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A New Perspective of the Cyber-Physical Production Planning System

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***Abstract* –The following three research fields and levels can be identified in the field of production planning and control (PPC): production planning, production scheduling and production control. These topics were thoroughly investigated from different points of view by several authors in the recent years. However, the connection and interaction of these fields in the era of cyber-physical production systems (CPPS) has not received so many attention from the research community. The objective of this conceptual paper is to overview the current status of these fields; to examine the possible connection possibilities considering the different artificial intelligence solutions developed for the separate fields and to give an outlook regarding future research activities in PPC in the context of industry 4.0.**

Keywords – production planning and scheduling, artificial intelligence, machine learning.

I. INTRODUCTION

One of the biggest challenges of today`s production (planning) systems in the era of Industry 4.0 and CPPS is to be flexible and adaptive whilst being robust, resilient and efficient. This challenge is present on all levels of a production planning system. Mid-term production planning includes production order scheduling, lot-size calculation and capacity planning [25]. The term "production scheduling" refers to planning of dates, sequences (combined) and routing of products. It provides answers to the question: "When is order O processed on machine M" [20] In [25] production scheduling is described as short-term planning on the operational level and includes occupancy and sequence planning. Production control takes all actions into account, that are needed to guide a production order through the production system after its release. During the execution of a production schedule several unforeseen disturbances may occur (e.g. machine breakdowns, illness of the workers) that could result in discrepancies between planning and reality. Production control includes monitoring and controlling activities in order to implement a production schedule. Controlling is responsible for providing transparent and interpretable information with the evaluation and regulation of the production system in its basic settings – without a concrete order reference [25].

In the recent years several new topics have appeared in the field of production planning and control (PPC), such as:

- The high variety of product variants [24] leads to complex systems. Because of the flexibility of the production system the expenditures are getting higher. Today's production systems are no longer tradable by humans.
- Companies are facing the challenge of achieving short delivery times and a high ability to deliver despite increasingly shorter planning horizons, a large number of internal and external planning changes and increasing planning complexity.
- Today, many technological possibilities are available (AI, OR) whereas only few practical approaches exist in the manufacturing environment. [1]
- The topic of energy and resource efficiency has been on the rise for several years now. The pressure on producers to save CO_2 equivalents is also increasing significantly as a result of public interest. [26]

The above mentioned issues might be investigated with different artificial intelligence (AI) - based solutions. Mid-term production plans commonly neglect capacity restrictions or dynamic effects as described above, which can influence lead times. This often leads to high deviations between the plan and the later execution. Dynamic models that incorporate stochastic effects and interdependencies instead of static average values from the enterprise resource planning system (ERP) or manufacturing execution system (MES) could increase the planning quality of a mid-term production plan. If the deviations between the real and planned (time) data is smaller, more reliable production schedules could be created. Reliability of production schedules can be further increased if different aspects such as condition monitoring, energy efficiency, predictive maintenance etc. are considered. Resilient, decentralized and adaptive production control can be achieved with the help of modern AI or information-communication technologies (ICT) (e.g. Industrial Internet-of-Things, cloud computing, sophisticated sensors, robotics etc.) solutions.

The current reference model for the PPC (Aachen PPC model) [25] dates from 2006 and is based on scientific findings and facts at the turn of the millennium. Industry 4.0 and CPPSs were hardly researched at that time.

The main objective of the paper is to examine the possibilities of reducing the production costs and coping with the prior mentioned issues through the use of ICT (machine-to-machine communication), AI and in particular methods of machine learning (ML) at all mentioned levels of production planning.

The paper is structured as follows: First the stat-of-the-art results are revised for the above mention three fields of production planning: mid-term planning with ML, condition-based scheduling and adaptive, decentralised control with reinforcement learning. In the subsequent chapter the connection and interaction of these levels and a vision of a new production planning system are discussed. In the conclusion, challenges and potential research fields are identified.

II. RELATED RESULTS IN THE LITERATURE

In this Section the state-of-the-art results of the three research fields of PPC are presented.

