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Towards A Methodology For Economic Performance Increase Of Production Lines Using Reinforcement Learning

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Abstract

The increasing number of variants in product portfolios contributes to the challenge of efficient manufacturing on production lines due to the resulting small batch sizes and thus frequent product changes that lower the average overall plant effectiveness. Especially for companies that manufacture at high speed on production lines, such as in the Fast Moving Consumer Good (FMCG) industry, it is a central task of operational management to increase the performance of production lines. Due to the multitude of different adjustment levers at several interdependent machines, the identification of efficient actions and their combination into economic improvement trajectories is challenging. There is a variety of approaches to address this challenge, e.g. simulation-based heuristics. However, these approaches mostly focus on details instead of giving a holistic perspective of the possibilities to improve a production line or are limited in practical application.

In other areas of application, reinforcement learning has shown remarkable success in recent years. The principle feasibility of using reinforcement learning in this application context has been demonstrated as well. However, it became apparent that the integration of expert knowledge throughout the improvement process is necessary. For this reason this paper transforms five modules defined from an engineering point of view into the mathematical scheme of a markov decision problem, a default framework for reinforcement learning. This provides the foundation for applying reinforcement learning in combination with expert knowledge from an engineering perspective.

Keywords

Production Lines; Production Management; Reinforcement Learning; Discrete Event Simulation; Performance; Effectiveness; Economic Efficiency; Markov Decision Problem; OEE

1. Introduction and challenges in increasing the performance of production lines economically

The high product variance demanded by the market combined with steadily increasing cost pressure and price sensitivity are raising the demands on the management of production to achieve business success. The resulting small batch sizes and frequent product changes lead to a reduction in average overall equipment effectiveness (OEE) [1–3]. This applies particularly to production lines, which can be found for example in the fast moving consumer goods (FMCG) industry, are characterized by generally high production speed and low margins [1]. Furthermore, companies allocate products in production networks back to western countries due to a higher standard of digitalization [4]. This combination results in consolidation and hence in increased planned utilization of production lines. As a result, the demands on the productivity and stability of production lines are rising. For this reason, a focus on the topic of performance increase in industry and research is perceived. [5,6].

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OEE, the productivity and stability of production systems and ultimately the production costs depend strongly on the configuration of production lines, consisting of several machines, buffers, conveyors, etc.[7]. Improving these production lines is a complex problem and the complexity increases drastically with the number of involved aggregates. The buffer allocation sub-problem on its own is an NP-hard problem [8,9]. As these problems can not be solved analytically, Discrete Simulation-Based Optimization (DSBO) is widely used in the industry to improve the configuration of production lines [10,9]. However, Studies show that companies need support in conducting precisely this DSBO studies, interpreting their results and deriving feasible step-by-step actions from them [11,12].

Besides this complexity of such systems, which makes optimization per se demanding, the identification of effective adjustment levers is challenging because the restraining element of the system shifts dynamically, due to the mutual dependencies of the system's elements. Additionally, not only the system's output is difficult to describe, but also the input in terms of efforts made, which converts to costs. The OEE only represents the output, but does not consider the input to achieve this output. That's why the identification and prioritization of economic actions for improvement only makes sense by considering the overall system behaviour and costs, not only by focusing on the bottleneck-orientated OEE [5,13–15].

The combination of several small actions on different machines is expected to yield higher efficiency gains than a major improvement on a single machine [16], an isolated consideration of sub-problems is therefore of limited benefit [14,9,15]. For this reason, economic performance considerations must focus specifically on the combination of individual measures.

Looking for decision support in such complex but well-defined optimization problems, artificial intelligence (AI) methods, especially reinforcement learning (RL), receive increasing attention in the last years [17,18]. The motivation for applying RL is that the RL agent learns to react efficiently to the dynamics of the environment, without any prior knowledge of the system dynamics [19].

This paper presents a method for increasing the performance of production lines in an economic and practical way using RL. The focus is not the demonstration of technical feasibility, which [13] already showed, but the integration of RL into a holistic improvement methodology. The aim is to discover trajectories of sequential improvements, which could be interpreted by engineers and implemented successively, but not to find optimal parameter settings. The method intends to provide practical decision support in individual cases without losing the character of a generalistic method.

The work is structured as follows. Section 2 discusses existing approaches in terms of meeting these challenges. *Section 3* shows the opportunities of combining RL and DSBO in this application context. *Section 4* then presents an approach combining these two technologies taking domain-specific knowledge into account. *Section 5* provides a summary and outlines further planned research activities.

