Human-Machine-Interaction in Innovative Work Environment 4.0 – A Human-Centered Approach

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Abstract. The working environment is constantly changing and companies face the challenge of adapting to new and constantly changing customer requirements. Employees are faced with the challenge of identifying and learning new, helpful technologies and using them in order to achieve efficiency gains and increase productivity. This article addresses the three technologies Artificial Intelligence, Robotic Process Automation and Virtual Reality, which will play an important role in the future of work and will influence the Work Environment 4.0. Artificial Intelligence and Robotic Process Automation relieve employees of repetitive and manual tasks which thus accelerate and simplify business processes. Virtual Reality offers employees new opportunities to collaborate in virtual environments. Instead of performing routine tasks, employees will increasingly promote the use of such technologies in future and orchestrate their application. In addition, it is important for employees to continuously look for new use cases within their own organization and to collaborate with external partners. The article aims to describe the opportunities that arise from the application of the technologies and to explain their effects on the Work Environment 4.0 and the employee.

Keywords: Artificial Intelligence · Robotic Process Automation · Virtual Reality · Human-Machine-Interaction

1 Introduction

In industrialized countries, the competence of employees represents the most valuable resource and locational advantage. Today, however, employees are occupied with rule-based and time-consuming tasks both in the office and on the shop floor. Therefore, they are less able to focus on creative and value-adding tasks. Furthermore, collaboration is needed to connect employees with different domain knowledge and to enable efficient collaboration across departments and organizations for product development.

In order to take advantage of this opportunity, however, companies face the challenge of integrating intelligent and modular solutions into their own business processes. The

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key technologies Artificial Intelligence (AI) and Robotic Process Automation (RPA) play a central role in the new Work Environment 4.0. These technologies take over time-consuming, tedious, rule-based, and monotonous manual tasks from employees and free up employees' capacity for creative and value adding tasks. Furthermore, Virtual Reality (VR) has the potential to enable collaborative work throughout the product lifecycle and to visualize products and processes in real-time. In virtual environments, collaboration enables flexibility and reduces the carbon footprint, as employees do not have to necessarily travel for meetings, nor do they have to work at the same time.

This article presents and classifies three relevant technologies for digital transformation and gives an outlook on the Work Environment 4.0. In addition to the technical explanation, the article describes which competencies of employees are required in future. The scope of the article ranges from office work at the computer to the shop floor of industrial companies (Fig. 1). AI and VR address the shop floor and AI and RPA support employees in repetitive office tasks. Finally, these technologies improve business processes to meet customer requirements. The human orchestrates the use of the three technologies in Work Environment 4.0 and needs background knowledge about the possible approaches and areas of application. At all times, the focus is on the human being that orchestrates the different technologies through a human-machine-interaction approach.

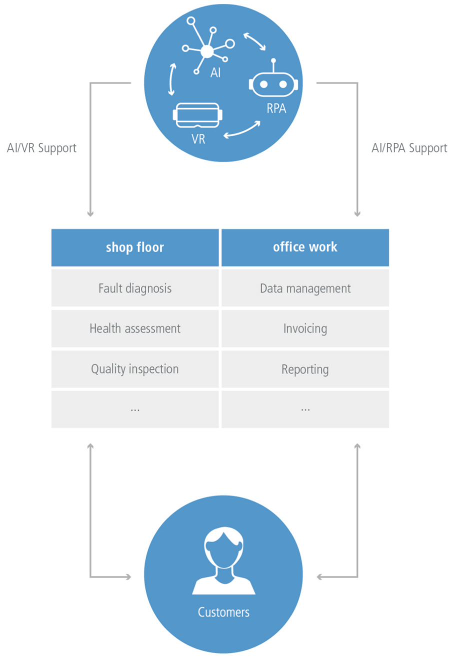

Fig. 1. Overview of relevant future technologies which are described in the article (own representation).

The article begins with an overview on the three future technologies AI (Sect. 2), RPA (Sect. 3) and VR (Sect. 4). Each section is structured similarly and starts with the motivation and introduction. Afterwards the respective technologies are described in detail and possible use cases are explained using examples to highlight opportunities offered by the technologies. The reader should be able to identify areas of application in their own organization, evaluate implementation options, and plan implementation. Finally, the article ends with implications on future of work, a conclusion and outlook on further research aspects (Sect. 5). The aim of this article is to understand the opportunities offered by the three technologies and to be able to better classify them. All of the technologies presented have the potential to optimize processes and to shape the Work Environment 4.0. Furthermore, there are also organizational changes and changing requirements for employees in Work Environment 4.0.