A. Mid-term production planning

Gyulai et al. [10] define the robustness of a production plan by comparing the performance indicators of the production system achieved, with those expected according to the planning. If the indicators are still at an acceptable level, he speaks of a robust plan that already anticipated unforeseen disruptions that occur during execution. Beside robustness, resilience – the ability of a system to cope with changes of all kinds – can take into account disturbances of a production system.

ML is one possibility to learn from stochastic fluctuation caused by different influencing factors and is therefore a common approach to deal with uncertainties. ML has gained increasingly high attention in the context of production in the recent past. Cheng et al. [4] found in their review article that most publications focus on production scheduling and other applications (defect analysis, quality improvement and fault diagnosis), and rarely explore the prediction of production planning relevant times (flow time, lot cycle time or lead time). The topic of production planning relevant prediction was investigated by several authors (see e.g. [11, 18, 22, 23, 33]), however, only a limited number of the analysed papers achieved a high technology readiness level. Moreover, data generated with the help of simulation models is dominating within the applied methods, suggesting that the usage of predictive data analytic techniques is seldom in PPC.

The overall objective of PPC is the creation of reliable production plans, so as their realization on the shop floor should be close to – or ideally the same as – the production plan as originally planned. With the help of ML data used for mid-term production planning might be dynamised in order to get more reliable production plans. However none of the related literature gives states a method how to apply the dynamised time prediction model within the planning to create more reliable production plans.

B. Condition- based scheduling

Condition Monitoring (CM), the measurement of the health of machines and tools, is a topic which is mainly discussed in the context of maintenance [2, 9, 12]. However, CM information is an important factor in PPC as well. This is especially true in manufacturing as an equipment's condition influences its capability of producing qualitative products. This influence can be described as a bidirectional correlation between the production program and an equipment's condition. In [15] an example concerning the food industry is presented: "In the food industry [...] the contamination [...] with allergens plays a fundamental role. Once an equipment is contaminated with e.g. gluten, it cannot produce gluten-free products anymore. PPC therefore needs to consider this change in condition [...]."

Traditionally, the topics PPC and maintenance are considered separately [8]. When it comes to CM there is even less literature available which deals with the integration of CM data within PPC. When CM is considered within scheduling or sequencing the condition is often modelled binary – a machine is either operative or non-operative [30]. However, there exists some research in the semiconductor industry. In [7] the production yield is considered as correlating with the machine conditions. The authors conclude, that wafer with a bigger diameter should be produced on machines in a better condition in order to increase yield. Another paper from the semiconductor industry [13] highlights the fact that the production quality drops, if the equipment's condition decreases. Nevertheless, approaches considering CM data in PPC are scarce, especially when it comes to applicability in different industries.

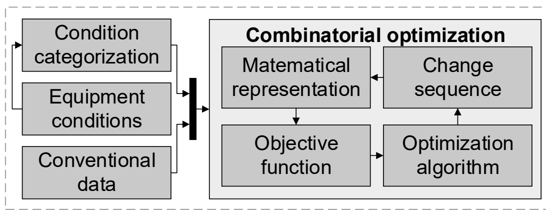

Fig. 1. Condition-based scheduling

In past research [15, 16] a condition-based scheduling was introduced. Based on a categorization of products' condition demands using a single-digit health parameter a decision supporting process can be modelled. Based on the decision supporting process a sequencing technique can be developed in order to optimize the production program by considering the condition of the equipment. Figure 1. shows the concept of condition-based scheduling.

Condition-based scheduling builds on the mid-term production plan (MTPP) and can be used for process and sequence planning. The basic dates from the MTPP are used as main constraints. Furthermore, the machine conditions (capabilities of certain resources to produce certain products) are considered as well. Taking these auxiliary conditions into account, condition-based scheduling creates a short-term production plan that resolves machine assignments as well as sequences.

