Towards Standardizing Reinforcement Learning Approaches for Stochastic Production Scheduling

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Abstract

Recent years have seen a rise in interest in terms of using machine learning, particularly reinforcement learning (RL), for production scheduling problems of varying degrees of complexity. The general approach is to break down the scheduling problem into a Markov Decision Process (MDP), whereupon a simulation implementing the MDP is used to train an RL agent. Since existing studies rely on (sometimes) complex simulations for which the code is unavailable, the experiments presented are hard, or, in the case of stochastic environments, impossible to reproduce accurately. Furthermore, there is a vast array of RL designs to choose from. To make RL methods widely applicable in production scheduling and work out their strength for the industry, the standardization of model descriptions - both production setup and RL design - and validation scheme are a prerequisite. Our contribution is threefold: First, we standardize the description of production setups used in RL studies based on established nomenclature. Secondly, we classify RL design choices from existing publications. Lastly, we propose recommendations for a validation scheme focusing on reproducibility and sufficient benchmarking.

1 Introduction

The field of production planning and scheduling is often characterized by a high degree of dynamism, given that production reality changes constantly. As production data and computing resources become more readily available and production itself becomes more versatile, the incorporation of machine learning techniques for production scheduling is increasingly an option.

1.1 Motivation

Production scheduling is NP complete for most real world cases, and, as such, difficult to solve optimally for large production instances. Furthermore, unexpected events such as new job arrivals, operation duration deviations or resource availability issues, may invalidate schedules. In such a case fixed schedules need to be recomputed. This makes RL solutions highly attractive, since deployed RL schedulers are fast and can rapidly adapt to unforeseen events \cite{1}.

While the surge in interest for RL solutions for production scheduling is undeniable, with four times as many papers on the topic of RL production scheduling in 2020 as in 2018\textsuperscript{1} most studies suffer from reproducibility issues owing to a lack of clarity pertaining to RL modeling and/or production problem description, code and simulation input unavailability and non-reproducible stochasticity. Furthermore, RL solutions should be benchmarked against more established meta-heuristics (e.g. genetic algorithms) and typical simple heuristics on a sufficient number of scheduling problem instances to avoid cherry picking \textsuperscript{2} suspicion.

1.2 Related Work

A solid but very general standard for experiments in the field of Operations Research (OR) is available in \cite{3}. Here eight criteria for benchmarking are given, namely clearly stated goals, well-specified problems, suitable algorithms, adequate performance measures, thoughtful analysis, effective and efficient (experiment) designs, comprehensible presentations, and guaranteed reproducibility.

For basic scheduling problems, e.g. flow/job/open shop scheduling problems, an implicit problem defini-
tion standard is set through benchmarking instances available in Beasley’s OR library [1]. Benchmark instances for more intricate setups are sometimes made available through dedicated publications, e.g. flexible job shop scheduling problem [5, 9, 7, 8].

First steps in the direction of RL project standardization were taken by OpenAI Gym, whereby a general RL application programming interface (API) is defined. Through [9], OpenAI Gym simulations for varied combinatorial optimization problems from the field of OR, e.g. the bin packing or the traveling salesman problem, are made available.

For the dynamic production scheduling problem of the semiconductor industry an environment that respects the OpenAI Gym API is provided in [10]. This environment is fixed to the semiconductor industry material flow and does not guarantee reproducible stochasticity. A more flexible setup is required so as to cover more generic problem definitions.

1.3 This Work

This work seeks to standardize the description of RL approaches for production scheduling problems. This is achieved in three steps: First, we look at production setups used with RL experiments and propose a clear nomenclature scheme by extending a well established OR literature standard in Section 2. Secondly, we investigate RL design choices available for production isolating different possible Markov Decision Process (MDP) formulations in Section 3. Thirdly, we lay down how to ensure reproducibility and avoid cherry-picking in stochastic settings in section 4. Section 5 concludes our analysis and presents some avenues for future work.

