Machine Learning for Dynamic Job Shop Scheduling Problem: Literature Review

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Abstract: In the last ten years, Machine Learning (ML) techniques have taken a huge leap forward and researchers have started to consider ML for job scheduling problems in the industrial field, especially dynamic job shop scheduling. In this paper, we mainly focus on the dynamic scheduling problem, which is more complex and difficult to solve and we propose to regroup the methods and approaches used to face it. Therefore, we give a review of machine and deep learning methods applied to dynamic job shop scheduling problems. In this way, our work provides a resume of the concerned studies.

1 INTRODUCTION

Among the problems encountered by researchers and engineers, optimization problems occupy a prominent place in our time. Formulating optimization problems and trying to solve them is the main objective of many researchers. To solve the planning problem, two objectives must be reconciled. The static aspect includes the development of implementation plans based on predictive data. The dynamic aspect is to make decisions in real time given the state of the resources and the progress in time of the different tasks. Workshop scheduling consists of predicting the sequence of all the elementary operations required to carry out manufacturing orders on production resources while taking into account internal and external constraints. In a complex production environment, scheduling can become an extremely difficult problem to solve. Production scheduling is the determination of the order in which a number of jobs are to be executed. This determination concerns the planning of the use of available human and machine resources in order to better control the costs and to master the manufacturing delays of the decided productions. The resolution of a scheduling problem goes through an identification and modelling phase and a research phase of the adequate resolution method. The development of new technologies in the manufacturing world has allowed manufacturers to meet the ever-increasing challenge of dealing with multiple objectives and unforeseen events to which they are subjected, such as a change or cancellation of a production order, or the arrival of a rush order. Most planning problems are, or come down to, dynamic optimization problems.

In our work, we pay more attention to a dynamic job-shop scheduling problems in order to group and present the different optimization methods developed in the literature and the different criteria to optimize.

The remaining sections of the paper are organized as follows: In Section 2, we defined the dynamic job scheduling problem in detail. Section 3 is devoted to a comprehensive review of the literature on dynamic shop scheduling. A complete review of the literature on dynamic shop scheduling with machine learning is illustrated in Section 4. The discussion of the various contributions is presented in section 5. We end this paper with a general conclusion that summarizes the different phases of work in section 6.

2 DESCRIPTION OF DYNAMIC JOB SCHEDULING PROBLEM

A collection of jobs to be done on a set of resources in order to optimize the objective function describes

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the scheduling problem. The scheduling problem resides in the continuous adaptation of the process of a set of resources to execute a set of tasks to the real situation of the considered system. This type of problem is often encountered in manufacturing workshops that work to order where the delivery time represents one of the major difficulties. The job shop problem is one of the most studied and most difficult problems in scheduling theory (NP-hard). It is essential to know, in the resolution of this type of problem, if one must privilege the quality of the sought solution, the speed of the calculation time or find a compromise. The optimal solution is therefore impossible in most cases because of its combinatorial character. Therefore, we generally resort to the so-called approximate methods, which give approximate solutions in a reasonable time.

Dynamic scheduling problems formulated as optimization problems are often classified as NP-hard, especially those related to production systems. The solution of such problems requires dedicated methods; while exact methods cannot solve this type of problems due to the huge computational time, approximate methods offer the possibility to find a feasible solution in a reasonable time.

In our paper, we are particularly interested in real-time scheduling problems for a job shop system in a dynamic environment. This system is subject to a disturbance of the environment represented by the occurrence of new urgent orders, which it must execute, machine breakdowns, unexpected processing delays and cancellation of orders. The problem imposed here is how the system should react to the occurrence of one of these events.

3 SCHEDULING APPROACHES ON DYNAMIC JOB SHOP SCHEDULING PROBLEM

Production scheduling systems are generally applied in real-world manufacturing systems under the impact of unpredictable or dynamic events including machine breakdowns, unforeseen processing delays, random arrivals of urgent orders, and order cancellations. Because of these dynamic occurrences, the initial scheduling strategy is suboptimal and/or infeasible. Therefore, a proper dynamic rescheduling approach is needed to deal with these dynamic events.

To cope with a dynamic job shop scheduling problem that takes into consideration random work arrivals and machine failures, (Zandieh and Adibi, 2010) proposed a variable neighbourhood search (VNS) based scheduling approach. They selected an event-based policy to deal with the problem's dynamic nature. An artificial neural network with an error backpropagation learning algorithm is used to adjust the VNS parameters at every rescheduling point based on the issue circumstances to increase the efficiency of the scheduling technique.

