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Investigating the Potential of Smart Manufacturing Technologies

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Abstract

Over the past years, the topic of smart manufacturing has been in the focus of researchers and manufacturing experts. Smart manufacturing describes the technology-driven ability to solve existing and future problems in a collaborative manufacturing infrastructure, which responds in real-time to meet changing demands. However, many companies are still unsure what smart manufacturing entails and which potential (and challenges) it holds. To get an insight into the issues addressed, a technology laboratory for the development of innovative technologies and concepts for intelligent production along the product life cycle was established at University of Applied Sciences Upper Austria. This paper offers an insight into the challenges and lessons learned from a 6-year research project where a subset of smart manufacturing technologies have been collaboratively investigated, including Mixed Reality, Additive Manufacturing and Predictive Maintenance. With our work, we want to support companies in better assessing the potential of smart manufacturing.

Keywords: smart manufacturing; augmented reality; additive manufacturing; predictive maintenance

1. Smart Manufacturing

Smart manufacturing (SM) describes fully-integrated, collaborative manufacturing systems that respond in real-time to meet changing demands and conditions in tomorrow's smart factory. Today's consumers expect personalized products and faster delivery, both of which require a shift towards mass customization. SM is a technology-driven approach that utilizes Internet-connected machinery and new hardware approaches to monitor production processes, to raise flexibility and to support workers in their daily routine using novel ways of human-computer-interaction. These measures are necessary to achieve the required degree of flexibility. Smart manufacturing technologies include Collaborative Robotics, Simulation, Internet of Things, Data Analytics, Additive Manufacturing and Augmented Reality. It is the ratio of feared costs and outcomes (that cannot be clearly estimated) that makes companies hesitant to introduce smart manufacturing technologies.

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This position paper describes the challenges and lessons learned from the 6-year research project ”Smart Factory Lab”, where a subset of smart manufacturing technologies have been collaboratively investigated at University of Applied Sciences Upper Austria. With our work we want to support companies in better assessing the potential of disruptive technologies. In the subareas Augmented Reality, Additive Manufacturing and Predictive Maintenance, concrete application scenarios along with opportunities and risks are discussed.

In Chapter 2 we describe our approach to identify the requirements of an AR-supported tool for industrial remote assistance, followed by a discussion of results. Chapter 3 deals with current challenges of Additive Manufacturing with focus on laser metal deposition processes. Chapter 4 covers the topic of Predictive Maintenance to monitor and analyze a system in real-time in order to trigger maintenance proactively. Based on our research results, we discuss the overall findings in Chapter 5 and conclude our paper with possible future research.

2. Augmented Reality-supported Remote Assistance

Augmented Reality technology (and respective hardware) still needs to evolve, but as pace of innovation picks up, more and more promising use cases are implemented and evaluated for industry. Augmented Reality (AR) describes a technology that superimposes a computer-generated image on a user’s view of the real world. In the course of this project, research has been done in the areas of AR-supported assistive system for manual assembly tasks [32] and VR-supported engineering design review [31]. We put the strongest focus on researching the potential of AR-supported remote assistance, because comparable solutions have received a lot of attention recently. Following this concept, a worker conducts maintenance tasks hands-free while a remote expert provides visual cues and contextual tools need to complete the jobs quickly, safely, and on the first visit. This approach is commonly known as ”Remote Support” or ”Remote Asstistance” and is already available for smartphone, tablet-PC and smartglasses. First commercial solutions exist (for example *Chalk* by Vuforia and *Remote Assist* by Microsoft), but little is known about the requirements of the industry in regards to usability and necessary features. To fill this research gap, we conducted basic scientific research on industry specific requirements on AR-supported remote assistance. In a first step, four Austrian-based companies were asked to share their expectations and usage scenarios in their field of maintenance work and how they would imagine using AR-supported remote assistance in the daily work routine. Afterwards, one company was chosen to provide detail information in form of seven expert interviews. The following subsections cover recent related work, the methodology of our research, as well as a discussion of findings derived from these interviews.

