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and

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COMBINING DISCRETE EVENT SIMULATION AND REINFORCEMENT LEARNING FOR HUMAN-CENTERED PRODUCTION PLANNING: AN EXEMPLARY APPLICATION TO JOB ROTATION SCHEDULING

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Industry 5.0, Human-centered, Job rotation scheduling, Reinforcement learning, PPO algorithm, Discrete event simulation

ABSTRACT

To enhance simulation models, both combining them with artificial intelligence (AI) and integrating human aspects to achieve a human-centered simulation are suitable approaches that gain significance due to the recent development towards Industry 5.0. In this paper both approaches are being pursued by using reinforcement learning (RL) and discrete event simulation (DES) to develop job rotation schedules, that respect human aspects. For the introduced use case the PPO algorithm is selected and the combination with the simulation model is established. A first set of experiments reveals the functionality of the combination and generates job rotation schedules, which then are analyzed. Although the schedules are not usable in practice the experimentation indicates, that the optimization of the hyperparameters offers the potential to improve the generated schedules.

INTRODUCTION

The recent development of Industry 4.0 to Industry 5.0 encompasses a shift towards a more human-centric perspective on production (Xu et al., 2021). This development can be supported by emerging technologies including simulation and AI (Müller, 2020). Simulation enables experimentation in early design phases as well as alongside ongoing operations (Ahmad et al., 2025; Verein Deutscher Ingenieure, 2014). Due to increasing heterogeneities of demands, products, processes and other requirements, new challenges arise in manufacturing (Gao et al., 2024). These include the complexity of detailed process modelling for parameter optimization and challenges in production planning and scheduling and motivate the use of AI in manufacturing (Gao et al., 2024).

In production contexts, machine learning is the most widely used AI technology (Nti et al., 2022). For the learning process the agent needs training data, while simulation and especially the subdivision DES allow the generation of unlimited synthetic data (Belsare et al., 2022). Therefore, the

combination of machine learning and DES is considered beneficial. One subdivision of machine learning is RL (Jordan & Mitchell, 2015). The learning process of an RL algorithm consists of trial-and-error interactions with the environment through which the agent learns to take advantageous actions by receiving rewards while observing the system state (Sutton & Barto, 2018). Since the main feature of DES is the event-triggered change between states by actions (Pritsker, 1998), the combination of RL and DES appears favorable. Furthermore, large problems can be studied in a simulated environment with the combination of DES and RL to gain general knowledge (Belsare et al., 2022). In their literature review Kranz et al. (2023) elaborate five versions of connecting AI and DES. These include the use of AI to control, create or optimize DES models, the use of DES to train AI systems and the use of AI for analyzing DES results (Kranz et al., 2023).

Incorporating human aspects into DES is an important step to enhance the accuracy of these models (Baines et al., 2004). Therefore, Baines et al. (2004) connect human performance modelling and DES, while Dode et al. (2016) integrate human fatigue and learning into DES. In their literature review Greasley and Owen (2018) identify five aspects of human behavior in DES models: decisions, availability, task performance, arrivals, and movement.

In this paper a use case is introduced, that combines DES, RL and human aspects. The use case encompasses the job rotation at a manual assembly line that is scheduled by an RL algorithm. One motivation for establishing job rotations at assembly lines is the reduction of ergonomic stress on workers by distributing the ergonomic stress more evenly among them (Otto & Battaia, 2017). The concept of job rotation can be defined as a systematic change of workstations and requires a simultaneous, temporary assignment of every worker to a workstation. The integration of various aspects into the assignment increases the complexity of the scheduling (Asensio-Cuesta et al., 2012). The mathematical problem behind the worker assignment during a job rotation is NP-hard, which motivates the use of heuristic solution methods (Miralles et al., 2008) or, as proposed in this paper, AI.

To identify studies published since 2015, that schedule job rotations at assembly lines using AI while considering ergonomic characteristics, a specific literature research was conducted. Four of the nine determined studies use evolutionary or genetic algorithms (Assunção et al., 2022; Diego-Mas, 2020; Sana et al., 2019; Song et al., 2016). The

other five studies (Elyasi et al., 2026; Pabolu & Shrivastava, 2021; Pabolu et al., 2022, 2024; Safaiyan & Rastgar, 2025) use different subdivisions of AI. RL was not amongst the AI methods used for job rotation scheduling. However, the combination of RL and DES is considered beneficial for solving the job rotation problem, since the aforementioned availability of training data and the conceptual similarities of RL and DES.