2. State of the art

The following literature search is based on the procedure according to BORREGO ET AL [20], was conducted to identify an overview of previous approaches. First, a search string including synonyms is defined, see **Figure 1**. To ensure a broader search, no narrowing word related to *economic* increase is included in the string. This search string is used in the following search engine*s ScienceDirect, Web of Science, IEEE Explore, Scopus, Google Scholar* and returned 765 results. Removing duplicates resulted in 431 unique papers. Based on the title the number of relevant papers is reduced to 151. In the next step, figures and abstracts of the remaining papers are reviewed, resulting in a final 51 papers to be considered.

OR		OR		OR
Production Line		Efficiency		Improvement
Assembly Line	AND	Effectiveness	AND	Analysis
Manufacturing Line		Productivity		Increase
Shopfloor		Performance		Enhancement

Figure 1: Search words used resulting in 64 search strings by combination

The majority (34 out of 51, 67%) of these papers do not present a methodology, but a case study on a unique application. Thus, these approaches can not be generalized and applied to other similar problems. Based on the other approaches presenting a method, additional papers of relevance are identified using the snowballing method. The combined results are discussed below.

The approaches can be roughly divided into mathematical and simulation-based approaches [21]. Even though mathematical approaches cannot cover the complexity of real use cases [22,10,9], a variety of specific analytical models for sub-problems exist [23,24]. Especially the optimization of buffer allocation has received much attention from researchers [25], such as in [26,8].

[14,9,15] argue that optimization is only possible by considering the entire system and not by focusing on improvement actions in such a specific way as the analytical models do, due to the complex dependencies of aggregates of production lines. At the same time, after a certain point, optimizing cycle times of individual aggregates is more economical than further improving the availability of all machines [14].

[1,27–29] explicitly consider fill-and-pack lines in the FMCG industry. However, they do not present an optimization approach, but rather simulation case studies as mentioned above. They underline the potential of optimizing such lines and show the need for a combined consideration of improvement costs and increased performance nevertheless and thus underline the motivation above.

[21,30,31,15] show that without considering the overall system, prioritizing improvement activities such as maintenance activities is not advisable and that this is not adequately addressed in the literature. None of the approaches listed systematically considers improvement trajectories, i.e. a sequence of independently realizable actions to improve a production system. Rather, they focuses on finding an (near-) optimal overall solution rather than looking at the path to get there, i.e. the improvement trajectories.

[12] gives an overview of DSBO approaches in manufacturing in general and shows that machine learning approaches for optimizing production systems are getting more and more attention in research. [10] sees the need for further research combining statistical learning in combination with DSBO. [17] predicts a vast increase in the importance of automated decisions based on AI in production management.

Due to the fact, that the improvement of production lines has been the subject of research for decades, the discussion above can only be a short summary. For more detailed references, the reader is advised to refer to [21,25,12,9].

In summary, there is a lack of approaches that provide practical support for improving the performance of production lines while considering the inherent complexity. As described in *Section 1*, reinforcement learning offers new methods to meet this challenge. The following paragraph discusses these opportunities.

3. Chances of combining reinforcement learning with simulation for the improvement of production lines

Discrete-event simulations (DES) are suitable for the evaluation of complex, stochastic systems, where a closed-form mathematical model is hard to find. Simulation is not an optimization technique itself and needs to be combined with optimization methods to improve problems of the real world [22]. It is advisable to statistically extract information from existing simulation runs to guide the parameter search and thus to closely integrate the optimization with simulation [32,10] Thus, optimization methods may need to be adapted to the specific problems [33,32].

For this reason, more and more approaches use AI for optimization in combination with simulation [12]. What makes RL a promising solution candidate is that it does not require holistic knowledge of the problem or a dedicated mathematical model of the production line setup. RL is model-free in the sense that the RL agent learns about its environment simply by interacting with it [22].

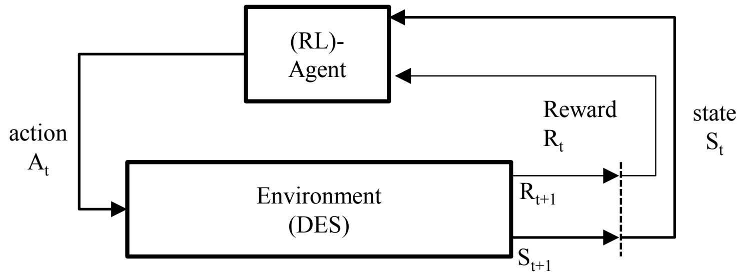

Figure 2: Markov Decision Process (MDP) as Default Framework for Reinforcement Learning (RL) [19]

