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Case study on technological applications for production planning and control in the context of industry 4.0

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Abstract

In the course of the fourth industrial revolution, a rapid technological change proceeds in the manufacturing industry. Numerous new technologies enable multiple opportunities for industrial applications. In order to keep pace with this development, companies are forced to cope with a high amount of new technologies and arising application trends. For a successful positioning, knowledge of the industrial relevance of possible applications and the technologies associated with their implementation is required in particular. In this context, the Fraunhofer Institute for Production Technology IPT and the Centre of Excellence in Production Informatics and Control (EPIC CoE) conducted a two-stage case study to identify and evaluate promising industry 4.0 based application fields, such as self-optimizing production scheduling. The case study is proceeded as part of the European Union's Horizon 2020 research project under grant No. 739592. Within the first stage of this project a systematic screening for industrial application fields was conducted. Several potential application fields were identified and their advantages and disadvantages outlined. Furthermore, the application fields were evaluated according to their potential industrial impact and maturity level. In the second stage, technologies for the implementation of the most promising application fields were identified. At this, technologies were investigated and evaluated according to their readiness level for the identified application fields. In this paper, the methodology as well as the results of the first stage of the study are presented.

Keywords

Industry 4.0; Trend Analysis; Potential Evaluation; Industrial Impact

1. Introduction

In the course of the fourth industrial revolution, a rapid technological change takes place in the manufacturing industry [1]. Digitization, connectivity and the rise of new manufacturing technologies bring immense growth opportunities for companies by driving new business models, sustainable and efficient use of limited resources, and cost-effective manufacture of highly customizable products [2]. These developments are summarized under the term industry 4.0 and its implementation is expected to have the potential to relocate outsourced manufacturing activities back to Europe [2], [3]. This advancement in industry 4.0 has given rise to numerous new technologies enabling multiple opportunities for industrial applications [4]. In order to keep pace with this development and to achieve competitive advantages, companies are forced to cope with the high amount of new technologies and arising application trends, e.g. digital twin or smart work pieces. Especially the importance of the identification of promising trends has gained significantly in importance in recent years [5]. As a result, the ability to identify the industrial applications of upcoming technological trends has become a critical competitive factor for success. However, this identification makes companies often facing major challenges [6].

First, the technology foresight in particular constitutes various difficulties for companies. Technology foresight is necessary in order to recognize technologies at an early stage to enable radical innovations [7]. Especially the implicit, unpublished knowledge gives an edge over the competition. Generating this knowledge, however, is particularly difficult for companies in an early stage, due to a lack of access to the required knowledge. The situation is further exacerbated by the fact that companies today operate in a complex environment with many different players and influences [8]. The challenge is to find relevant trends and technology fields in the flood of data and the multitude of data sources [9]. In addition, companies are forced to determine the benefits for their customers and to select appropriate technologies [10]. As a result, the interpretation of complex technological trends is increasingly difficult for companies in practice.

In order to face these challenges and to successfully position the company, knowledge about the industrial relevance of potential applications and the technologies required for their implementation is of major importance. Therefore, the department of technology management of the Fraunhofer IPT conducted a two-stage case study on technology trend scouting for EPIC CoE, within the context of Horizon 2020 research and innovation program. The main objective of this technology trend scouting approach is to identify potential industry 4.0 based application fields for production planning and control (PPC) and to support the associated cyber-physical system of EPIC CoE.

2. Definitions and related work

2.1 Definitions

The following section serves to achieve a consistent understanding on relevant fundamental terms. Therefore, the meaning of *industry 4.0* and *trend* will be detailed below.

2.1.1 Industry 4.0

The given understanding of industry 4.0 exceeds the mere networking of machines and products via the internet. Although modern technologies make it possible to build up an ever broader database, the use of the underlying potential depends as much on the organisational structure and culture of the company. Accordingly, organisational and cultural areas of a company must also be transformed in the course of digitisation. The overall goal is to build a learning, agile company that can continuously adapt to a changing environment [2]. Sub goals of the implementation of industry 4.0 are the reduction of costs, the sustainable production and the optimization of the collaboration productivity, which lead to an improvement in infrastructure, to a cultural proximity and to an advancement in expertise. According to GAUSEMEIER and KLOCKE, these factors are essential for a competitive advantage [11].