2.1. Related Work

As relevant technologies further improve, more and more scientific publications investigate the use of AR in industry. Ong et al. [21] provide a comprehensive survey of developed and demonstrated AR applications in manufacturing activities. The authors expect that the HMDs will become smaller, lighter and no longer be a physical and obstructive burden to the users. In the context of maintenance, Palmarini et al. [22] conducted a systematic literature review to investigate the current state of the art of AR in maintenance and the most relevant technical limitations. The authors still see some technical issues, which prevent AR from being suitable for industrial applications. With a focus on real application scenarios, Linn et al. [17] developed a concept for visual remote inspections of manufacturing machines based on Virtual Reality technology. The approach focusses on the usage of real-world recordings that enable the viewer to virtually move to a machine in need of service. Aromaa et al. [4] studied knowledge-sharing solutions using AR and wearable technologies in actual industry cases, where two maintenance technicians tested the technologies. Data was collected using questionnaires, interviews and observation. In general, the user experience and usefulness of both systems was positive. To learn more about challenges in maintenance, Amo et al. [3] conducted four one-hour interviews with their industry partners. Based on the findings, the authors developed an information framework to enable the integration of AR in existing maintenance systems.

In summary, we see that AR technology is not completely ready for industry usage, but there is a huge potential in the area of maintenance. Following the approach of Amo et al. [3], we spoke to our industry partners to gain a deep understanding of the requirements and needs of the industry in regards to AR-supported remote assistance.

2.2. Methodology

In a first step, four Austrian-based companies were asked to share their expectations and usage scenarios in their field of maintenance. We organized semi-structured workshops (each lasting two hours) with the goal to learn more about their field of activity, current challenges and preconditions of their work environment (e.g. safety regulations, hands-free work etc.) and the expectations for MR-supported remote assistance. Details on this work can be found in [33]. The results show that hands-free work is crucial to fulfill most of the maintenance tasks, which makes it impossible to use smartphones or tablets. In addition, we found out that factors like rough weather conditions, noise, dirt and safety regulations play an important role in everyday's work life and complicate the use of smart glasses. To gain a deeper understanding of the current situation of industrial maintenance work, one company was chosen to conduct a series of expert interviews. We chose this specific company, since it has the strongest focus on maintenance and service with over 20.000 employees worldwide. Following the concept of expert interviews, a loose guideline with questions was prepared to keep the flow. The main goal was to better assess the potential of AR in service and to collect requirements for an AR-based system from experts in the field. We asked them about their current field of activity and recent challenges when conducting maintenance tasks at the customer's site. Afterwards, we focused on their ideas, how AR can support the work of the future work routine.

A total of seven people agreed to take part in the interviews, each lasting around one hour. We talked to three service engineers, two customer support employees with experience in service and maintenance, one team leader of the service crew and the head of service. The interviews started with an explanation of our research focus and a definition of the term Augmented Reality. Afterwards, we showed them a prototype of an AR application on tablet-PC and Microsoft HoloLens, where a company-related 3D CAD model is visualized on a visual marker. By this means, we wanted to make sure that everyone understood the concept of AR and got familiar with the hardware. The interview started as soon as there were no more open questions.

On average, the participants were 35.1 years old (SD = 12.7), ranging from 20 to 57 years. They were all male, with a highly diverse level of experience in maintenance work, between 1 month (a young employee directly from school) and 41 years (team leader with specific focus on operational planning). Six out of seven participants described themselves as tech-savvy, who are open to new technologies. The following paragraph sums up the most important statements from the interviews.