To keep within the frame of this work we defer some of the details of the introduced categories. We do not, for example look at every possible information available for state, action and reward formulations during RL design. We do however give examples of such. Similarly, we do not consider RL algorithms in detail. Instead, we briefly describe the main categories and give examples of where these were used for production scheduling.

2 Job Shop Scheduling Variants

An established format for defining a production scheduling problem in OR literature is the $\alpha|\beta|\gamma$ notation described by Pinedo in [11]. The three parameters describe the machine setup $\alpha$, a possibly empty set of additional constraints $\beta$, and the optimization target $\gamma$. In what follows we introduce these parameters, defining new ones as needed to cover the setups present in RL production scheduling literature.

2.1 Machine Setup – $\alpha$

Production scheduling is the problem of assigning start times $s_{ji} > 0$ to a number of operations $o_{ji}$ with processing times $p_{ji}$ grouped into $n$ jobs, onto one of $m$ production resources to optimize some target value, for example makespan, $C_{\text{max}}$, which is defined as the maximum over the set of all job completion times $C_j$, with $j$ being the job index. Operations are executed one at a time in the absence of preemption. Release dates $r_j$ defining when job processing can commence and due dates (or deadlines) $d_j$ complete the picture. Depending on the number and order of operations within jobs and the number and speed of resources available for different operation types, machine setups can be categorized into one 10 groups which we now introduce.

Figure 1 shows the hierarchy of scheduling problems. The problems on filled rectangles were studied in the RL literature, while the problems with a white background were not. The green color indicates that the problems were defined in [11], while red indicates that they were defined by us. The generalization relationship between problem classes is indicated with arrows.

Single machine problems (1) are defined in terms of $n$ jobs, with one operation each, and a single processing resource. By replicating the processing resource we obtain the parallel machines ($Pm$) setting, $Pms$ with different processing speed scalars $v_i$ define the heterogeneous machines ($Qm$) setup. Operation processing times are herein scaled by the machine speed to obtain the operation completion times. If the machine speed depends not only on the machine index $i$ but also on the job index $j$, the unrelated machines ($Rm$) setup is in place.

Setsups with $m$ resources and $n$ jobs containing $m$ operations, define shop-scheduling problems. Operations can only be processed by resources of corresponding types, and each resource is visited exactly once to complete a job. If operations within a job need to be processed in a fixed sequence (total order), which is identical for all jobs, then the production setup is that of a flow shop ($Fm$). Allowing distinct sequences for different jobs yields a job-shop environment ($Jm$). No operation precedence constraints are indicative of an open-shop ($Om$).

Any shop setup can be extended by replicating one or more resource types and grouping them into work-centers. Operations are now fixed to a work-center, rather than a machine. If the setup prior replication
was flow or job shop, post replication the setup is that of a flexible flow shop (FFc) or job shop (FJc) respectively.

The class of partially open job shop scheduling problems, POm, has an intermediary position between Jm and Om. Here job operations are partially ordered, with precedence constraints described by a directed acyclic graph. Analogously to the other flexible variants, in flexible POm, i.e. FPOc, operations of a particular type can be executed on one of the machines of the corresponding work-center. Examples of RL approaches over such setups can be found in [12] [13] [14].

A routing choice for jobs is required additionally to operation sequencing decisions in parallel machine setups (Pm, Qm, Rm) and flexible shops. The same applies for setups where the precedence constraints allow for more than one operation to be executed immediately after a particular one has finished (i.e. in Om, POc). We refer to this as routing flexibility.

2.2 Additional Constraints – β

The β values modify the scheduling problem by adding constraints or changing existing ones. Figure 2 contains an overview of the constraints to be discussed. The green color indicates that the constraints were defined in [11], red indicates that they were defined by us. If a rectangle is filled in (either red or green), then it is part of the setup considered in at least one of the RL publications. Arrows indicate an extension/generalization relationship. We refer to [11] for some less frequent constraints (no wait-time nut, pre-emption prmp, permutation prmu, and job precedence prec) that we do not extend in what follows.