2.1.2 Trend

According to SCHUH ET AL., a trend describes the general direction of a development in a certain area or subject area and can thus include the coherent development of different variables in this area. Trends often arise from the interaction of different factors following a continuous process. The content focus includes social, political, economic, scientific or technological effects and the impact focus is based on global or regional effects. [10].

2.2 Related work

Technology foresight is a component of company-wide strategic early detection (Business Intelligence) [12], [13]. The aim of this early detection is to provide relevant information about changes in the entire environment of the company in order to identify potential opportunities and risks at an early stage. While early detection is focused on any future development and event in the corporate environment, technology foresight as part of these activities focuses on the analysis and prediction of the technological potential of new technologies and the determination of technological performance limits of existing technologies [12]. The objective is to identify developments in relevant fields of technology as a basis for technology decisions within the company [14].

During the technology foresight, the evaluation task is of huge importance. The main objective of the evaluation is to assess the significance of technologies or technological developments, by comparing them to each other or in relation to the company. Depending on the given evaluation background, different criteria can be derived [15]. To be able to focus on the most important criteria, first all conceivable criteria need to be taken into account. After considering these criteria it is possible to specify on the essential criteria [16].

In the context of technology foresight, the aim of a trend analysis is to derive the corresponding technological effects from the predicted development. For this purpose, an observation object is selected and the underlying trend is examined. The application of the trend analysis is especially useful in the phases of determining information needs and evaluating information [15]**.** When evaluating the trend, the effect of the development on the company and the probability of occurrence of the forecast are taken into account [17].

To be able to establish a successful trend analysis and to support the evaluation process, different methods can be used. The most common methods in the context of this paper are the scenario technique, the lead user analysis, the TRIZ-like methodology and the trend extrapolation. Based on the scenario technique potential future scenarios are examined and evaluated with regard to the business environment [16]. To evaluate future technologies from the key customer perspective, the lead user analysis can be used [18]. The TRIZ-like methodology helps focusing on a general problem and enhances the solution space in order to identify as many technological solutions as possible. Finally, these solutions are transferred to a specific problem [19]. The trend extrapolation helps to transform a predicted trend into a technological application [15].

3. Methodology and results of the case study

Based on the existing scientific methods in the context of technology foresight a systematic process for generically identifying potential application fields of technologies was derived. Within a case study with EPIC CoE this process was developed and implemented. The methodology as well as the achieved results are addressed in this section.

3.1 Methodology of the case study

In the first stage of the case study, a systematic screening of technological trends was conducted in order to identify and evaluate promising technological application fields for production planning and control in the context of industry 4.0. The general procedure of the trend analysis and the results of the implementation in the case study are shown in Figure 1. The main process of identifying potential application fields of technologies is preceded by a trend analysis in which mega trends are broken down into sub trends in order to analyze their influences on different observation areas, e.g. industrial, economical, technological or political observation areas. For identifying industry 4.0 based technological application fields the mega trend of *connectivity* serves as the starting point in the conducted trend analysis. Connectivity can be further specified in its various sub trends e.g. *Internet of Things* (*IoT*), *Big Data* or *Smart Devices.*