2.3. Results

Asked about their daily work routine at the customer's site, all participants emphasized the importance of analogue aids like printed plans or construction manuals. Even though the service staff has smartphones and laptops, they prefer to follow the instructions in paper form, since it allows them to take measurements in an easy way. In addition, a printed plan can easily be put aside without paying particular attention to dirt or untrusted personnel. Smartphones and laptops are mostly used to communicate with back office workers or to read emails. They also state that 3D plans or exploded views of a 3D CAD data play a subordinate role, since it does not bring any additional value. Thus, they also see no benefit in the visualization of 3D data on tablet-PCs or smart glasses. Nevertheless, two of the interviewees are convinced that the paper documentation will be completely eliminated in the future. Before this happens, the hardware (especially smart glasses) must be light-weight, robust and more intuitive to use. In general, they believe that products are becoming increasingly complex and that nobody can be an expert on the entire product range. Instead, there will be more specialists for smaller areas. Nevertheless, there must be technology-based support options for new employees. Speaking of AR support in service, all interviewees agreed that current hardware is too heavy and must offer more value in the daily work routine. One advantage would be if the hardware could take measurements automatically in the real world.

Generally, the participants see a big potential for remote support. The customer uses the AR-device (like a HoloLens) and is guided through the repair process by a remote expert without having to share confidential construction plans. This can also save many travel activities. The interviewees think that remote assistance will become more important for customers than for service engineers. Another interesting comment relates to the annotation of construction plans using AR: CAD plans are sometimes confusing and details need to be explained by the creators. One participant thought of a system, which annotates 2D CAD plans with comments (or hints) added by the CAD engineer. These hints support the service personnel while conducting their work at the customer's site.

The biggest hurdle in the introduction of new technologies in the company are internal IT guidelines. All interviewees agree that IT-security is important, but it slows down innovation in the company. They said that even providing the service staff with smartphones was a complicated process that took years. Large companies are generally very careful when introducing new technologies because of security issues. In summary, one participant said: "If we want to be innovative, we must not be afraid of new technologies".

2.4. Discussion

AR-supported remote assistance is an intensively investigated topic in the scope of digitalization of production industry. The workshops with four industry partners as well as the conducted expert interview show that the technology still needs to evolve. We see that current hardware cannot fulfill industry requirements, since it is not suitable for outdoor usage in rough weather conditions. The interviews showed that there is still a lack of clarity about the real benefits for service and maintenance. Besides from that, the interviewees see potential for future applications, where the customer is able to carry out a repair task, guided remotely by an expert located at the manufacturer's site. We also see that strict IT-security guidelines slow down the usage of AR-supported remote assistance in industry. Nevertheless, as AR technology and respective hardware further improve, successful use cases will be tested in industry. Based on our research, we have developed a prototype of a AR-supported remote assistance application with specific industry focus (see [19] for details). Our future research includes evaluations with industry partners to get an insight into the usefulness of our solution in industry. We think that AR (and also VR) will play an essential role in the industrial sector, with the potential to disrupt every link in the manufacturing value chain.

3. Additive Manufacturing

Additive manufacturing (AM) is considered as a key technology of current and future challenges such as shorter development cycles, increasing competition for raw materials, an increase in component variants and the individualization of products. In particular, AM offers the possibility to manufacture complex components with integrated functions, yet without the need for specialized tools. For this reason, AM processes, such as powder bed and laser metal deposition processes (LMD) which is used in this research project, are increasingly used for the production of metal components.

During LMD an interaction of laser radiation with a substrate material, creates a localized melt pool. The additive material is transferred into the melt pool in the form of powder. The added material completely melts and cools down afterwards. This process results in a dense fusion metallurgical bond between the substrate and additional material with relatively little dilution, which forms the first layer. Repeated addition and melting of material gradually creates a three-dimensional component. A variety of metals can be used in this process, most weldable metals can be applied in the LMD process. That includes for example: titanium, stainless steel, aluminium and tool steels [27, 20, 5, 6, 14]. Application of different alloys as input is a highly studied subject and promising results indicate that the amount of available metal powders for LMD is likely to grow in the coming years [18].