RL can be understood as learning from a sequence of interactions between an agent and its environment, where the agent learns how to behave in order to achieve a goal [19]. The default formal framework to model RL problems is the Markov Decision Process (MDP), a sequential decision process modelled by a state space, an action space, and transition probabilities between states and rewards, see **Figure 2**. [18,22,19]

In an MDP, the agent acts based on observations of the states of the environment – in our case, these are the observations returned by the DES. The rewards received by the agent are the basis for evaluating these choices. The agent learns a policy resp. strategy, which may be understood as a function from state observations to actions. The agent's objective is to maximize the future cumulative discounted reward received over a sequence of actions [19]. This procedure is called *training*.

Especially the model-free character of reinforcement learning and the integration of simulations feedback data and thus the optimized parameter search motivate combining reinforcement learning with DES in this application. Previous work by the authors showed that this combination works in general and is very promising [13]. However, it is also stated that a promising practical application is unlikely without the explicit modelling of domain knowledge. Therefore, in the following paragraph an approach is presented, which describes the problem holistically based on a MDP and shows connecting points for the integration into a feasible improvement process for practice.

4. Methodology to improve production lines using reinforcement learning and simulation

To address the complex task of improving the economic performance of production lines, the task is formulated as a MDP for the approach presented here. This results in a problem structuring using a mathematical description, which remains comprehensible and application-oriented, since the problem is broken down into individual modules, which engineers can work with in a familiar manner based on their experience.

The basic idea of the approach is that an RL *agent* combines *actions* constrained by domain experts and sets explicit parameter values for them. For this purpose, the agent "plays" with the simulation model *(environment)* and learns from the observations of the returned *state* and the resulting monetary profit *(reward)* to choose reasonable improvement actions.

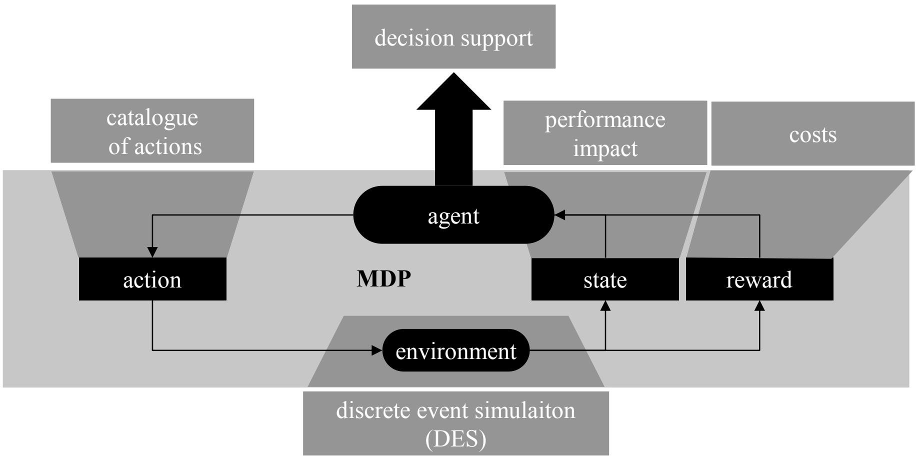

Figure 3: Approach interpreting the performance increase of production lines as MDP combining RL and DES

By evaluating these learnings of the agent (*policies)*, conclusions can be drawn about overall superior parameter combinations and their implementation order i.e. improvement trajectories to give decision support. **Figure 3** shows the interaction of these five modules and the translation into the corresponding formulation as a MDP. They are explained in more detail below.

Discrete event simulation (DES): Representation of the real production line taking into account the system complexity of production lines *(environment)*

The presented methodology requires a previously created and validated simulation model of a production line. A simulation model is necessary to represent the interdependence of the elements and thus the complexity of breakdowns in production lines. Methods for the data-based creation of such models can be found, for example, in. [34–36]. The presented approach uses standardized interfaces to communicate with established simulation software such as Siemens Plant Simulation [37].