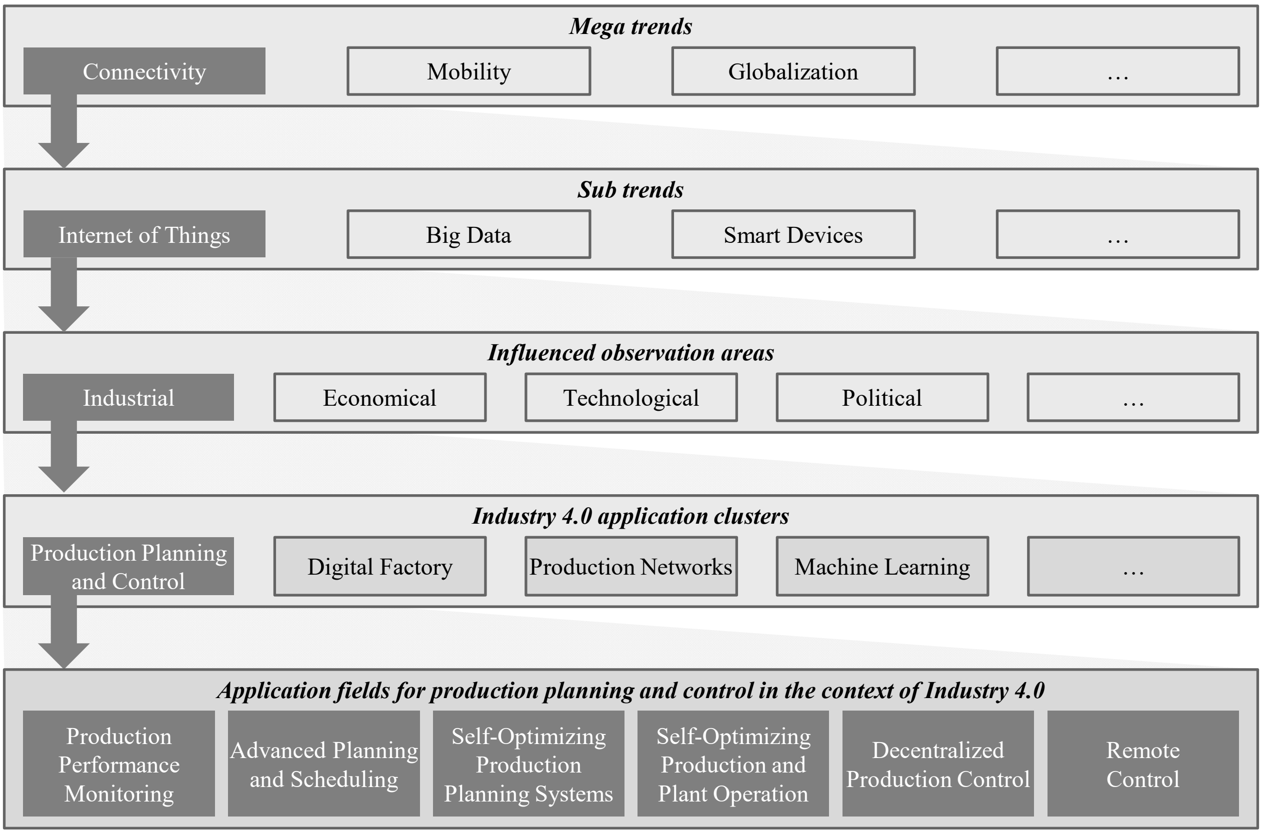


Figure 1: General procedure of trend analysis according to SEITER and OCHS [20][1]

Analyzing the influences of a specific sub trend on the different observation areas thus enables the derivation of relevant fields of application, which can be further detailed into specific applications. In the context of the case study, the influences of the sub trend IoT were considered in an industrial context focusing on industry 4.0. In the course of this, different application clusters such as *production planning and control*, *digital factory*, *production networks* or *machine learning* could be identified and detailed in specific application fields. This paper focuses on the application cluster *production planning and control* in the context of industry 4.0 and is detailed in six specific application fields: *production performance monitoring*, *advanced planning and scheduling*, *self-optimizing production planning systems*, *self-optimizing production plant operation*, *decentralized production control* and *remote control*. These six application fields were identified within a joint workshop of the members of the EPIC CoE.

In order to identify the relevance of industrial application fields, their impacts on industry and their probability of occurrence must be evaluated. In the case study, such an evaluation is carried out using a trend portfolio, which is visualized in Figure 2. While the standard trend portfolio consists of the two axis *impact on company* and *probability of occurrence*, an adapted version was derived according to the requirements of the project's scope. Instead of the specific classification (impact on company), a more general classification (*industrial impact*) is used. The classification according to the industrial impact is based on the target industries of EPIC CoE. The probability of occurrence is determined on the basis of several factors, such as the technology readiness level of the underlying technologies. A period of 3 - 5 years is taken into account for the evaluation. Using the trend portfolio, the application fields can be classified into different clusters to derive actions according to future strategic activities. For example, an application field classified in cluster I indicates a particularly high potential due to its significant industrial impact and its high probability of occurrence. Thus, the application field should be immediately integrated in the strategic decisions.