Despite a number of advantages over conventional manufacturing methods there are still some challenges that need to be examined to increase the application of this manufacturing method. Building and repairing functional parts out of metal alloys like hot work tool steels represents an application of LMD and is one major research topic in this research project. Hot forming tools e.g. have to withstand high mechanical and thermal loads. The fact that the built parts experience locally varying heat transfer coefficients during manufacturing leads to inhomogenious microstrucure [6, 14, 11]. An optimization of process parameters is necessary to get defect free parts with low distortion and desired hardness [29].

3.1. Research focus

The AM project is focused on the investigation of the LMD process. Additive manufacturing of hot work tool steels with high carbon content is related to certain challenges. Cracks, porosity and distortion due to high residual stresses are examples for part irregularities that have to be avoided. The right parameter settings are essential criteria for a reproducible process and a part quality that matches the requirements. One subgoal is the determination of process parameters for new materials that can be used for producing hot work forming tools. Finding economic applications respectively new business of additive manufacturing processes in the field of tool and mold making is another research topic. As these processes usually increase tooling costs, the added value must be generated. One could be the very efficient heat dissipation, by contour-matched internal cooling systems, that can reduce cycle times and the resulting wear during forming operations like press hardening, forging, metal powder pressing. In addition, the integration of AM technology into existing production environments is investigated.

3.2. Findings

One goal of this project was to determine the LMD process parameters of new materials. This e.g. was made for a hot work tool steel with a carbon content of 0,5%. The first target values were defined as high density and low porosity of crack-free specimens. A process window for small samples (cuboids with 30x30x10mm) could be determined, in which the material can be processed crack-free with a porosity lower than 0,04%. At the beginning of the investigations, the influence of substrate preheating was investigated as it was assumed that a preheating of the substrate plate is necessary to avoid cracks. For that reason the substrate plate was heated up to 300°C. It was found that crack-free samples can be produced even at room temperature.

Fig. 1. LMD built cuboids with 30x30x10mm (left) substrate preheating to 300°C; (right) no preheating of the substrate

The determined process parameters were used to produce bigger specimens (cuboids with 80x65x30mm), from which tensile and notched impact specimens are to be produced to determine the mechanical properties. It was found that in the case of larger specimens, the temperature introduced leads to overheating and the surface oxidizes. By gradually reducing the laser power it is possible to build up the cuboids without overheating problems.

Besides the process parameter investigations cost analysis for the LMD process were carried out that showed that simply replacing conventional subtractive manufacturing methods like milling and drilling by LMD is not supposed to be commercially viable. LMD technology has the potential to be more economical if it offers significant added value. The advantages of this manufacturing method has to be used for the manufacturing of components that cannot be manufactured in any other way, or if it is used, for example, as an isolated part of a production process that only performs a certain step. A case where this could be an option is when a product is manufactured by forging, for example, and the entire product cannot be finished due to process limitations. In this case, the ability of LMD machines to work on existing products is an advantage, as it allows the products to be finished more cost-effectively. One application of the technology that is not part of a production process is to use it for rapid prototyping [2]. The ability to repair existing complex expensive components out of materials like e.g. Ti-6Al-4V or in Aerospace Industry [10] or Inconel 718 in oil and gas industry e.g. for turbine blades [15, 38] represents another application of this manufacturing technology, especially because of its ability to work on existing components and add material with low tolerances. This makes it possible to apply a metal layer, a so-called coating, to an existing component to give it certain properties (e.g. improved wear resistance). This, in combination with the milling function of the used hybrid machine (Lasertec 65 3D Hybrid), creates the possibility of repairing tools used in production processes. One example is the repair of forming tools [6]. Investigations of the repair-ability of casting parts [35] showed that LMD compared to conventional wire based welding resulted in better mechanical properties regarding the measured strain rate. Samples showed a smaller heat affected zone where hardening mechanisms during the welding process occurred. They mentioned that LMD can be used for the repair of casting products but further studies have to be made e.g. on the fatigue. The possibilities and flexibility offered by the LMD process is e.g. already used by the company Sulzer. Sulzer uses the LMD process for the production of water pumps [24].