C. Production control with adaptive, self-optimizing agents

Different agent-based and event-driven approaches were applied in PPC in order to answer challenges of the technology development of recent time [5, 17]. With the increase of computation power there is a possibility to combine these methods with AI techniques and solutions. Reinforcement learning (RL) seems to be a promising approach for self-optimizing, adaptive production control. RL is one category of ML – next to supervised and unsupervised learning. In case of RL there is no dataset in which a function should be found to describe the relationship between inputs and output(s) (supervised learning) or elements should be grouped (unsupervised learning) but the dataset is generated during the learning phase. In RL a learning agent learns the best behaviour, the so-called best action to choose without any prior knowledge and through a sequential and situational decision-making process. If the agent makes a good decision gets a good reward, however in case of a bad decision it can be punished. With the help of this feedback the agent is able to learn a strategy that guides the agent toward achieving the desired goal. The RL process is shown on Figure 2.

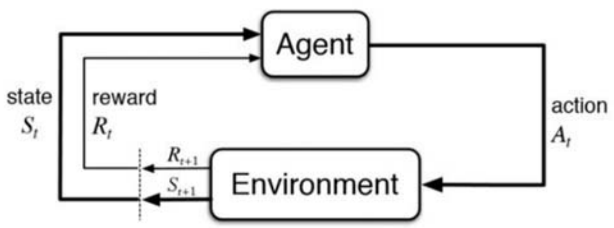

Figure 2.: Representation of RL

It must be mentioned here, that the RL agent needs a feedback from the environment during the learning phase. During the learning the agent has to test and learn the interrelation between the features and the consequences of its decision. In case of a production related problem this environment can exclusively be a simulation model, in case of a real production environment there is no possibility to try out different previously known bad outcomes.

Depending on the current state of the environment – described by different features of the system – the learning agent chooses always the action that results in the maximal expected reward. In this way, the learning agent is able to make real-time decisions in a dynamic environment that is a crucial ability in a cyber-physical production planning system (CPPPS).

Several production related topics were investigated with the help of RL in the recent decades. Das et al. [6] compared two well-known heuristics and a RL based solution for a *maintenance* problem and they received that maintenance policy learned by the RL agent was more flexible and could result in a better maintenance policy within a dynamic environment. With a modification of Das` model Mahadevan and Theocharous [19] were able to maximize the throughput of a transfer line while minimizing WIP and failures of the machines. Their model outperformed a Kanban heuristic. Kara and Dogan [14] studied the *ordering policies* of an inventory system and found that RL gives better result in case of a high demand variance. Rana and Oliveira [21] showed that RL can be used for dynamic *pricing* of interdependent products. In the recent years, RL has been applied to *motion planning* for industrial robots as well.

Production scheduling is the field of manufacturing that has been most widely investigated with the help of RL in the last decades. Several authors have studied this topic and showed that in a dynamic environment a strategy developed by a RL agent is able to outperform the conventional solutions currently applied in the industry. One of the first applications to a static job shop scheduling problem was presented by Zhang and Diettrich. [31] Wang and Usher [29] found that a RL agent is able to learn the best rules for different system objectives to a dispatching rule selection problem for a single machine. Bouazza et al. [3] applied two different agents in their simulation model: intelligent products – who chose a best machine – and intelligent machines – who select the most suitable dispatching rule. The successful implementation and application are presented in Sticker et. al and Waschneck et. al. [27, 28] They showed that RL can be used for adaptive production control in a dynamic, complex production environment. In the review article of Zhang et al. [32] it was concluded, that future research efforts should be shifted to smart distributed scheduling modelling and optimization. The vision of industry 4.0 for production planning and control to a decentralized, self-learning and adaptive production system can be achieved with the application of RL in production control.