[1] The contents were created by experts in several workshops by transferring the general approach to the case study.

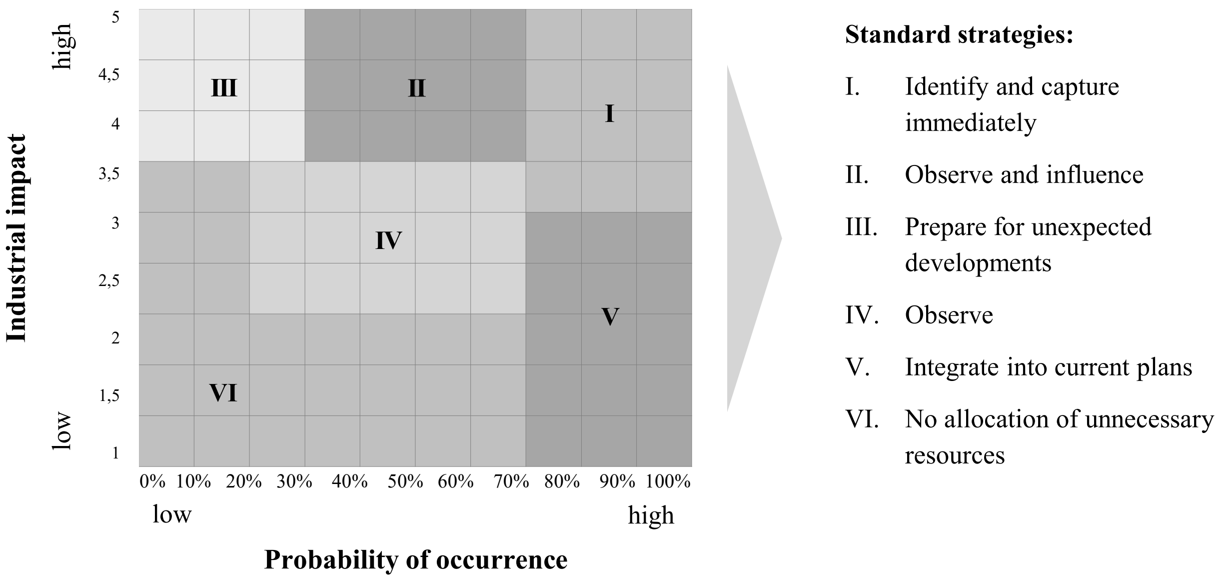


Figure 2: Trend portfolio following GAUSEMEIER ET AL. [21]

3.2 Results of the case study

This chapter examines the partial results of the implementation of the first stage of the case study. First, the application cluster production planning and control is described. Secondly, the specific application fields are detailed by describing them, addressing their advantages and disadvantages and evaluating their effects with regard to their industrial impact and their probability of occurrence. For assessing industrial impact and probability of occurrence, only the criteria with the greatest influence on the respective application field are briefly explained below. The following results were developed in workshops and are based on the expert knowledge of all institutes involved in EPIC CoE (Institute for Computer Science and Control, Hungarian Academy of Sciences (SZTAKI), Fraunhofer Institute for Manufacturing Engineering and Automation (IPA), Fraunhofer Institute for Production Technology (IPT), Fraunhofer Institute for Production Systems and Design Technology (IPK), Fraunhofer Austria Research GmbH (FhA) and Budapest University of Technology and Economics).

3.2.1 Industry 4.0 based applications for production planning and control

Production planning and control deals with the operative, temporal and quantitative planning, monitoring and control of production systems as well as the administration of all processes necessary for the production of goods and merchandise. The overall objective is the economic design and the smooth running of the production processes, which today takes place not only in particular companies but also in networks of several companies and organizations. The field of production planning and control therefore focuses on the development and implementation of process-oriented management systems and paperless production monitoring systems, in order to maximize the productivity of manufacturing processes. This can be done by providing appropriate models capable of solving complex planning and scheduling problems and suitable IT solutions for automated or semi-automated production planning and control.