Performance impact: Data based description of the influence of each element of a production line on the overall performance *(state)*

An explanatory model and method for measuring the influence of individual aggregates on the overall performance of a production line form the *performance impact* module. For this purpose, layout and aggregate information (main and auxiliary elements like conveyors) need to be linked with machine downtime and performance data. Layout information is collected through drawings, measurements and read-out data from machine controls and is already available in digital form in most companies of concern. Aggregate information is available in real resp. near time with modern production lines, since machine communication has become established through communication standards such as OMAC PackML [38]. An algorithm uses the combination of this data to allocate the performance losses to an individual aggregate taking into account the auxiliary and coupling elements. From breakdown of the losses per aggregate, the influence of each aggregate on the total performance of the production line can be determined. This influence on the performance of the production line from each individual aggregate makes it possible to prioritize based on the potential performance increase per aggregate, taking into account the performance losses in terms of OEE at constant machine speed. In terms of a MDP, this module of the method represents the observation of the current state and forms the state space. By integrating domain knowledge into the description of this observation, it is intended that the agent can identify potential process improvements more quickly and that learning time is reduced.

Catalogue of actions: Description of generic measures of performance increase for individual line elements *(action)*

In this module a catalogue of generic improvement measures as an explanatory model serves as a basis for later concretized improvement measures. For each of these measures, a description and abstraction in form of changes in simulation parameters and a cost function is created. This takes into account both investment and operating costs. The consideration of costs already at the stage of the creation of generic measures enables the later evaluation of the economic aspects of the improvement measures. On the basis of this catalogue, technically sensible and possible adjustment ranges for each parameter will be determined company and application specific to ensure practical applicability in individual settings. The description of this potential solution space forms the basis for the definition of the action space in terms of the MDP. Constraining the action space with expert and domain knowledge eliminates nonsensical parameter configurations, thus reducing the solution space and simplifying the agent's learning of effective strategies to improve the production line.

Costs: Evaluation of the concrete improvement measures in terms of economic benefit *(reward)*

This module evaluates the improvement measures chosen by the agent according to expected costs and potential performance improvement. For this, an equation is developed mapping the expected increase in performance and the expected costs of an improvement measure. The potential increase in performance is the result of the simulation. The costs are the result of the catalogue of actions. The development of this equation is based on traditional investment theory see e.g. [39,40]. Since different measures with different cost functions can change the same parameters of the production line, a heuristic is necessary to decide for the most economic measure for the parameter setting range of concern.

Decision support: Forming strategies for the economic performance increase of production lines in the form of improvement trajectories *(agent)*

The last module generates concrete action trajectories for improving production lines. These incremental steps can be interpreted by engineers and are practical and application-oriented, since adjustments to production lines in practice must also be made successively. For this purpose, the MDP descripted above is solved, which means an RL-agent learns to improve the system in terms of economic performance increase by maximizing the cumulative *reward*. Over time, the agent therefore identifies superior parameter combinations in the sense of sequencing individual measures at specific machines to trajectories. This is achieved by recording all parameter configurations tried throughout the training. The probability that a trajectory is superior is therefore higher for combinations of parameter configurations executed later, as the agent improves its strategies over time. Subsequently, these trajectories can be sorted according to the highest achieved reward and thus the most economical combinations are found. **Figure 4** shows such trajectories. The diameter of the circles in this figure represents the cumulative profit of the action. Thus, it can be seen that different trajectories can cause similar profits and that not every single change in the production system has to generate positive profit in isolation.

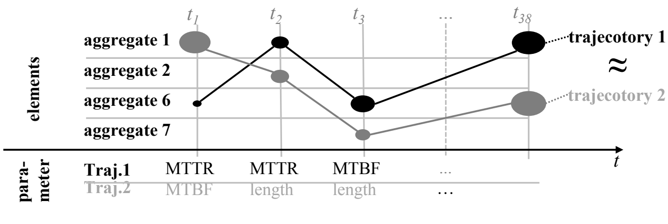

Figure 4: Visualisation of improvement trajectories as decision support for increasing performance of production lines

These combinations yield the basis for recommendations in terms of improvement trajectories. For these recommendations, a representation is developed which, in combination with a multi-criteria evaluation, provides the decision support for the practical modification of the production line.

5. Conclusion and further research

In this paper, a methodology for increasing the performance of production lines economically by identifiying alternative improvement trajectories using RL has been presented. The basic functionality has been proven by [13] and validated on an FMCG line. This paper embeds the problem solving method presented by [13] into a higher-level methodology for practical application.

Discussions of this approach with industrial enterprises continue to reveal a desire for a fixed budget for an optimization or improvement trajectory, which can be given to the RL-agent as additional constraint. In the detailed design it becomes apparent that the definition of the action space is critical for success and that the selection of variables by experts requires more precise support, since many engineers are not used to dealing with simulation-relevant parameters. A combination of the validation in [13] and this extended methodology is outstanding and is planned together with a comparison of different available algorithms as in [9].

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Biography

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