The block parameter is defined by Pinedo to model limited buffer space between production stages in Fm. Machines can only process an operation if there is enough space in the buffer following it. We define the more generic parameters blockin and blockout for input and output buffers in machine setups with routing flexibility. A full input buffer, blocks routing to the corresponding machine. Conversely, a full output buffer blocks processing on the afferent resource.

The re-circulation parameter recrc, loosens the constraint whereby jobs visit each machine type exactly once in the shop setups. Instead some jobs may require revisiting work-centers. This results in cycles in the operation precedence graph. We introduce the heterogeneous number of operations parameter, hnotps, to model situations where different jobs can revisit some machines while not visiting others at all, as is the case in [12] [13] [15].

In many cases, processing an operation requires additional setup time. The parameters fmls, Sjk and Sjki define different setup time penalties in an increasing order of generality. With fmls setup times are required when switching between job families. Sjk penalizes switches between any jobs. If Sjki is present, the sequence dependent setup times are additionally machine dependent.

Until now, any particular resource could only process one type of operations. This is not the setups of [16] [17] [18] [19]. Pinedo defines machine eligibility restrictions Mi for Pm environments only. Machine i can only process operations from jobs contained in the set Mi := J′ ⊂ J, where J is the set of all jobs. We additionally introduce the Mi parameter to distinguish between the original machine eligibility constraints for jobs and our more general ones for
operation types: \( M^o_i := O' \subset \text{type}(O) \) where \( O \) is the set of all operations and \( \text{type} \) the mapping defining operation types.

The \textit{batch} parameter relaxes the constraint whereby resources can only process one operation at a time by allowing fixed size and processing time batches on specified resources. However, both batch sizes and processing time can be dynamic as in the setup of \cite{15}. We add the \textit{dbatch} parameter to reflect this. In the setup of \cite{20} resource capacity could vary dynamically, with resources being added to work-centers during the scheduling process. To cover this case, we define the flexible resources \textit{fres} parameter. The dynamic batch, and the flexible resource constraints are fringe cases in the scheduling literature, but potentially very impactful for real world applications.

Parameters of core importance are those encoding stochasticity, namely \( r^s_j \), \textit{brkdwns}^s, \textit{dmds}^j and \( p^s_{ji} \). Release dates, could be deterministic, depending on the underlying planning process, but are most often stochastic (\( r^s_j \)). Similarly, breakdowns are deterministic (\textit{brkdwn}), if resources are taken offline for planned maintenance, and stochastic in case of unexpected failure (\textit{brkdwn}^s). The presence of \textit{dmds}^j implies that release dates are a system inherent choice. In a \textit{dmds}^j system, finished jobs are consumed from a sink buffer as per incoming demand. A stochastic demand is indicated by \textit{dmds}^j. This situation is considered in \cite{21,22,23}. Operation processing times can also be stochastic (\( p^s_{ji} \)) since these too are estimates, and thus, subject to noise.

Transport times and resources are often not explicitly modeled. In such a case, two implicit assumptions are made: (a) distances and hence transport times are either negligible, constant or part of the processing times \( p_{ji} \), and (b) transport resources are always available to transport a job to its next resource. As soon as (a) does not hold, transport times should be modeled separately. If the production setting to be scheduled contains enough transport resources, (b) can still hold. We mark this setup by means of \( tr(\infty) \), e.g. \cite{20}. If conversely, transport resources are scarce, we have to model their current position explicitly \( tr(n) \) as in \cite{23,10}, since this transport availability directly impacts the schedule.

### 2.3 Objectives - \( \gamma \)

As can be seen from Figure 2 there are many possible optimization targets for production scheduling, depending on the emphasis on the particular industrial use case. The green rectangles represent targets available in \cite{11}, while the red ones were extracted from RL literature. The gray rectangles represent intermediary variables needed for the target definition.

We categorize optimization targets as job-centric (throughput, makespan, flow-time, latency, tardiness, unit cost) or resource-centric (machine utilization, transport resource utilization, job idle time, machine failures, buffer length, buffered times, setup times, inventory levels). These metrics target different aspects of the production system and can be combined into a joint optimization target either by constructing a score function as a function of multiple targets (scalarization), e.g. \cite{22,23,15,25}, or by following a pareto front, e.g. \cite{20}.