3.2.1.1 Production performance monitoring

In the digital factory, large amount of data is collected to monitor production performance. With the increasing amount of data it becomes essential to prepare and visualize the data so that employees can quickly access and understand the relevant information. Statistical algorithms and machine learning can be utilized to derive additional information and to conduct root cause analyses. There are numerous software

tools available, which provide information, such as the overall equipment efficiency and profitability of assets in real-time as well as the assembly station performance and the identification of bottlenecks.
The most advantageous aspect of this sub trend is the increase in transparency in production and the associated support in decision-making. However, the effects on production performance are implicit, and thus, its industrial impact is relatively low, even if transparency in production is relevant for most companies. The probability of occurrence can be seen as high, because several software solutions for advanced monitoring of production performance are commercially available.

3.2.1.2 Advanced planning and scheduling

Advanced planning and scheduling (APS) includes software tools to optimize supply chain and production planning and scheduling in real-time. Those software tools require predictive algorithms to forecast the demand, as well as optimization algorithms for production schedules, which consider product and capacity availability. APS tools are typically linked to Enterprise-Resource-Planning (ERP) or Supply-Chain-Management (SCM) systems to retrieve the required information locally and to return the optimized schedules. APS tools usually encompass supply chain planning as well as factory planning and scheduling. Supply chain planning includes demand and sales forecasting as well as inventory and transportation planning in contrast to factory planning and scheduling, which considers e.g. lead times and delivery times. The advantages of APS range from optimized production schedules over improved delivery reliability and optimized inventory level to real-time reaction to unexpected events. In contrast, the associated complex and costly implementation is a major disadvantage.
The probability of occurrence of APS is high, due to its creation in the 1990's and the continuous improvement being made to the prediction and optimization algorithms. In terms of industrial impact, APS software tools are relevant for all manufacturers with complex, make-to-order production and products, which are composed of a large number of parts. Thus, the industrial impact is also high.

3.2.1.3 Self-optimizing production planning systems

In large and dynamic production environments, production scheduling problems become highly complex and finding global optimums becomes a time consuming challenge. Machine learning algorithms can be used to create virtual production models capable of autonomously optimizing the production plan. Besides the interface to the production planning system, some sort of feedback is required to monitor the actual production and to detect deviations from the planned production schedule. Potentials for self-optimization production planning systems can exist at various levels of the value chain, e.g. in supply chain design, production management or assembly management. Example applications include ramp-up decision support, whereby potential errors, bottlenecks etc. are predicted and avoided.
Self-optimizing production planning systems have the potential to lead to optimized production schedules, greater flexibility and faster response to unexpected events. Apart from these advantages, there are some disadvantages, such as long learning or training period in case of complex systems. In addition, machine learning models are black box models and, therefore, difficult to predict in unknown situations.
The probability of occurrence can be assessed based on the degree of the incorporation of the required machine learning algorithms into production planning systems. Machine learning algorithms are only recently incorporated into production planning systems, while holistic approaches are still limited to research projects. Thus, the value is still to be considered low. Additionally, self-optimizing production planning systems can have a potentially high impact for manufacturers with a complex and highly dynamic production. Dedicated from this, the industrial impact can be seen as relatively high.

3.2.1.4 Self-optimizing production and plant operation

Production lines are often not running at optimal conditions. Self-optimizing control systems constantly monitor process parameters, intermediate and product quality and important Key Performance Indicators

(KPIs). They are able to detect, if the process is not running optimal and readjust the process autonomously. Those control systems require accurate models of the whole process to be able to predict the process behavior. For processes, which are too difficult to describe with analytical models, machine learning algorithms provide a promising alternative. For instance, waste water plants monitoring the incoming waste water contents can adjust the process parameters accordingly in real time.
The greatest advantages of such self-optimizing production and plant operations are automated process control, increased process efficiency and improved process reaction to raw material changes. On the contrary, high costs and high expenditure of time due to a complex implementation needs to be considered. The core technologies for self-optimizing production line are available. However, implementing such systems for large production processes is very complex. Thus, the probability of occurrence is evaluated as medium. In terms of the industrial impact, the fact that even small increases in production performance can provide significant return on investment for large process plants is encountered by high costs for implementation of advanced process control systems, often impeding the use in process plants. However, the industrial impact of self-optimizing production and plant operation is evaluated as relatively high.