2 Artificial Intelligence

2.1 Motivation and Introduction

Since computing hardware has improved in the 2000s, AI has started to influence many aspects of daily life and is making rapid advancements e.g. finding anomalies in machine behavior or optimizing business processes in shop floor and office work. AI is broadly usable and a technology which changes work environments and will be able to shape the workplace of tomorrow.

In this section we define AI and describe the fields of application of AI for practitioners in the Work Environment 4.0. We also describe technologies that are researched right now and will likely have a significant impact on the workplace. Since employees in various departments can benefit from these technologies we will present use cases for both work on the shop floor as well as work in the office. Finally, we will give an outlook on the implications of these technologies for the human being.

2.2 Theoretical Background

AI has the ability to solve complex problems. For this purpose, methods are used that are similarly used by humans [1, 2]. For example, AI can communicate with customers, help to identify anomalies in data, read documents, send out digital ads or predict scenarios.

There are numerous definitions for AI e.g. weak- or strong AI. Weak AI focuses on solving specific existing problems and on one aspect of mental function. Strong AI is an approach that tries to reproduce and imitate the human being e.g. empathy [3]. This article focuses on weak AI, as it is the most commonly used in practice.

Machine Learning (ML) is the area of AI that is mostly associated with the term today. In the context of Smart Manufacturing and Industry 4.0 ML plays a crucial role in the intelligent usage of data and thus in the modern industrial process environment. The amount of data being generated in the processing industry is increasing rapidly. ML algorithms lead to an effective and efficient use of those data quantities. ML is at its core about learning from data and can be defined after the general learning task as: “A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E." [4].

Deep Learning as a subset of ML refers to neural network architectures that use an input and output layer of neurons as well as multiple hidden layers [5]. This form of ML has gathered a lot of interest due to the increased performance of computing hardware (Graphics Processing Units, Neural Processing Units, dedicated Field Programmable Gate Arrays) and the resulting feasibility of the execution of more sophisticated artificial neural network architectures e.g. Convolutional Neural Networks (CNN), Recurrent Neural Networks, Generative Adversarial Networks, Transformer Networks, etc. ML can be divided into unsupervised, supervised and reinforcement learning. The approaches behind these three categories are explained after introducing the concept of training.

The AI system is supposed to learn a generalized rule or behavior from a dataset. Thereby, the ML model achieves to accurately predict on new and unseen sets of data. In principle, two stages of model usage are distinguished: training and inference. Training in this context means the process of building or shaping the model. In ML, many kinds of models can be used, e.g. Decision Trees, Regressions, Support-Vector-Machines (SVM) or Artificial Neural Networks. The second stage in ML is model inference. At this stage, an already trained model is executed in order to accomplish the task. Therefore, the model works on test data or with live data. In some applications data is still used for further training, in others it is discarded after model execution. Often the decision-making process of trained ML models is unclear and difficult to verify due to the black box character of ML methods. For example, a model that identifies bananas does not look for a curved yellow object, but only for a blue sticker. Recent developments in the field of explainable AI try to alleviate some of these challenges [6].

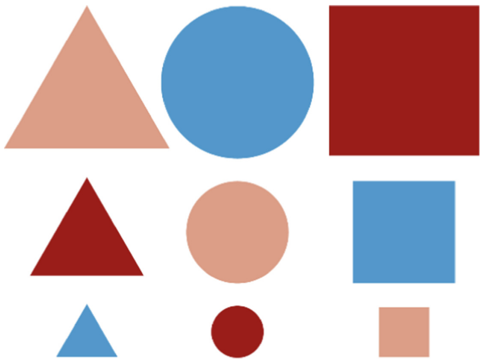

Fig. 2. Sample input data for a ML model (own representation).

One approach used in ML is unsupervised learning which uses unlabeled data. This means that nothing is known except for the input. The resulting model can be used to identify patterns or groups within a data set. This step is defined as knowledge discovery [7]. As the example of input data in Fig. 2 shows, a model for unsupervised learning could cluster in terms of many different metrics, such as size, shape or color. Nevertheless, a model could also identify squares and circles that are point-symmetric.

In supervised learning, the raw data has been labeled before training. Therefore, the trained model has to learn a mapping between input and output, i.e. shape, size and/or color of the input [7]. However, the act of labeling can be very time-consuming since often it is still a manual task involving human labor.

Reinforcement learning is another approach and in contrast to unsupervised and supervised learning, the feedback to the model is punishment signals or reward. The algorithm must find the actions which maximize its incentive function [7]. For example, when playing chess, AI has to take actions that lead to reward and finally to success. The environment is often represented by a Markov decision process. Reinforcement learning is used to solve many problems that are analytically infeasible [8]. When training a reinforcement model, we try to find an optimal policy for an agent, to find an appropriate action in any given state of the environment to maximize the reward and to not get stuck in local optima.