**Job-Centric Goals:** The most often encountered metric is the previously discussed makespan, i.e. the maximum completion time over all jobs. While \( C_{max} \) makes sense for static contexts with a fixed number of jobs, for dynamic environments a throughput measure needs to be used. In literature average job throughput \( Tpt_{ave} := 1/t \sum 1\{C_j \leq t\} \) at time \( t \)
is used \[20, 10\]. Additionally, operation throughput \( T_{\text{pt ave}} := 1/t \sum_{j,i} p_{ji} \cdot 1\{s_{ji} + p_{ji} \leq t\} \) could be considered. Flow-time (also lead time) \( F_j \) measures the time between job release and job completion, \( F_j := C_j - r_j \). The average flow time \( F_{\text{ave}} := 1/n \sum F_j \) is an indicator of a system’s reactivity/flexibility. Yet another measure based on the job completion time is the job idle time \( I_j \) defined as the difference between flow time and the summed job processing time: \( F_j - \sum p_{ji} \).

Timeliness related metrics computed using the lateness intermediary variable, i.e. the difference between completion time and due date, \( L_j := C_j - d_j \), are perhaps the most relevant for the industry \[24\]. Tardiness extends lateness by ignoring early jobs \( T_j := \max\{0, L_j\} \). Tardiness based optimization goals encountered are constructed by aggregating the tardiness variables, e.g. \( T_{\text{ave}}, T_{\text{max}}, \sum T_j \). Alternatively, the number of tardy jobs can simply be counted using the unit cost variables \( U_j := 1_{C_j > d_j} \), e.g. \[28\]. Finishing jobs too early can be detrimental \[24\]. As such, earliness \( E_j := |\min L_j, 0| \) can be another minimization target as it is considered in \[25\] where tardiness and earliness are jointly minimized.

**Resource-Centric Goals:** Resource utilization is defined as \( U_{\text{ti}} := 1/t \sum p_{ji} \cdot 1\{s_{ji} + p_{ji} \leq t\} \), i.e. the time the machine was working over the up-time \( t \). Similarly one can define the transport utilization \( U_{\text{tr}} \) as the time spent carrying a load over the total elapsed time. The buffer composition can also be used as an optimization target. In general one would like to keep buffer lengths to a minimum. In \[23\] the number of buffered operations \( B_{fi} \) at resource \( i \) was used as an optimization goal within a more complex cost function also involving lateness and the total number of tool switches.

## 3 RL Modeling for Production Scheduling

To solve any problem with RL first an MDP must be modeled for the particular domain. The MDP defines an agent-environment interaction. The agent, whose goal is to maximize the received reward, senses the current environment state and takes an action, whereby the environment is moved to a new state. This loop continues until an end-state is reached. The agent receives feedback by means of a reward signal, which it tries to maximize. While for many RL settings the MDP is fairly obvious, for production scheduling environments, there are many design choices to be made. In what follows we categorize the available RL design options available for production scheduling problems in terms of rough MDP breakdown, agent algorithms and the state, action and reward spaces.

### 3.1 MDP Breakdown

MDPs for production scheduling are currently broken down in one of five ways we refer to as operation sequencing (1), routing before sequencing (2), interlaced routing and sequencing (3) transport-centric routing (4) and re-scheduling (5). In addition, we propose...
the holistic routing and sequencing breakdown (6) to better tackle \( tr(n) \) settings.

**Operation sequencing:** The idea behind iterative operation sequencing is to use the moments when resources become free as the discrete time steps when decisions can be taken. An operation \( o_{ji} \) from the machine queue is then assigned to it, marking its start time \( s_{ji} \) as the current time \( t \). This process is repeated so long as there are still jobs to complete. In setups with no routing flexibility, the iterative operation sequencing MDP breakdown is sufficient for defining all possible schedules, e.g. \([24, 35, 10]\).