A recently developed framework for the integration of RL and DES encompasses seven steps and is presented in Figure 1 (Kranz et al., 2026). In this paper the framework is followed. The gray background in Figure 1 indicates that these steps have been executed and completed in this paper.

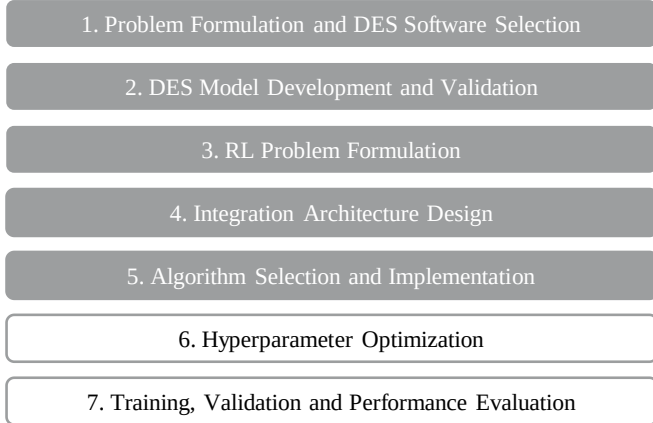


Figure 1: Framework for the Integration of RL and DES after Kranz et al., 2026

After establishing a usable connection of RL and DES the first aim of this paper is using the connection to generate job rotation schedules for an assembly line while including ergonomic characteristics. The second aim is to analyze the generated rotation schedules. The third and last aim is to explore the potential of the hyperparameter optimization.

FRAMEWORK IMPLEMENTATION

The following sections include the description and implementation the framework mentioned above. The first subsection encompasses the first three steps: problem formulation and DES software selection, DES model development and validation and RL problem formulation. Step four, integration architecture design, and step five, algorithm selection and implementation, are described afterwards.

Use Case and Problem Formulation (DES and RL)

The use case in this paper is a DES model of an assembly line at a German manufacturer of white goods in the software FlexSim®. The cycled assembly line contains 34 manual workstations as shown in Figure 2. It was assumed that 34 workers of the same height and gender need to be assigned to the 34 workstations. Furthermore, all workers are able to work at all stations and to meet the specified time. The job rotation resulting in eight assignments per workday. Per rotation the solution space contains $n = 34^{34}$ possible solutions and is discrete.

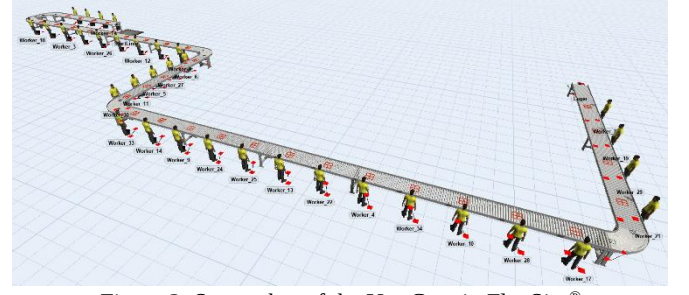


Figure 2: Screenshot of the Use Case in FlexSim®

As a human aspect one score of the ergonomic assessment method MTM-HWD® for each workstation is considered. The advantage of this method is the combined determination of the assembly time and the ergonomic evaluation of a workstation resulting in a score (Finsterbusch et al., 2015). Important to notice is, that the evaluation using MTM-HWD® always applies to a specific worker at a specific workplace, since height and gender as individual characteristics are included in the assessment. Since only one score is available for each workstation it is assumed that this score is valid for all 34 workers.

Looking at the use case, AI is used to control DES, since decisions are made by the RL algorithm and therefore is assigned to this version of connecting AI and DES after Kranz et al. (2023). Of the five aspects of human behavior in DES after Greasley and Owen (2018), the use case can be assigned to the aspect of movement due to the movement-based scores of MTM-HWD®.