In the following section, we will present some technologies that are likely to reshape Work Environment 4.0.

Human beings communicate and share knowledge using written and spoken language. Oftentimes it takes a whole childhood to learn how to form words, associate words with things, form sentences, learn how to read and how to write. Enabling machines to work together with human is one of the big aims of current AI-research in the field of Natural Language Processing (NLP). NLP focuses on solving tasks involving the human language e.g. by analyzing syntax, semantics and context. BERT (Bidirectional Encoder Representations from Transformers) [9] and all its derived versions, GPT (Generative Pre-trained Transformer) [10], XLNet (Generalized Autoregressive Pretraining for Language Understanding) [11], PaLM (Pathways Language Model) [12] enable machines to perform increasingly well with a multitude of difficult NLP tasks.

Practical applications in the context of NLP tasks range from the processing of text using Optical Character Recognition (OCR), handwriting recognition, text summarization, text prediction and Natural Language Generation (NLG), chat-bots, document understanding, Natural Language Understanding (NLU) or text to image generation.

Furthermore, generative models, in particular "Generative Adversarial Networks" (GANs) enable the generation of realistic synthetic data in a variety of fields, finding application e.g. in photo realistic image generation, video generation or music generation [13]. Recent image generation models from OpenAI (DALL-E, DALL-E 2) [14] and Google's Imagen [15] enable the creation of artistic and photorealistic images using simple text-based prompts as input.

With the introduction of CNNs and their improved architectures image classification tasks can be solved on a level surpassing human ability [16].

2.3 Application

Processes are digitalized and automated in almost all areas within an organization. Mature technologies which come from the field of NLG, NLU and NLP, e.g. OCR and handwriting recognition can speed up this process even further. Furthermore, AI influences jobs which have already been digitized. For example, product development teams with jobs in design and engineering, simulation and programming may use AI assisted systems and enhancements which will lower entry barriers, decrease cycle times and time to market, speed up decision making processes and increase customer satisfaction [17].

AI assisted engineering also increases the potential for more complex products and cost savings in production as well as for a sustainable climate [18]. Repetitive and pattern-based digital tasks in engineering can be performed faster by using algorithms which employ deep neural networks [19].

Methods such as SVM, Naive Bayes and k-nearest Neighbor are already used in industry to ensure quality assurance in production [20–22]. In addition to the early identification of quality problems, it is also crucial to initiate process improvements immediately and to transfer findings to other production lines or the supplier network in order to reduce quality costs. Transfer learning offers the opportunity to apply existing ML models to comparable problems, thereby exploiting synergies and saving development effort [23].

In the last 50 years, with the emergence of new data processing capabilities, there have been big changes in the handling of machine maintenance and prognostic health management. The integration of large-scale sensory data feedback (big data) as well as edge devices or smart sensors systems on the shop floor enable production data to be monitored and stored in real time [24].

Data Mining methods facilitate shop floor data association analysis [25].

Additionally, wireless communication technologies enable distributed manufacturing resources to collaborate with each other. By integrating the physical and the information layer, the concept of the "Industrial Internet of Things" (IIoT) becomes more relevant. Industrial big data is therefore particularly concerned with the meaning of the data and its association with failures and value creating mechanisms [26].

This means that the analysis of industrial big data requires domain knowledge, for example, in failure mechanisms, process knowledge etc. Fault diagnosis and health assessment models usually rely on accurate, clean, and frequently adequately labelled training data, thus making the data quality an essential aspect of the industrial success of these solutions [27].

The use of digital twin technologies further increases the possibilities for optimization, autonomous decision-making as well as increased transparency for management [28].

3 Robotic Process Automation

3.1 Motivation and Introduction

Today employees are responsible for numerous business processes and have to perform manual and tedious tasks, whereas creative and value-adding activities like the development of innovative products are often neglected. In addition to processes on the production line, activities carried out on the computer offer further potential for automation. Organizations may achieve faster and more accurate business processes by using the future technology RPA. Furthermore, employees may focus on customer requirements and the development of new products and services to ensure competitiveness. RPA is of particular importance in office work to achieve efficiency gains for organizations and to respond promptly to customer needs and to secure a sustainable competitive advantage.