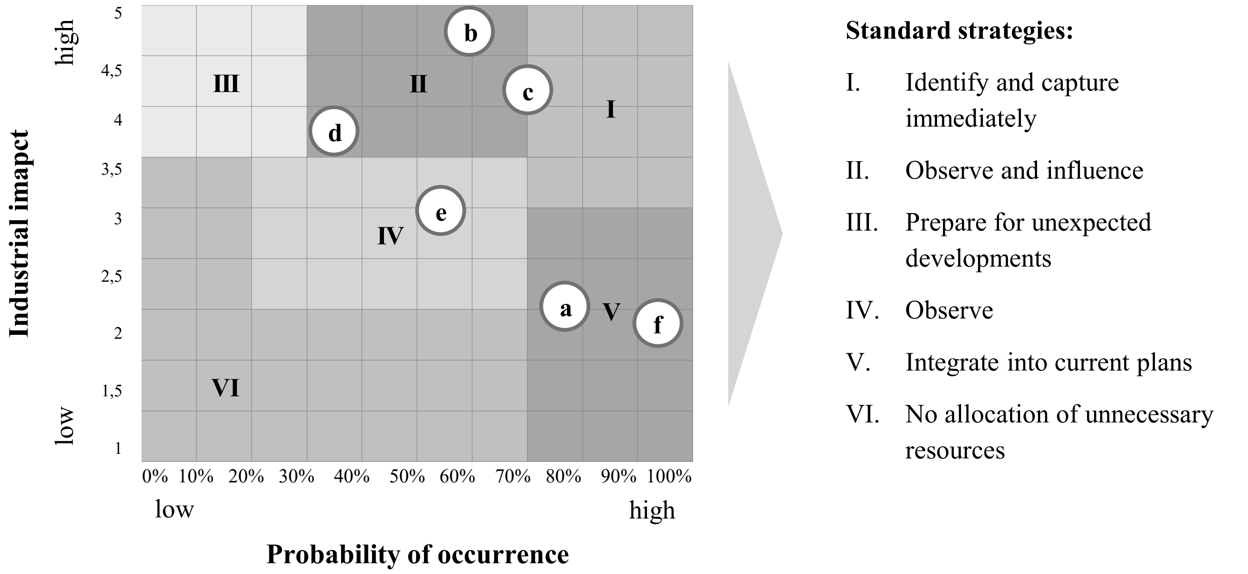
3.2.1.5 Decentralized production control

In industry 4.0, machines, assets and work pieces become cyber-physical systems (CPS). Those CPS are equipped with sensors and logical controllers and are capable to communicate directly with each other (machine-to-machine communication) in real-time via standardized communication protocols. This enables decentral process control, whereby the production planning system is merely required to control the overall production goals. For instance, work pieces can receive their production order from the ERP and autonomously find a path through the production.
Beneficial about decentralized production control are the rapid reaction to unexpected events as well as the reduced complexity of the production control, as only a local optimum remains to be striven for. However, in contrast to centralized controls, the decentralized control is currently less efficient.
Although the described examples have already been implemented at production sites in pilot scale, completely decentralized production control systems still remain a concept. Therefore the probability of occurrence of decentralized production control is currently rated slightly more than medium. In terms of industrial impact, partially decentralized control can help to manage production environments of high complexity, though it is unlikely to completely replace centralized production control.