The dynamic flexible job shop scheduling problem (DFJSSP) with publication dates was explored by (Nie et al., 2013). For the dynamic scheduling problem, they present a heuristic for implementing reactive scheduling. They also suggest using Genetic Expression Programming (GEP) to build reactive scheduling strategies for dynamic scheduling automatically. Three factors, such as shop floor utilization, proximity to due date, and problem flexibility, are considered in the simulation experiments in order to evaluate the performance of the reactive scheduling policies constructed by the proposed genetic expression programming-based approach under a variety of processing conditions. The simulation considers the minimization of makespan, average flow time, and average latency as scheduling performance measures.

(Kundakc and Kulak, 2016) presented a dynamic shop floor scheduling issue in which new tasks arrive, a machine fails, and the processing time changes. Heuristic techniques are effective for tackling dynamic shop floor scheduling issues since they are NP-hard combinatorial optimization problems. The authors offer hybrid GA (Genetic Algorithms) methods in which a novel KK + exchange heuristic and well-known dispatching rules (SPT, LPT, SRPT, and LRPT) + exchange are combined with a GA algorithm to give quick and efficient solutions to large dynamic shop scheduling issues.

In order to solve the dynamic scheduling problems of flexible job shop, the authors (Ning et al., 2016) proposed an improved multiphase hybrid quantum particle swarming algorithm. First, they planned a dual-chain structure coding method including a machine distribution chain and a process chain. Then, they proposed a dynamic periodic and event-driven scheduling strategy. Finally, these authors applied a new method to the Brandimarte(1993) set, including 10 examples, used for the verification of the effectiveness of the proposed method and for dynamic simulation.

(Wang et al., 2017) developed a dynamic rescheduling approach based on a variable interval rescheduling strategy (VIRS) to cope with a job shop's flexible dynamic scheduling problem by considering machine failures, arrival of urgent work, and work damage as disruptions. They suggest, on the other hand, an enhanced genetic algorithm (GA) to reduce the makespan. A random initialization population mixture is meant to create a high-quality starting population in our enhanced GA by combining an initialization machine and an initialization operation with random initialization. To prevent slipping into the local optimal solution, the elitist strategy (ES) and the enhanced population diversity strategy (IPDS) are utilized.

Besides the classical scheduling approaches, such as metaheursitics, the recent studies are focused on machine/deep learning. In the following section, we present the recent studies based on machine/deep learning for dynamic scheduling problems.

4 MACHINE LEARNING BASED METHODS ON DYNAMIC JOB SHOP SCHEDULING PROBLEM

The scheduling of production processes has long been the subject of extensive research. Dynamic job shop scheduling problems are known in the literature as the most difficult problems to solve.

The difficulty lies in the choice of the best approach for their solution as well as in the determination of the best scheduling in reasonable times, as close as possible to the optimal solution. Several authors have studied the solution of these types of scheduling problems using Machine Learning. The authors (Bouazza et al., 2017) used intelligent products (IPs) as a solution to solve shop floor scheduling problems. The product gathers information from the existing planning environment and needs machines to perform a set of tasks. The IP divides the choice into two steps to schedule production tasks in a simulated environment: choose a machine and reschedule the selected queue. The following scenario and configurations were used to test the proposed model: Six different SPs (service providers) compose the manufacturing cell, and nine families are estimated to add sufficient complexity to the scheduling challenge. They used the Boltzmann distribution rule by Q-learning method to create stochastic decisions. The PIs gradually converge to an ideal behavior as a result of this two-step decision process. We use the most popular machine selection criterion, shortest tail, to compare the Q-learning method. It is used in conjunction with four different allocation rules: First In, First Out, Shortest Job First, Highest Priority First, and Last in First Out. With respect to Cmax, the results are almost identical.

By taking machine failures into account, the authors (Zhao et al., 2019) suggested an enhanced Q-learning method with dual-layer actions to address the dynamic flexible job scheduling problem (DFJSP). The suggested Q-learning Agent based on dispatching rules achieves the initial scheduling scheme, while the Genetic Algorithm (GA) obtains the rescheduling approach. Experiments based on the FJSP issue Mk03 are created and executed to show this method. The findings show that, as compared to utilizing a single SPT, FIFO, or EDD method, the agent-based system can choose the optimum strategy for diverse machine failures, increasing efficiency. This demonstrates the effectiveness of the suggested Q-learning in a dynamic and flexible job-shop setting.