The traditional automation of processes is carried out by Business Process Management Systems (BPMS) which are often referred to as workflow systems. Such workflow systems require the programming of interfaces as well as the adaptation of the IT architecture. These solutions, known as heavyweight IT, are invasive and fully integrated. "Heavyweight IT denotes the well-established knowledge regime of large systems, developing ever more sophisticated solutions through advanced integration." [29]. In contrast, RPA depicts lightweight IT and represents a non-invasive option for digitizing and automating as business processes are automated without changing the existing IT architecture [29]. The term RPA is often associated with robots that perform manual operations such as assembly tasks and relieve humans of their daily workload. RPA technology, however, addresses repetitive time-consuming tasks that are performed by humans on a computer. Thus, robotic in this context refers to installable and flexible computer software which supports employees in daily tasks like data transfer or data manipulation [30].

RPA has become increasingly popular in recent years and is now used in various industries and companies. In an empirical survey, 400 decision-makers from companies in the US, UK, France and Germany with at least 50 employees were questioned. The survey examined the use of RPA solutions. According to the survey, only 33% have already deployed RPA solutions, and 31% intend to do so in the next 12 months. Accordingly, the greatest opportunities are seen in the area of customer experience, as 39% of those surveyed assume that process automation will have a positive effect on this area of the company [31]. Today companies have access to a wide range of automation software to develop RPA solutions like the three leading platforms: UiPath Studio, Automation Anywhere and BluePrism [32].

In this section we describe the RPA technology and show possible use cases in office work as well as the combination of RPA and AI.

3.2 Theoretical Background

There are numerous definitions of RPA in the literature. IEEE Corporate Advisory Group (CAG) emphasizes that a RPA solution is software: "A preconfigured software instance that uses business rules and predefined activity choreography to complete the autonomous execution of a combination of processes, activities, transactions, and tasks in one or more unrelated software systems to deliver a result or service with human exception management" [33]. The Institute For Robotic Process Automation (IRPA) also defines RPA as a software solution: "Robotic process automation (RPA) is the application of technology that allows employees in a company to configure computer software or a "robot" to capture and interpret existing applications for processing a transaction, manipulating data, triggering responses and communicating with other digital systems." [34].

RPA solutions are based on the three different technologies: workflow automation, screen shaping, and AI. Workflow automation automates data transmission and the processing and routing of data and files. Screen shaping includes all processes for reading text from computer screens and further processing these data in other software. AI enables organizations to transfer human learning and automating more complex business processes [35].

RPA software applications combine these three technologies so that time-consuming, recurring and error-prone tasks can be performed in Work Environment 4.0. The RPA solution is faster than the corresponding manual process by humans and the proesses is also logged. This means that all steps performed in RPA are always traceable and ensure a higher quality in terms of results.

RPA operates on the user interface of a computer and aims at replacing people [36]. Likewise, RPA is known for the creation of simple procedures which do not necessarily require programming, but can be created with drag and drop functions. However, programming skills are necessary to implement more complex procedures [37]. To get RPA running in an organization a configuration and scripting of this incident is required once. After that, the routine can run permanently or may be scheduled to run e. g. daily at the same time.

Using RPA hardly affects the existing IT infrastructure in the company because RPA works on the user interface [30]. The operation of these routines is simple. If errors occur during the execution of the automated process, specialized personnel needed quickly to identify the error and possibly adjust the configuration. In this respect, RPA is only suitable if the rules or the working environment at the user interface do not change constantly. Thus human errors can be avoided with RPA, e.g. due to the lack of concentration and motivation. Thus, RPA has a wide range of applications in companies and organizations for process automation and acceleration as well as an expansion of capacity with high quality in the completion of tasks. RPA, however, cannot replace a human per se; rather, RPA can be used to relieve people of usually quite simple and often very monotonous and tedious tasks on the computer so that they can attend to more difficult tasks or other activities.

Companies looking for RPA opportunities have to consider several criteria for identifying the processes best-suited for RPA. A four-step approach which supports companies to evaluate process eligibility is given in literature. According to this approach, automation only suits rule-based processes that require manual interaction with a software application [38].

3.3 Application

In the literature, numerous case studies are described in various industries. Typical tasks that are often replaced by RPA software tools are logging into applications on the Internet or from Enterprise Ressource Planning (ERP) providers, merging statistical data from different IT systems and preparing these data as a graph or report in a program, any kind of copy and paste activities for data transfer, saving, renaming and moving documents, executing simple if-then rules. Likewise, bots can perform calculations as well as generate and send emails even with attachments [39].

Figure 3 lists further processes that can be automated by RPA.