Iterative operation sequencing can also be used to implicitly define routes for setups with routing flexibility, if the assumption of negligible transport times and endless capacity buffers is present. After an operation finishes, the next eligible resources for the job can be seen as sharing a virtual buffer wherein the job lies. As soon as the job is assigned by the agent to one of these resources, the job is no more available for processing at the other resources. Such an approach can be found in \([23, 20, 1, 34, 19, 15]\).

**Routing Before Sequencing:** Within this breakdown, whenever a new job arrives, the agent iteratively assigns processing resources to it, until it has a fixed completion path through production. When the job route has been set, the scheduling process described above can continue. Such is the approach of \([16, 17]\).

**Interlaced Routing and Sequencing:** The combined routing and sequencing problem can also be solved in an interlaced fashion. The agent decides upon the next processing resource to transport a job to on demand, when an operation is finished. This decision is then immediately followed by a sequencing decision on the freed resource. This breakdown is employed in \([15]\).

**Transport-Centric Routing:** In \( tr(n) \) settings, there are two behaviorally distinct resource types present, namely processing and transport resources. Within this MDP breakdown, processing resources sequence operations following a simple priority rule, e.g. first-in-first-out (FIFO). Decisions are required when transport resources are idle. The agent alternates between the selection of source processing resources and destination processing resources. The oldest job in the source output buffer is picked up and transported to the destination input buffer. Examples are \([24, 35, 10]\).

**Holistic Routing and Sequencing:** The caveat of the breakdown above is that not all schedules are possible. To complete the picture we propose that decisions be requested of the agent either when transport or processing resources are idle. In the case of transport resources, the agent behavior is the same as in the transport-centric breakdown. When dealing with processing resources, the agent should behave as in the operation sequencing breakdown.

**Re-Scheduling:** Finally, whenever a stochastic event occurs, the agents can be tasked with deploying an external solver to compute a new plan. Such is the case in \([36]\), where an agent selects the parameters of a variable neighborhood search (VNS) \([37]\) on new job arrivals. VNS is used to create a new schedule which is followed until a new job arrival.

### 3.2 Agent Types

RL agents are then trained according to the generalized policy iteration principle. Herein two stages are distinguished, namely policy evaluation and policy improvement. During policy evaluation, agents select actions according to a policy function, and observe their returned reward. During the policy improvement stage, the policy is adjusted based on the observations made. The interdependence and granularity of these stages, which are repeated until convergence (hopefully), depend on the particularities of the algorithm. RL algorithms can be classified along three discrete axes: value, policy or actor-critic methods (1), model-free or model-based methods (2), and on- or off-policy methods (3) (cmp. \([38]\)).

**Value, Policy and Actor-Critic Methods**

Value methods try to estimate future reward by means of a value function, which is used to estimate the “goodness” of either states or actions from given states. During the policy evaluation stage, actions are selected by using the value function to ascertain the quality of the states reachable from the current one. The observed rewards are used during the subsequent stage to improve the value function. Examples of such methods are State Action Reward State Action (SARSA) \([39]\), Q-Learning (QL) \([40]\), Deep Q-learning (DQN) \([41]\), and Double DQN (DDQN) \([42]\). QL is particularly popular with the production scheduling community, and Double DQN is popular with the production scheduling community with implementations using tables to represent value functions used in \([28, 43, 23, 18, 36]\), or neural networks as function approximators in \([22, 17, 27]\). DDQN was used in \([44]\) and SARSA in \([19, 44, 34]\).

Alternatively, parameterized agent policies \( \pi_\theta \) can be used directly to select actions during the evaluation stage. Based on the observed rewards, the reward expectation under policy \( \pi_\theta \) is estimated, its gradient with respect to \( \theta \) is computed and the policy is updated using stochastic gradient ascent. Examples include REINFORCE \([45]\) used for production scheduling in \([46]\), Trust Region Policy Optimization (TRPO)
introduced in \[ \text{[17]} \] and used for instance in \[ \text{[10]} \] and Proximal Policy Optimization (PPO) \[ \text{[48]} \] used in \[ \text{[49]} \], albeit for a deterministic scheduling problem.