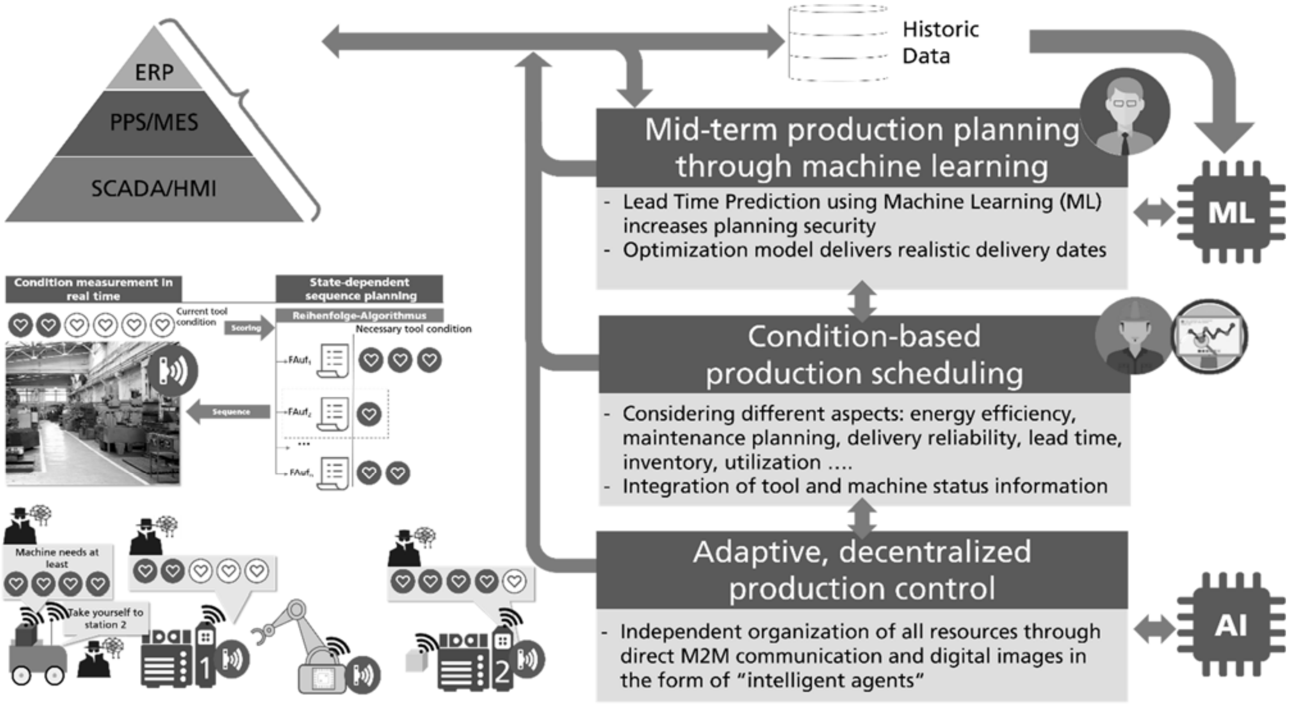

Figure 3. A new perspective of production planning and scheduling

III. DISCUSSION

As can be seen from the literature review several approaches have been researched so far to face the current challenges of manufacturing industries. These approaches use ML, AI, agent-based systems and traditional operations research methods. Still, they have been researched on the one hand only in isolation and on the other hand only to a certain extent. Therefore, only isolated solutions exist. To the best to our knowledge, there is no holistic view or model that combines all above mentioned methods into a single model for PPC. According to the authors, a radical new perspective of PPC is needed, in order to respond to the challenges PPC will phase in the near future when trying to fully utilize the potential of CPPSs. Figure 3. shows the different levels of the production system that need to be adapted as well as their related data sources. On the right hand side of the picture the three levels of the PPC system can be seen: mid-term planning, scheduling and controll. Traditionally, there could only be a direct connection or interaction between two adjacent levels. That means there is strictly hierarchical information flow between mid-term planning and controll level. However, the objects network of industry 4.0 enables this possibility. The different data sources – used as inputs on the given levels – are illustrated on the left hand side. At this point the authors want to mention, that the automation pyramide is just a simplified, yet very common representation for the different systems within the production environment. With this simplification we also address all intelligent subsystems of modern CPPSs. These different intelligent elements are connected in a network shaped structure and exchange information directly among each other and with the PPC system. However, the intelligent elements of the production system (machine, product, order) control the production based on different sensor data. It is a characteristic of such a decentralised system, that the intelligent elements can make sub-optimal decision for themselves in order to achieve the global optimum of the whole production system. The interaction and communication between the autonomous elements enables the creation of a more reliable and realistic production schedule. This new perspective of PPC leads to several research questions that need to be answered. In the following this research topics are discussed.