A deep Q network (DQN) was developed by (Luo, 2020) to deal with the ongoing production status and learn the most suitable action (i.e., dispatch rule) at each rescheduling point. When an operation is done or a new task comes, he suggested six compound dispatch rules to pick an operation at the same time and allocate it to operable machines. As a result, seven general state characteristics are derived to characterize the rescheduling points' production status. The state action value (Q-value) of each dispatch rule may be determined by feeding the continuous state characteristic into DQN. Deep Q-learning (DQL) is used to train the proposed DQN, which is further enhanced by two enhancements: dual DQN and smooth update of target weights. Furthermore, in the practical implementation of the trained DQN, a "softmax" action selection policy is employed to favour rules with higher Q-values while retaining the policy's entropy. In a simulated flexible shop with 30 machines, 20 beginning tasks, and 100 additional insertions, the suggested DQN is trained. They put the DQN and other comparison criteria to the test on 20 distinct cases, each with 20 independent replications. DQN outperforms the suggested composite dispatch rules and other well-known dispatch rules in both trained and untrained production configurations, according to the findings. Simultaneously, comparisons of the DQN and the Q-stand learning agent demonstrated the DQN's superiority in handling the continuous state space.

(Liu et al., 2020) views JSSP to be a sequential decision-making issue and suggests that it be solved via deep reinforcement learning. An actor network and a critical network, both of which comprise convolution layers and a fully connected layer, are included in the proposed model. The agent in the actor network learns how to act in various scenarios, while the critic network assists the agent in evaluating the statement's worth before returning to the actor network. To train the model, this paper offers a parallel learning approach that combines asynchronous updating and a deep deterministic policy gradient (DDPG). Different basic dispatching rules are considered actions, and the entire network is trained in parallel in a multi-agent environment. The evaluation is based on more than ten examples from the OR-Collection, a well-known reference problem library. The results show that the model can cope with unexpected incidents, such as a machine failure or a sudden extra order. Furthermore, the quality of the solutions found by is also comparative, outperforms traditional dispatch rules, and runs almost as fast as simple dispatch rules.

To cumulate the advantages of real-time response and flexibility of deep convolutional neural networks (CNNs) and reinforcement learning (RL), the authors (Han and Yang, 2020) proposed a deep reinforcement learning (DRL) framework, to acquire behavioral strategies from the captured manufacturing state. Moreover, it is more suitable for real-world manufacturing problems related to control. In this framework, the scheduling process using disjunction graphs is considered as a multi-step sequential decision problem, and deep CNN is used to approximate the value of the execution state. The execution state is represented as a multi-channel image and input to the network. Static computation experiments were performed on 85 instances of JSSP (Job Shop Scheduling Problem) in the well-known OR library. The results indicate that the proposed algorithm can obtain optimal solutions for small-scale problems, and outperforms any single heuristic rule for large-scale problems, with performance comparable to genetic algorithms.

The authors offer a new dynamic scheduling technique based on Petri nets via DQN with graph convolutional network (Hu et al., 2020). (GCN). First, based on operation sequence, resource usage restrictions, and processing time, flexible manufacturing systems (FMSs) are modeled using timed S^3PR (system of simple sequential processes with resources). Then, a PNC layer with two graph convolution sublayers is built to implement feature propagation from a location to a transition and a transition to a location, respectively, according to the unique sub-network structure of the S^3PR time. The advantage of the PNC (Petri-net convolution) layer is that the number of its training parameters is only related to the number of filter channels, and has nothing to do with the scale of the S^3PR clock. Therefore, it is possible to overcome the problem of parameter explosion when building a deep neural network. In comparison to heuristic approaches and a DQN with basic multilayer perceptrons, the experimental findings demonstrate that the proposed DQN with a PNC network may give superior answers to dynamic planning issues in terms of manufacturing performance, computing efficiency, and flexibility.

For online scheduling in flexible manufacturing systems, the author (Bar et al., 2020) proposes a reinforcement learning (RL) technique (FMS). Scheduling becomes more complicated when numerous activities with various optimization goals are considered, and unexpected occurrences result in prolonged downtime until a new plan is formed. As a solution to this problem, they use the MARL (Multi-Agent RL) version of Deep Q-Networks (DQN) without explicit information exchange between agents, with agents that have learned to efficiently guide products through the factory and achieve near-optimal timing regarding resource allocation. These agents control the products and can react to unexpected machine failures and reconfigurations of the module (machine) topology. An FMS with six different manufacturing modules and six positions in which they can be placed is used. All experiments start with a fixed number of three agents controlling three identical products in the order stack in the initial state of each period. The agents must complete a fixed job specification with four operations, each operation having two alternative manufacturing modules with different processing time required to execute the operations.