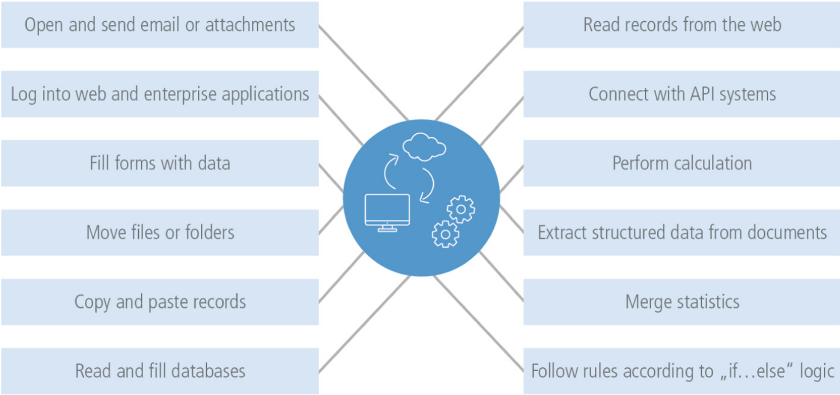

Fig. 3. Process steps that are particularly suitable for RPA implementation (own representation based on [39]).

RPA technology has the potential to automate business processes in quality management and to ensure product compliance. In a case study, Mercedes-Benz AG achieves a faster and more accurate business process, saves 5.075 FTE (full-time equivalents), and increases product quality [40].

A business process outsourcing (BPO) service provider automated the invoicing process so that over 21% more cases can be processed by employees. Thus, productivity (measured by cases processed per employee) increases as the RPA solution processes multiple cases simultaneously [41]. Furthermore, RPA may be used in the field of audit [42], finance [43], procurement [44], customer service [45], among others.

In contrast to these advantages, there are risks that need to be managed. Immature RPA solutions carry the risk of decreasing productivity and additional manual steps, and increase error rates [46, 47]. In addition, stuff members might reject RPA solutions due to their fear of job losses resulting from the personnel savings which are achieved incidentally. These employees are then freed up for more creative and challenging activities. At an early stage, however, companies may have to prepare these employees for new fields of activity in Work Environment 4.0 through training.

Furthermore, smooth operation of RPA software tools can only be guaranteed, if these solutions are regularly updated and checked. Likewise, when scripting the routines, engineers have to make sure that they are programmed as robust and stable as possible. User interfaces that do not change often are an essential prerequisite for stable running bots, as any change usually means adjustments in the program. Such adjustments and also errors that occur in bots during operation require skilled personnel who can intervene quickly and at any time.

The more intelligent an RPA solution is, for example by using OCR for automated reading and processing of delivery bills, the more complex and demanding the scripting of the solution is. In some cases, this requires adjustments to the process and also specialized personnel who can implement these solutions [48].

Since RPA can be implemented easily on a company's own computer, in some cases, even without IT experts, RPA also offers the potential to increase shadow IT in the company, especially in the specialist departments. This aspect, in return, can have a negative impact on IT security and operation as well as on adherence to compliance guidelines [37].

The following Fig. 4 shows the key advantages of RPA implementations for companies and organizations.

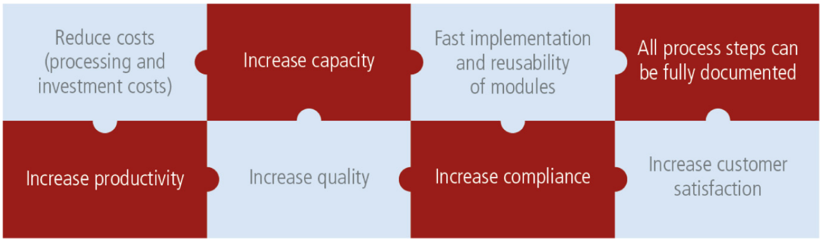

Fig. 4. Key advantages of RPA implementations (own representation).

RPA software will become even more powerful with the further development of functions that incorporate AI. RPA software providers are already offering such functions that play a central role in Work Environment 4.0.

ML is another growing area of AI related to RPA. This area uses algorithms to generate artificial knowledge from existing data so that certain patterns are recognized. The bot learns from these patterns and then applies this knowledge to new data sets. A typical application here would be a bot that has learned to distinguish invoices from other documents, scans them by using OCR and enters them correctly into the company's ERP system.

NLP functions enable bots to copy texts and insert individual words in other places. The bots, however, are not yet able to understand these words. Extensions that can be expected in this direction in the future fall into the areas of NLU and NLG. Then a bot will also be able to understand texts and generate its own texts. This is also referred to as "social robots" or "digital assistants". These will then be able to simulate human judgment [30].