Policy and value approaches can be combined into actor-critic algorithms. Instead of using environment interaction to approximate the expected reward directly, the (state) value function approximator (critic), is used to inform the policy approximator (actor) of the quality of its action. AlphaZero (AZ) \[ \text{[50]} \] used in \[ \text{[15]} \] and Deep Deterministic Policy Gradient (DDPG) \[ \text{[51]} \] used in \[ \text{[52]} \] fall in this category.

**On- vs Off-Policy:** On policy methods (e.g. SARSA) use the same policy during evaluation stage that was adjusted during the improvement stage. This leads to more stable learning at the expense of exploration, which can lead to local optima. Conversely, in off-policy methods (e.g. QL, DQN, DDQN), the policy used during the evaluation stage can differ from the one used in the improvement stage, which leads to more exploration at the expense of convergence speed.

**Model Based vs. Model Free:** RL algorithms can be furthermore split into model-free and model based approaches. Model-based approaches use an environment model to plan a few steps into the future before deciding on an action. The involved environment model is either estimated by the agent itself, e.g. Imagination Augmented Agent (I2A) \[ \text{[53]} \], or simply given to it, e.g. AZ.

**Single- vs Mult-Agents:** Rather than having a single decision entity, we can allow multiple agents to act within the same environment. These agents can be cooperative, i.e. striving to jointly maximize the expected reward or competitive, with each agent targeting a maximization of his reward only. For production scheduling multi-agent systems are often deployed. Depending on the MDP breakdown, agents can be associated with different setup components. Agents posted with each processing resource for sequencing decisions can be found in \[ \text{[17]} \], \[ \text{[18]} \], \[ \text{[11]} \], \[ \text{[52]} \], \[ \text{[21]} \]. Agents deployed per job for sequencing are used in \[ \text{[22]} \] and for routing in \[ \text{[17]} \]. Routing agents are deployed per job family by \[ \text{[18]} \] or per transport resource in \[ \text{[24]} \]. Figure 4 gives an overview of various deployment schemes described.

### 3.3 State, Action and Reward Modeling

**States:** The information based on which the state transition occurs, also known as the environment state, depends on the production setup considered and the MDP breakdown chosen. Take, for instance, a standard job-shop scheduling problem $Jm|C_{\text{max}}$ with a sequencing breakdown. Here the complete state information can be encoded as four $n \times m$ dimensional matrices, the system time $t$ and index $i$ of the processing resource requesting a scheduling decision: $(T, P, L, A, t, i)$. The type matrix $T$ keeps track of the precedence within jobs (rows) and the type of resource the job operations need. The corresponding values in the $P$ matrix represent the remaining processing time for each operation. The location of all operations is be encoded using a matrix $L := (l_{ji})$, with $l_{ji} = m_k$ if operation $o_{ji}$ is at the machine $m_k$. To distinguish between operations being actively processed and those waiting in the machine buffer, the boolean matrix $A$ is used.

This is just one possibility of state encoding. One could, for instance, reduce the dimensionality of the state without loose of information by making use of the precedence constraints within jobs. Since there is only one eligible operation per job at any time, $L$ and $A$ could both be flattened to a vector.

If we present the environment state information in its entirety to the agent together with a machine requesting a new operation, we are in a fully observable environment situation. This means that the agent could, in theory, perfectly approximate the state transition and reward functions. However, a large state space and limited computational resources can make learning very time consuming. Additionally, it could be desirable that the agent learns a good policy with only local information, so as to enable the production system to easily scale up by adding a new resource, for example, without the need of a global monitoring system.

As such, the agent is mostly only presented with a subset of the environment state information available, which corresponds to a partially observable environment. We distinguish between raw state information, e.g. any subset of the $(T, P, L, A, t, i)$ in the situation above, or information in condensed form, i.e. environment state features, or both. Employed features fall
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into one of three categories, namely job properties, resource attributes and optimization targets.