For the RL algorithm the reward function (R) entails the sum of rewards assigned to the individual workers (R_i) as shown in equation (1). Equation (2) contains the calculation of the individual rewards as a case differentiation. Since the assignment problem encompasses 34 workers that have to be assigned to the 34 workstations, the algorithm receives a penalty (p) in the form of a negative reward for duplicate assignments. This penalty is set to $p = -1$ to establish a symmetry to the maximum possible reward ($\max r_t = 1$).

$$R = \sum R_i \quad (1)$$

$$R_i = \begin{cases} r_t, & \text{reward} \\ p, & \text{penalty} \end{cases} \quad (2)$$

For a correct assignment of one worker to an empty workstation, the algorithm receives a positive reward (r_t). This reward contains the load history of the specific worker. The load history is calculated by adding the normalized (r_{norm}) (4) and time-weighted (r_t) (3) scores of the MTM-HWD® method (r).

$$r_t = \frac{r_{norm} + (t - 1) \cdot r_{t-1}}{t} \quad (3)$$

$$r_{norm} = \frac{r - \min r}{\max r - \min r} \quad (4)$$

For the algorithm one episode was set to eight rotations with the first rotation encompassing fixed assignments. Therefore, the reward for the first assignment was set to $R = 0$.

Integration Architecture Design

To establish a combination of the DES software and RL, an approach provided by FlexSim® is followed. With this approach, the RL agent receives the system state in form of model parameters in FlexSim® and answers with a set of model parameters, that trigger actions. Afterwards the RL agent receives a reward (see equations (1)-(4)).

Algorithm Selection and Implementation

In order to choose an RL algorithm, the RL-Picker by (Bongratz et al., 2024) has been applied. This approach encompasses 13 questions about the use case and provides suggestions for suitable algorithms (Bongratz et al., 2024). The proposed algorithms for the use case described above are the PPO, A2C-SVPG and A2C/A3C. Since the A2C-SVPG applies to continuous problems (Liu et al., 2017) and the performance expectations of PPO are higher than of A2C/A3C (Schulman et al., 2017), the PPO algorithm was chosen. The PPO algorithm optimizes the policy in a clipped range to avoid huge changes in a possibly wrong direction (Schulman et al., 2017). Thereby the algorithm is adjustable by tuning the hyperparameters. These hyperparameters include, among others, the number of steps to be run per update (n_steps), and the learning rate ($learning_rate$).

EXPERIMENTATION

After the Implementation of the PPO algorithm, the combination of DES and RL was tested. The hyperparameter optimization is considered a complex, time-consuming process (Eimer et al., 2023). The experimentation therefore aims to clarify the potential of the implemented combination of RL and DES and to justify the execution of step six of the applied framework, hyperparameter optimization.

Experimental Setup

For testing the combination, the pre-set PPO hyperparameter were used (see experimental setup 1 in Table 1). For the investigation of the potential of the hyperparameter optimization, different sets of hyperparameters of the PPO were tested. The other system- and hyperparameters meanwhile remained constant. In a first set including six experiments, two of the 11 hyperparameters of the PPO (Eimer et al., 2023) were varied as shown in the table below. Furthermore, two random assignments were added as a baseline. This random baseline, however, was calculated using python and not DES or PPO.

Table 1: Experimental Setups

No.	n_steps	$learning_rate$
1	2048	$3e^{-4}$
2	2048	$1e^{-4}$
3	2048	$5e^{-4}$
4	256	$3e^{-4}$
5	256	$1e^{-4}$
6	256	$5e^{-4}$
B	-	-

For each of the six experimental setups and the two sets of random assignments two test runs were performed resulting in 14 job rotation schedules. For the setups using the PPO algorithm, the initial assignment was set manually and the received reward was set to $R = 0$. The following seven assignments were set by the algorithm. Therefore, each random baseline consists of seven assignments.

Implementation

To test the combination of RL and DES the assigned work stations of the workers in the simulation model in the last step of a test run were compared to the outputs of the PPO algorithm.

Due to limited computational resources the number of steps the algorithm was allowed to learn had to be set to 8000. The PPO algorithm was implemented using the Python libraries gym and stable_baselines3.

Results

The test of the combination of RL and DES resulted in the assignments of the workers following the outputs of the PPO algorithm.