RPA is also used in combination with Process Mining (PM). PM enables companies to analyze and improve their existing processes with the help of accumulated data on the computer. Thereby, transaction data collected in the form of log files is read from the company's existing systems, such as ERP and Customer Relationsship Management (CRM) systems, and imported into process mining software. If the data is factually assigned correctly, the PM software analyzes the data and presents it by means of a model of the processes that actually took place. In addition, dashboards can be used to display various key figures such as the lead time and statistics for the process. These figures provide information, for example, about all process variants that have occurred or about existing bottlenecks in the process. On this basis, it is relatively easy to define and automate a new target process. In addition, processes executed by bots also generate transaction data, which can also be analyzed and subsequently improved by PM.

For automation, workflow software can be used for processes with an enormously high degree of standardization and high case frequency, or RPA software for a medium degree of standardization and medium to high case frequency [30].

4 Virtual Reality

4.1 Motivation and Introduction

Global events like the pandemic put a spotlight on remote work and on the demand for virtual education and collaboration across departments and organizations. Embedding the human user into a virtual learning environment can lower the inhibitions and fear through the possibilities of free experimentation and the benefit of making errors in virtual environment without the risk of damage or financial loss. Tutorials can be set up individually, tailored for the learner's level of knowledge. More advanced applications are the training of workers for the configuration, operation and maintenance of products, machines or production plants.

VR in engineering encompasses the whole product life cycle and supports it with a variety of applications like the design review during the product development process, production planning for manufacturing or training applications just to name a few.

The concepts, methods and systems are all well known for years, but struggle to get adopted, especially in small and medium-sized enterprises. We want to give an insight into current research and will look at VR from a technology perspective, but also from the engineer and worker perspective.

In this section we describe the opportunities of VR along the product development process and present a specific education use case.

4.2 Theoretical Background

According to the Reality-Virtuality Continuum [49], two environments are distinguished: On the one hand, there is the real environment which consists of real objects and illustrates the real-world and on the other hand, there is a virtual environment with virtual objects which are monitor-based or immersive. Mixed-Reality (MR) environment is in between and comprises real objects and virtual objects. The term immersion refers to the feeling of being in VR. According to studies [50], immersive technologies are suitable for communication and understanding of emerging products.

The product development process controls and manages all activities linked to the aim of developing a product that meets customer requirements and also fulfills the organization's financial and technical conditions. During the product development, the development status must be continuously checked and tracked. Therefore, humans need to work together in interdisciplinary teams and in a collaborative and virtual environment.

There are a few tools that provide the classic range of functions of a design review tool e.g. IC.IDO from ESI and CMC ViewR from CMC Engineers. Both tools offer a wide variety of data and communication interfaces in order to be able to visualize CAD data in immersive VR hardware systems. Then engineers can validate the CAD design with various tools such as measurement tools, cutting planes, drag-and-drop interaction or a physics simulation of the model components [51].

In contrast to these tools, TechViz is a middleware that extends Computer-Aided Design (CAD) software and other 3D-Software and taps the data as an Open Graphics Library stream. Since TechViz can display data in immersive VR hardware systems [52] its focus is on the design review application.

In the field of virtual commissioning, research and development at manufacturers of automation solutions exists. This includes, for example, Simit [53]. Virtual commissioning generally facilitates extensive validation of the planning data during product development, especially in individual machine construction. On the other hand, however, virtual comissioning presents an enormous effort as it entails the effort to create functional virtual models, to model the dynamics and kinematics, to parameterize the interaction with scripts and the real-time simulations.

The automation of the creation of virtual functional and interactive machine models is a research field that has been addressed at the Institute for Information Management in Engineering (IMI) for several years [54]. This is the basis for all Virtual Engineering (VE) methods like design reviews during product development, the virtual commissioning of production lines, training applications, maintenance simulations, material flow simulations and much more. VE as a new working method in product development makes it much easier for engineers and product managers to validate the partial development or interfaces between groups, departments and organizations. In addition, Software in the Loop (SiL) and Hardware in the Loop (HiL) enhances work steps that can already begin with virtual instead of real components.

In order to consistently validate Mechanical Computer-Aided Design (MCAD) and Electronic Computer-Aided Design (ECAD) as well as programming, automated virtualization systems must integrate all planning data into a Virtual Twin (VT) of the machine, system or integrated production line at the push of a button. Generic intelligence is automatically added using Semantic Web technologies, enabling complex interactive models that can be used for training, monitoring, and many other applications beyond just validating design data [55]. In order to achieve this high degree of automation, geometry analysis algorithms are used to capture as much intrinsic knowledge as possible from the MCAD and thus automatically parameterize kinematic simulation. Such interactive simulation modules are important to simulate the behavior of machines and processes and to give the user extensive interaction options. Another aspect is the automated aggregation of all knowledge from the planning data, especially the merging of the component data in MCAD and ECAD.