Job property features condense job information. Examples of such are remaining job operations, remaining job processing time [54] or number of jobs in the system [36]. Resource related features target an aggregation of machine properties, such as remaining processing time in buffers [24], resource workload [54, 25], ratio of remaining processing times for machines and buffered processing time [43], number of product types in each buffer or machine health [23]. Estimates of the target function, or of other targetable indicators, are also often included in the construction of the agent state. Such examples are estimated total tardiness [28, 19], average machine utilization [20, 19], average transport resource utilization or the aforementioned average buffer length [20].

**Actions:** In terms of actions, there are two main approaches to production scheduling. The agent either takes an action directly, or selects a scheduling/routing rule appropriate for the current state.

In the operation sequencing MDP, direct actions are operation indices, e.g. [54, 55], or job indices, e.g. [17], depending on whether the job operations are totally ordered (latter) or not (former). For the routing decision, the raw actions are processing resource indices, e.g. [10].

The basic intuition for the priority rule approach is that different rules will be more effective in different production scenarios. Given a production state, the agent will output a rule from a fixed set. The rule is then applied to prioritize the operations in the buffer (iterative scheduling) or viable downstream processing resources (iterative routing). The highest priority operation/machine gets selected. Mostly, the encountered priority rules are very simple. The most frequent examples of operation prioritization rules are shortest processing time (SPT), longest processing time (LPT), earliest due date (EDD), first in first out (FIFO) or last in first out (LIFO). The rule names are self explanatory. Machine prioritization rules work analogously (e.g. [18]). One could, for instance, prioritize the downstream machine with the shortest queue (SQ) in terms of processing time, the one with the least elements (LQE) or the shortest setup times (SST).

A completely different approach to action modeling was taken in [36]. The RL agent gets deployed on occurrence of new job arrivals. At this point a VNS is started to recompute a schedule for the operations not yet started. The RL agent action outputs the VNS parameters for the given state.

**Reward** The last modeling decision to be made pertains to the reward signal produced by the environment. For production scheduling, the reward is most often proportional to the optimization target or a value that highly correlates with it (e.g. makespan and average utilization). That being said, there is no universally accepted scheme by one should construct a reward functions. In [33, 54, 17] the number of queued operations at the current machine is used to build the reward signal (the shorter the queue the better), though the optimization target was makespan.

Reward functions also differ based on when the agent receives a non-zero reward, e.g. at every decision point, at the end of the game, or at any point in-between. Other design choices include whether the reward is discrete or continuous [56], strictly positive or both positive and negative and many more [38].

4 Validation

In this section we take a closer look at what is needed in order to ensure reproducibility and provide sufficient validation of RL production scheduling experiments. Table 1 summarizes the relevant RL literature in terms of production setup clarity (SC) and RL design clarity (RLC), simulation input availability (Ipt), train-test split (TT), state of the art coverage through baseline algorithms (Bsln) and, finally, cherry picking potential (CP).

Table 1: Reproducibility and baselining fulfillment for stochastic RL production scheduling; Filled, and empty circles for fulfilled and unfulfilled criteria.

| Source | SC | RLC | Ipt | Stch | TT | Bsln | CP |
|--------|----|-----|-----|------|----|------|----|
| [32]   | .  | .   | .   |      |    |      |    |
| [28]   | .  | .   | .   |      |    |      |    |
| [43]   | .  | .   | .   |      |    |      |    |
| [17]   | .  | .   | .   |      |    |      |    |
| [23]   | .  | .   | .   |      |    |      |    |
| [18]   | .  | .   | .   |      |    |      |    |
| [36]   | .  | .   | .   |      |    |      |    |
| [20]   | .  | .   | .   |      |    |      |    |
| [1]    | .  | .   | .   |      |    |      |    |
| [35]   | .  | .   | .   |      |    |      |    |
| [57]   | .  | .   | .   |      |    |      |    |
| [44]   | .  | .   | .   |      |    |      |    |
| [58]   | .  | .   | .   |      |    |      |    |
| [14]   | .  | .   | .   |      |    |      |    |
| [52]   | .  | .   | .   |      |    |      |    |
| [34]   | .  | .   | .   |      |    |      |    |
| [19]   | .  | .   | .   |      |    |      |    |
| [25]   | .  | .   | .   |      |    |      |    |
| [10]   | .  | .   | .   |      |    |      |    |