3.2.1.6 Remote control

With increasing connectivity throughout factories, machines, assets and systems become remotely controllable. Production planning systems can be accessed and controlled anywhere via mobile devices. Management can rapidly react to changes or adapt production schedules without the need of being on site. Machine operators do not need to be at the machine to monitor the current status and can receive notifications in case of unexpected events. In addition, entire plants, such as offshore oil platforms, can be controlled from central operation control centers, which reduces stress and risk for the human workers.
Remote control has the potential to realize faster responses to changes or unexpected events as well as increased transparency. Nevertheless, with increasing connectivity, network security is also becoming more important, since an internet connection is required. This online access can result in a vulnerability. In addition, physical task still require technicians on site.
Remote control for IT systems and large production sites are common in the production industry. Furthermore, machines, which can be controlled via a mobile device, are a more recent development. Thus, the probability of occurrence is evaluated as high. The medium industrial impact of remote control is based to its limited relevance for large multi-site companies, especially in the process industry. But, remote control for individual machines via mobile devices can be useful for machine operators in larger production sites.

Summarizing, the six identified application fields for production planning and control in the context of industry 4.0 can be classified in the trend portfolio as shown in Figure 3, in order to identify relevant and promising application fields for future development and strategic focus of EPIC CoE.



a) Production performance monitoring	d) Self-optimizing production and plant operation
b) Advanced planning and scheduling	e) Decentralized production control
c) Self-optimizing production planning systems	f) Remote control

Figure 3: Classification of application fields for production planning and control in the trend portfolio for EPIC CoE

As a result, advanced planning and scheduling as well as self-optimizing production planning systems have a particularly high potential for EPIC CoE, since both application fields fall into the core competencies of the centre and have a high industrial impact for the targeted industries.

4. Summary and Outlook

In this paper, a case study for identifying potential application fields for production planning and control in the context of industry 4.0 was presented. Therefore, the authors derived a systematic process from existing scientific approaches on trend scouting. Within the case study, the process was implemented and validated by identifying and evaluating promising industry 4.0 based application fields for production planning and control. In the first stage, a total of six application fields in the cluster of production planning and control were identified: production performance monitoring, advanced planning and scheduling, self-optimizing production planning systems, self-optimizing production and plant operation, decentralized production control and remote control. The application fields were described in detail according to their application focus as well as advantages and disadvantages. Furthermore the potential industrial impact and the probability of occurrence of the application fields were outlined. Finally the identified application fields were classified using the trend portfolio to be considered within future strategic decisions of the EPIC CoE.

Implementing the trend portfolio for EPIC CoE has proven to fundamentally helpful in deriving relevant application fields for the future strategic alignment of the centre. Thus, the classification can serve as a guideline for aligning further activities of EPIC CoE as well as future development focuses. However, the results represent only a general orientation which requires subsequent detailing in the form of an implementation strategy for the centre's activities. The added value is achieved in particular in the expert discussions, the methodology's systematic approach for the identification of the different application fields as well as in the estimation of impact and probability.

To further validate the results of the first stage, a critical reflection on the positioning of the application fields in the trend portfolio will be accomplished through expert interviews. Subsequently, in the second stage, technologies for the implementation of the most promising application fields are to be identified. Hereby, the technologies will be investigated and evaluated according to their readiness level for the identified application field.

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Biography

Prof. Dr.- Ing. Dipl.- Wirt. Günther Schuh is the head of the chair of production systems at RWTH Aachen University and a member of the directorate of the Laboratory for Machine Tools and Production Engineering (WZL) at RWTH Aachen University and of the Fraunhofer Institute for Production Technology IPT in Aachen. In addition, he is Director of the Institute for Industrial Management (FIR) at RWTH Aachen University. Professor Schuh is also a member of several supervisory boards and directorates and was prorector for industry and commerce at RWTH Aachen University from 2008 to 2012. His most important research findings include relevant methods and instruments for complexity management, resource-oriented process cost accounting and participative change management, as well as the concept of the virtual factory.

Patrick Scholz, M.Sc. RWTH studied mechanical engineering at the RWTH Aachen University with a specialization in production engineering. Since 2017, Mr. Scholz has been a research assistant in the Technology Management Department and since 2019 also Manager of the Business Unit Lightweight Production Technology at the Fraunhofer Institute for Production Technology IPT in Aachen. As part of his work at the Fraunhofer IPT, he has already carried out various consulting projects in technology and innovation management. His research is concerned with the selection and evaluation of technologies in the early phase of the innovation process. The focus is on the efficient design of decision processes on the basis of individual potentials and risks.