The software system used to implement the above-mentioned subsystems, data interfaces, interactive simulations and VE applications is the VR authoring system PolyVR. This open source project was initiated in 2009 at the IMI, Karlsruhe Institute of Technology [55, 56].

The automated virtualization is a fundamental game changer for design reviews with functional models up to virtual commissioning. But this method also greatly simplifies the authoring of more advanced applications that can use those functional machine models for software and HiL, operation and maintenance training applications and VTs for configuring and monitoring. In this regard, the impact of optimizing data interfaces, simulating as many aspects of machinery as possible and interactively, goes way beyond the product development process. For engineers in the Work Environment 4.0, this offers a new horizon of possibilities, especially to create and deploy VR-supported applications like training and monitoring in production settings and not only as demonstrators in academic settings.

4.3 Application in Tunnel Boring

In this use case, we will show how the implementation of a VT coupled with a physical setup can help human learners to understand processes in a quicker time frame and more controlled environment (Fig. 5). In this MR training setup, a tunnel boring machine was replicated virtually and coupled in a HiL approach to behave similarly to the real counterpart. While the human operator still stands in front of a physical control panel on the construction site, the tunnel boring machine itself is physically missing and only digitally existing as a VT. The logic control program of the machine is used to drive the virtual machine. By running and communicating with the control software in real time, exactly as it would run in the physical environment on site, we gain the possibility to design virtual scenarios for individual learning settings. These user specific scenarios and stress situations can be deployed to emulate failures during the process without the fear of harm for either the machine or the human worker. Different solution approaches can be discussed as well as effortlessly and repeatedly tried during the training by the learner to see how the machine will behave according to varying control inputs.

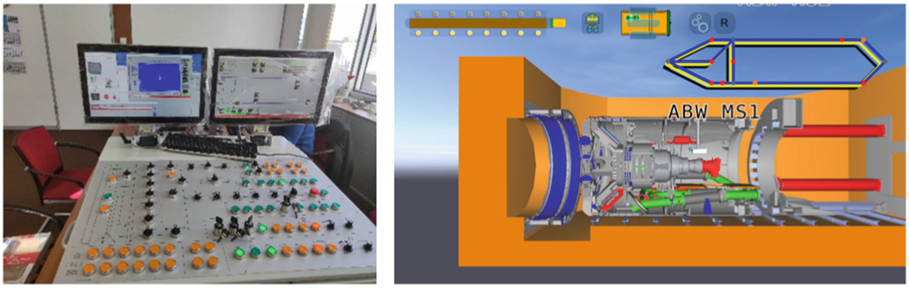

Fig. 5. On the left: Physical operator terminal, steering panel and display for showing system status. On the right: Visualization of the virtual tunnel boring machine (own representation).

The simulator consists of three parts (Physical Control Panel, Programmable Logic Controller (PLC) Program, Machine Simulation) which are subdivided again into further modules.

The physical control panel with two attached displays is the Human Machine Interface (HMI) which the operator faces on a construction site to control the tunnel boring machine. This is necessary for both the real machine as well as the simulator to guarantee that the learner has the same haptic feeling and visual cues just like on site. While within the virtual simulation a virtual representation of the control panel is possible and implemented as well, the benefits of a real control station already imitate the feeling of familiarity of the machine operators.

The PLC program is between the physical control panel and the simulation and is responsible for the behavior of each moving component of the tunnel boring machine.

In this program the data from all the sensors are consolidated and processed. Depending on set targets and safety limits, specific behavior (e.g. power cut off, or safety valve position) is programmed into the software to protect both the machine as well as human personnel in the vicinity. Reactional behavior according to the operator's input is also commanded by this software (e.g. variable pump output, valve position, motor speeds).

On the virtual side of the simulator, the virtual representation covers the tunnel boring machine up to a certain degree of detail (Fig. 6). In the best case of implementation, the machine would be virtually identical to the real counterpart but due to typical restrictions such as computational power of the simulators and the required real-time capabilities of the simulation only a scaled down VT is deployed in this use case.

The VT of the tunnel boring machine consists of the machine's visual representation, which is derived from the CAD-model. This model's geometries are positioned in real time to show the current position and direction in 3D-space as well as to depict functionality such as cylinder expansions of the cutting head's steering capabilities and it's cutting wheel speed. To calculate these parameters, the virtual simulation is implemented on a physically based model of the machine. The modular architecture of the simulation contains the following subsystems of the tunnel boring machine: The propulsion of the whole machine is handled by hydraulically actuated cylinders which have pressure sensors to show how much force is applied to drive the boring machine into the earth.