How can machine learning be used to create mid-term production plans? Although we list several approaches that use machine learning methods for time prediction e.g. for lead time or process time prediction, there are hardly any applications where such models are used to calculate a production plan. High prediction accuracy is dependent from the features that describe the production system best. It is very likely that at least a few of the feature, that are needed for a high prediction accuracy are not available as long as the planning doesn't reach a certain state.

How can different aspects be integrated into a production schedule? Although several examples can be found where different energy or resource efficiency aspects or the health condition of tools or machines are considered in case of creation of a production schedule, mostly only one aspect is investigated at the same time and the different aspects are not combined.

How could production control be efficiently performed? In the era of industry 4.0 – where everything is automated and through various sensors a lot of data about the current status of the production is available – how could disturbances be handled? In case of a machine brake down an intelligent product or an intralogistic element transporting the products might be able to choose an alternative machine on their own. Is RL the most suitable method to deal with such disturbances or are there other adaptive, self-optimizing approaches?

How is the information exchange between the different planning levels (mid-term planning, condition based scheduling and production control with RL) of the planning system organized? Traditional planning systems follow a successive planning approach. The planning result of one planning level is the direct input of the next level. The possibilities through embedded systems and modern communication technologies have the possibilities to achieve a faster response in case of disturbances. Therefore, information from the shop-floor can be distributed among all relevant parties and systems. On the other hand it is not yet clear how the systems will interact exactly among each other. Hence, it is clear that the constant information exchange is needed. One important question of this topic is the frequency of the information exchange, as (quasi) real-time data can have different granularity, resolution, transition time depending on the industry branch or company.

Is the architecture of the future PPC centralised, decentralised or hybrid? One conclusion of industry 4.0 might be the decentralised production system, that brings flexibility into the supply chain, as well as interactions and collaborations into problem-solving and decision-making. The remaining question is to what extent the production planning process can be decentralised.

How can a simulation model of the production system be generated automatically? Whereas time-prediction to some extent can be done from confirmation data, scheduling and RL need a simulation model that depicts the production system. These models need high effort to build and to maintain. Therefore, a method for automatic generation is needed. Especially for new machines, where there is no historic data available for the start this is still a big challenge in the industrial practice.

How can condition monitoring data be utilized in order to enhance production scheduling and how does it interact with the other two levels of production planning?

In [15,16] it was shown, how condition monitoring data can be integrated within production sequencing and scheduling. However, the topic was considered in an isolated view, where the auxiliary conditions, such as basic dates, where considered as given. Further research should consider a holistic view of condition-based-sequencing and consider its bidirectional interactions with mid-term production planning (on the upper level) and short-term production control (on the lower level).

What role should the human factor play in future CPPPS? As system become more intelligent and to some point autonomous, the role of the human worker will change. On the one hand, one important consequence of decentralisation might be the empowering of the employees. This results in increased responsibilities and skills of the human worker, as he is dealing with highly complex systems. However, on the other hand it is an interesting question how the human worker will react when their decision making scope is limited by an intelligent system. Furthermore, the same question arises for the role of the production planer.

IV. CONCLUSION OUTLOOK

It is obvious, that the PPC will be affected by industry 4.0. As a consequence, the current reference model of PPC, the Aachen PPC model is not well suited towards the needed changes. However, it might be adapted to the requirements of the recent time.

In this concept paper the authors highlighted some key questions that are relevant for future research in the domain of production planning in the paradigm of CPPSs. It was shown, that there do exist different isolated solutions for mid-term planning, production scheduling and production control. When it comes to an integrative consideration of these topics, relevant research is scarce. It can be concluded, that current changes lead to an increase in complexity and it is the responsibility of the research communities to provide solutions which can elevate the production planning to the next level.

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