The achieved cumulative rewards for one episode in the experimental condition ranged from $-84,01$ to $-125,57$. Thereby, two test runs were performed for each of the six experimental setups. The results of the test runs are presented in Table 2.

Table 2: Cumulative Reward Received in Test Runs

No.	Test Run 1	Test Run 2
1	-104.85	-125.57
2	-94.38	-112.14
3	-104.66	-106.16
4	-84.01	-113.69
5	-109.29	-112.27
6	-87.82	-119.86
B	-	-

As an indicator for the usability of the generated rotation schedules the percentage of duplicate assignments out of each assignment was analyzed. Table 3 presents the average percentage of the seven assignments in each experimental setups.

Table 3: Average Percentage of Duplicate Assignments

No.	Test Run 1	Test Run 2
1	68.49 %	62.61 %
2	64.71 %	59.66 %
3	62.61 %	63.03 %
4	56.72 %	65.13 %
5	63.87 %	64.71 %
6	57.98 %	66.81 %
B	68.49 %	63.03 %

Discussion

The combination of RL and DES for generating job rotation schedules was successfully established and tested.

By looking at the cumulative reward for an episode of the test runs in Table 2, the highest and therefore best reward received was for experimental setup No. 4 in test run 1. The lowest and therefore worst reward was received in experimental setup No. 1 in test run 2. Since both experimental setups have a *learning_rate* of $3e^{-4}$, this indicates that the hyperparameters *learning_rate* and *n_steps* are dependent. This aligns to the findings of Eimer et al. (2023).

The greatest improvement of the cumulative reward for an episode of the test runs accounts for 17,3 % of the average cumulative reward for an episode of all six experimental setups. This indicates that a sufficient optimization of the hyperparameters has the potential to improve the results.

The negative cumulative rewards received for the test runs of the experimental setups using PPO algorithm require a discussion about the value of the penalty. It might be beneficial to choose a higher value for the penalty to moderate the effects on the received reward.

Furthermore, the negative cumulative rewards indicate a large number of duplicate assignments. The analysis of the average percentage of duplicate assignments in the test runs confirms this assumption. Since a generated rotation plan is not executable when at least one penalty is received, the rotation plans are far from usable in practice.

The comparison of the average percentage of duplicate assignments of the experimental setups using the PPO algorithm to the random assignments show that even for the best test run (setup No. 4, Test Run 1) the improvement amounts to roughly 6 %. To reduce statistical effects, however, more detailed experimentation is necessary.

CONCLUSION

The connection of DES and RL was successfully established in this paper and RL was used to generate job rotation schedules. For the implementation, a framework was followed and the first five steps were executed. The second aim of this paper included the analysis of the generated rotation schedules. A first set of six experimental setups resulting in twelve job rotation schedules has been analyzed regarding the received cumulative reward and the percentage of duplicate assignments. These analyzed schedules are not usable in practice and only a small improvement could be shown compared to a random assignment. However, the statistical significance of the improvement must be evaluated in further experimentation.

For an improvement of the cumulative reward, more experimental setups with different values of the penalty for duplicate assignments need to be conducted.

One lesson learned is, that 8000 steps are not enough to train the RL algorithm for this use case. Therefore, a key requirement for achieving usable rotation plans is the significant increase of the number of steps. This results in the demand for higher computational resources, which can be an obstacle for smaller manufacturing companies.

However, the experiments indicate the potential of the optimization of the hyperparameters to improve the generated rotation plans. Therefore, referring to the third aim of this paper, a more detailed hyperparameter optimization for the

use case is recommended following the set of best practices composed by Eimer et al. (2023).

Furthermore, experimentation with another RL algorithm, A2C/A3C, might improve the generated plans despite the aforementioned lower performance expectancies.

In addition, the DES model itself can be enhanced by integrating other human aspects into the simulation. These aspects could include competence and limitation criteria (Moussavi et al., 2018), individual preferences (Hochdörffer et al., 2018), the diversity of the ergonomic load (Assunção et al., 2022), and other individual characteristics of the workers. The integration of multiple human aspects aims to satisfy the human-centric principle of Industry 5.0 and therefore must be considered in future developments of the DES model.

CONTRIBUTIONS

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