4.1 Reproductibility

In the absence of standardization, it becomes difficult not to forget to include all production setups details. In the literature at hand the presented setups were described transparently with respect to most of their
details save for the exact problem size (e.g. number of machines in each work-center, total number of scheduled jobs) and sometimes some constraint details. Similarly, more effort should be put into a clear presentation of all the RL design elements. Particularly the state and action designs suffer from a lack of clarity.

In order to compare production scheduling approaches, the exact inputs, e.g. the job sequence with the corresponding operation precedence constraints and duration, need to be provided. Unfortunately, this is mostly not the case. Instead the input sampling scheme is given. While this may be sufficient for a proof of concept, it is not sufficient for an effective comparison with other approaches, particularly when only a few experiments were ran and no statistical testing was performed. Moreover, the simulation code associated with the experiments needs to be provided as in [10].

Code availability alone does not suffice to ensure reproducible stochasticity, though it is a necessary condition. There is a simple way to ensure that a sequence of sampling actions produces the same output irrespective of the system the simulation is ran on: random number generator seeding (RNG). To ensure that the occurrence time of the stochastic events is independent of simulation control, one should sample all the stochastic events together with their occurrence time during simulation initialization. These events can then be queued and triggered at the appropriate time.

4.2 Baselines

As with all machine learning approaches, the phenomenon of over-fitting can occur for RL schedulers. This refers to a situation where a strategy is developed that is very well suited for the training instances, but cannot generalize well to unseen situations. Only reporting results on the production instances used for training is tantamount to assuming that the scheduling problem optimized is recurrent. In such a situation one may be better served by using other approaches, seen as whenever the comparison is available, RL fails to outperform the literature lower bounds, e.g. [16] [46] [55]. In the dynamic setting, the test-train separation is not mandatory, since the stream of product specification induces a test-train separation, with the beginning of the stream being used for training and the latter part for testing.

RL solutions for stochastic settings are almost exclusively baselined against simple heuristic solutions. It could very well be, however, that constructing schedules as if there were no stochasticity and simply ignoring plan deviations thereafter could be a competitive approach to RL or heuristics. Yet another approach would be to recompute a schedule on occurrence of unforeseen events. Constraint programming solvers such as ORTools [59] allow for the use of a time limit for the solution space search procedure. Therefore, RL solvers for large production instances could at least be benchmarked against search, which is a standard OR strategy.

Cherry picking as a concept, is very simple: One runs n experiments, but only reports the results on m < n of those that fit the own hypothesis. Whenever the results are reported on only a small number of experiments, the experiment design is not reproducible, and there is no statistical testing involved, this lingering suspicion remains.

5 Tracks for Future Work

In this work we made steps towards standardizing RL experiments for stochastic production scheduling problems by introducing and extended an OR standard for the problem formulation (Section 2), describing the core elements of production scheduling RL design (Section 3), and proposing a scheme guaranteeing experiment reproducibility and sufficient validation (4).

For stochastic setups, RL shows promise. Intuitively, RL agents can be trained to adapt to unforeseen situations, while incorporating estimates about the future. As such they position themselves between myopic heuristic approaches and the re-planning approaches which could be easily broken by stochasticity. We theorize, that whether re-planning, RL, or heuristics work best, is highly dependent on the amount of stochasticity inherent to the problem considered. For setups with little to no noise, re-planning would most likely work best. For situations with an intermediate level of uncertainty, RL could outperform other approaches. In completely “chaotic” situations, where patterns are difficult to discern, the choice of an optimization algorithm may not matter at all.

In terms of RL algorithms employed, there should be more focus on approaches other than value based. Last but not least, the multi-agent approaches should be more closely investigated. First steps in this direction were taken in [23], where a single agent was benchmarked against a multi-agent approach, with the single agent over-performing the alternative.
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