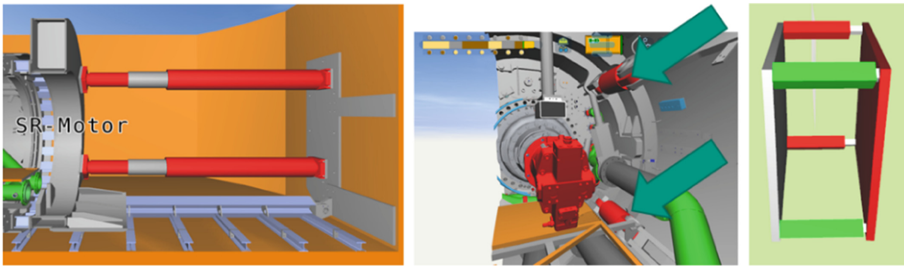

Fig. 6. On the left: Propulsion cylinders in red. In the middle: Directional steering cylinders marked with arrows. On the right: Visualization of the underlying physics simulation of the steering cylinders (own representation).

The movement speed of the whole machine results from the interplay of how much earth is removed in front of it and how hard these cylinders press the machine into the earth. The cutting head's parameters define the behavior of the boring machine such as the direction (controlled by hydraulic steering cylinders) and the rotational speed of the drill. The quicker the head spins, the more volume is removed by the boring machine. The loosened and disheveled sediment is transported out of the tunnel by a pipe system which provides the transport medium to the cutting head. The back flowing water mixture is filtered, recycled and moved by pumps and controlled by valves. After the maximum length of one tunnel segment is reached, the propulsion cylinders are retracted and a new segment is added to the setup (Fig. 7).

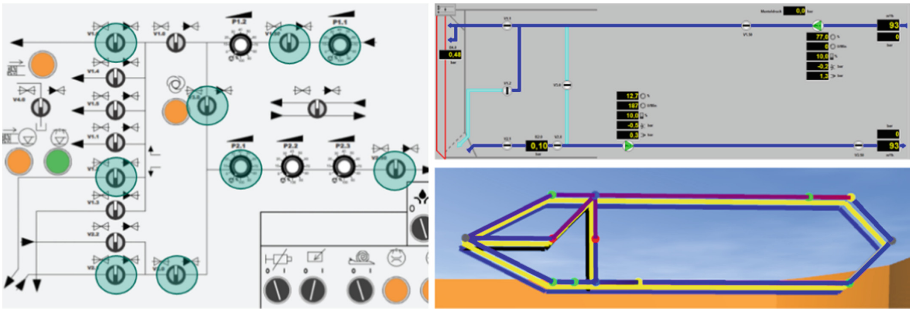

Fig. 7. On the left: Operator panel of the water cycle, the deployed valves and pumps are marked in green transparent cycles. On the right: Top: Operator visual feedback display of the machine's water cycle. Bottom: Virtual display of the water cycle simulation (own representation).

By means of this simulator, the learning operator gains a tool worked out with all the necessary components, safety settings and machine behavior which mirrors real working situation on a construction site. Thereby, the operator is able to concentrate on the control strategies without the possibilities of real damage to physical parts or human co-workers.

5 Conclusion

The future of work will change continuously and the three technologies presented in this article may increase productivity and efficiency of organizations. The requirements on employees at shop floor and office work will constantly change. At office work, efficiency increases and productivity gains will result from AI and RPA. Instead of processing rule-based tasks, employees will see themselves in the role of identifying rule-based and monotonous work themselves and automating it using suitable RPA and AI solutions. In addition, cross-departmental and cross-organizational processes must be optimized, digitized and finally automated. Constantly changing external requirements require continuous adaptation of business processes and thus adaption of RPA and AI solutions. Employees need technical know-how and process knowledge to plan, build, run and manage automation solutions.

In addition, the use of VR enables new possibilities for collaboration. Collaborative working is becoming an essential part of our everyday lives, with multiple individuals organizing themselves into teams to jointly develop products and services. The increasing networking of individuals is not only influencing our social life but therefore also our everyday work. Tomorrow's engineer will need to understand and handle much more complex systems and tools to cope with the ever increasing demands and complexity of product development. These methods will not focus on simplifying modeling and planning as CAD systems do, but rather on simulations and AI to enable much faster development, much more advanced optimizations and much more efficient validation iterations.

It is necessary that employees get to know the three proposed technologies and acquire knowledge. The further development of the three technologies is progressing and thus even more use cases will be possible in the future that will help organizations to maintain their competitiveness. RPA and VR solutions will become more intelligent through the use of AI and their areas of application will expand as well as improve their performance.

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