep convolutional neural networks are used to evaluate the scheduling framework on benchmark situations with up to 100 jobs on 20 machines. For bigger scenarios, the framework outperformed standard dispatching procedures. Finally, use convolutional neural networks and iterative local search to schedule job shops. Up to 20 computers can process 50 jobs.

V. CONCLUSION

Operating system integration, process automation, and data availability complicate scheduling in Industry 4.0. Three advanced solution strategies for large-scale scheduling difficulties with real-world extension address this trend's concerns in the organized literature review. Published approaches tackle over 1000 process issues using machine learning, constraint programming, and metaheuristics.

Metaheuristics may solve complicated problems. Genetic algorithms and trajectory-based heuristics like tabu search are promising. Several metaheuristics and techniques may intensify and diversify. Making huge issues into smaller, faster-solving subproblems stimulates study in this discipline.

Constraint programming is interesting and solves big challenges. Constraint programming solvers can manage hundreds of thousands of workloads, therefore prioritize them. Modern constraint programming solvers tackle scheduling problems, and their core components may be leveraged to create new approaches. Reinforcement learning-focused dynamic problems employ machine learning scheduling. In big problem settings, reinforcement learning approaches, particularly deep reinforcement learning systems using neural networks as learning agents, function well.

Mixed integer programming (MIP), the fourth scheduling issue solution class, isn't good for bigger issues despite its popularity. Undiscovered: mixed integer programming for large-scale scheduling. Even if MIP models can only handle a few problems, we appreciate the work put into incorporating real-world application components. Hansmann et al.'s accurate Branch & Bound technique for the FJSSP with blockages [14] and the MILP model for flexible job shop scheduling with sequence-dependent setup periods are examples. Ham [12] proposes flexible job shop scheduling using modified mixed integer programming, parallel batch processing, and suitable task families. Operator- and machine-dependent processing times are used to analyze sequence-dependent setup times for flexible job shop scheduling and diverse machine operator qualifications by Kress et al. [18]. The researched issue extensions are intriguing, however mixed integer programming will handle too small examples for practical usage. Mathematics becomes complicated quickly, making its practical use uncertain. We value their role in comparing approximation approaches to small-scale optimum solutions. Complex matheuristics may be possible using mixed integer programming and efficient metaheuristics. To lead a metaheuristic component over the search space, MIP models may optimize smaller subproblems.

After examining our findings, we advocate constraint programming for large-scale production scheduling applications using robust metaheuristics such self-adapting big neighborhood search and tabu search principles with evolutionary algorithms. Dissecting and integrating suitable subproblem management approaches may enhance these advanced metaheuristic solutions.

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