(Kardos et al., 2021) applied a reinforcement learning method, including Q Learning, to reduce the average lead-time of production orders in the shop floor production system. The intelligent product agents (intelligent elements, called agents, are able to learn the best decision strategy during a learning process in the RL to maximize the overall optimization objective) can select a machine for each production step based on real-time information. The performance of the strategies learned by the RL agent was tested against standard heuristics. Since these heuristics are known to be applicable to simple scenarios, it is important to understand how complicated the implementation of RL has become from a practical standpoint. To this end, by increasing the total number of process steps used and reducing the defined time interval between dynamically generated PIs, a set of problems with increased complexity was defined. In the addition, the performance of the policy is tested when the agent has the ability to directly select an IP, compared to the case where the agent is limited to choosing between standard dispatch rules. The simulation model is infused from Bouazza et al. (2017), however in this case the production process may have multiple phases, the distribution of manufacturing orders in each concentration is random, and only one decision needs to be made, namely the choice of machine. The simulation model and decision logic are implemented in the Python programming language and use the DES framework based on the SimPy process. Another important aspect of efficiency is the tight integration of the decision logic, which has been implemented using the Tensorflow library.

In the end of this section, we note that Machine Learning is also applied to Flow shop scheduling problems, such as (Zhang et al., 2013) and (Xue et al., 2018). A summary of related research is presented in Table 1.

Table 1: Summary of relevant studies by machine learning algorithms

Reference	Approach	Optimization criteria	Dynamic events
Bouazza et al., 2017	Q-learning + SMA	Average Waiting Times & Weighted Average Waiting Time	frequent arrivals of work, variation in processing times and set-up times
Zhao et al., 2019	Q-learning + GA	Time of delay	machine breakdowns
Luo, 2020	DQL	Total tardiness	new job insertions
Liu et al., 2020	DL + RL + SMA	Makespan	a machine breakdown + a sudden additional order
Han and Yang, 2020	CNN + RL	Makespan	order-driven manufacturing
Hu et al., 2020	Petri net via DQN with GCN	Makespan	shared resources, route flexibility and stochastic raw product arrivals
Bar et al., 2020	RL + SMA	Makespan	unexpected machine failures + plant reconfigurations + module (machine) topology reconfigurations
Kardos et al., 2021	Q-learning + RL	Average lead time	Fluctuating customer demands, expected short delivery times and the need to confirm orders quickly

Machine learning is not widely applied to the static case, we can cite (Wang and Usher, 2004) (Wang and Usher, 2005) (Lin et al., 2019) (Hameed and Schwung, 2020).

5 DISCUSSION

Scheduling is a field of operations research and production management concerned with increasing a company's efficiency in terms of production costs and delivery timeframes. From manufacturing to information technology, all economic sectors have scheduling issues. Operational planning for industrial production systems involves managing the allocation of resources over time while optimizing a set of standards. It also means scheduling the execution of a project by allocating resources to tasks and setting their execution dates. The problems of resource allocation, task organization, meeting deadlines and making decisions in a timely manner are all difficulties that must be overcome in the management of production systems in an industrial environment. Due of their limited real-time responsiveness, traditional methods to job shop scheduling difficulties are currently unsuitable for complex and dynamic production settings. Naturally, these methods must have a solid theoretical foundation to approach these complex problems with some confidence in the quality of the result. Among the most difficult scheduling problems are those related to dynamic job shop. Their optimal solution is, in most cases, very difficult because of their combinatorial character. In this paper, we have summarized the studies that focus on this problem and studied the application of machine learning (RL, DRL, DQL, CNN...) to a workshop production scheduling process considering dynamic events such as random job arrivals, machine breakdowns, job disturbances and changes in processing time with a criterion optimization objective.

6 CONCLUSION AND FUTURE RESEARCH LINES

This conclusion explains our approach in this article. Our goal is to be exhaustive and to make the reader aware of problems whose importance escapes less and less computer scientists, but still too many industrialists. Therefore, this article is structured as follows. First, we presented the static job shop problem by detailing the approaches used in each of the cited articles, the criterion (s) to be optimized, the types of scheduling problems solved, and the benchmark used. Secondly, we have done the same with the dynamic job shop and flow shop problems by taking into account dynamic events.

Therefore, in this paper we are interested in the consolidation of the literature review of the static job shop scheduling problem without machine learning, as well as the job shop and flow shop problems with machine learning in real time (dynamic).

Several dynamic scheduling methods have been presented, including, on the one hand, heuristics, meta-heuristics, and multi-agent systems, and on the other hand, machine/deep learning algorithms such as Q-learning, reinforcement learning, Deep reinforcement learning, and Deep Q-learning. Although there has been some research on dynamic scheduling systems, more effort is still needed to deal with these NP-hard scheduling problems. In the future, more aspects can be considered to expand the research by adopting new optimization methods, such as Biogeography-based optimization, to solve the dynamic JSSP, and by adopting new approaches based on deep learning, such as Convolutional neural networks.

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