The integration of the LMD system into an existing manufacturing system was another goal of this project. For this reason, possible variants for a safe connection between the AM machine and a flexible manufacturing system by using a robot was evaluated. Besides safety and costs the R&D environment where lots of different applications and parts increase the necessary flexibility were taken into account. All variants were subjected to the risk assessment and risk reduction process as specified in ISO 12100. This means that for each variant the limits of the machine were defined, the hazards identified, an initial risk assessment was carried out, the risk reduction measures defined and a new risk assessment was carried out. Therefore, a variant, which is very flexible and by that suitable for small and very small batch production, or when the presence of people is required in the robot's workspace, as is common practice in the Center of Smart Manufacturing at the Campus Wels has been selected. An autonomous transport system combined with a collaborative robot met these requirements best. Although this combination can only manipulate a significantly lower work piece weight, it has the advantage that it is collaborative, which means that additional protective measures can be dispensed. Therefore, this solution is advantageous for applications that change frequently and possibly take place at different locations.

3.3. Discussion

Laser metal deposition is a process which is characterized by its high flexibility and extensive performance. By combining several processes (milling, coating, welding, additive manufacturing and hardening) on one system, like the DMG MORI Lasertec 65 3D does, it is possible to manufacture even more complex parts. LMD represents a new type of component production, but also improves current conventional processes in the process chain. However, in order to release the full potential, there is still research work to be done in the field of the used materials. Integrating functions like complex conformal cooling channels in hot forming tools that can not be made by conventional methods represents an application that makes the process very interesting for the tooling industry. Challenges like locally varying heat transfer coefficients and the resulting influence on important material properties like hardness [6] have to be studied to ensure a high tool-quality. The possibility to work on existing parts with complex surfaces makes LMD interesting for the repair of expensive parts. Also in this possible use case research work has to be done to ensure a high part quality [35]. Based on the investigations carried out to date, material-testing is being further intensified in cooperation with industrial partners. In addition, further high-performance tool steels with carbon contents above 1.3% will be included in the investigations, their processability will be tested and the resulting material properties will be fundamentally.

4. Predictive Maintenance

Continuously monitored production processes using sensor equipped and digitally interconnected machinery are a central concept of the ongoing digital transformation of industrial manufacturing sites. The approaches to leverage the potential of monitoring data are manifold and span from continuous quality control, over automated parameter optimization, to the idea of Predictive Maintenance [9], which is in the spotlight of this section. While Run-to-Failure (R2F) or Corrective Maintenance (CM) means to trigger maintenance when equipment breaks and Preventive Maintenance (PvM) schedules service actions based on empirically gained knowledge regarding fatigue, wear and tear, Predictive Maintenance (PdM) relies on a machine's actual past and current condition [28]. Therefore, all available machinery data is constantly analyzed such that future critical situations can be predicted and hence, counteracting maintenance operations coordinated in advance. The general goal of a PdM implementation is to save time and material, thus, to increase the overall productivity, by preventing unforeseen, unplanned downtimes of machinery [9, 26].

In this project part, we concentrate on adapting and evolving methods for the online analysis of monitoring data streams from complex and crucial industrial machinery using machine learning methods, to support future implementations of Predictive Maintenance. The following subsection summarizes the core data evaluation methodology, used and enhanced in the scope of the basic research project. Several application cases, performed in cooperation with industry partners, verified the potential of machine learning based Predictive Maintenance, however, also shed some light on related challenges and limitations. The gathered key findings are detailed in the last subsection.

4.1. Methodology

Depending on the application scenario, the objectives for PdM implementations may vary from the microscopic prediction of changes in a single, crucial production step or equipment part [37], to enhancing comprehensive resource management systems by estimating the breakdown probability of individuals in a fleet of machines [13, 25]. A categorization of PdM approaches may consider many other aspects, such as the planned deployment environment (e.g. centralized vs. at-the-edge data evaluation) and the aimed alarm reaction speed vs. its robustness. Depending on the available collected data, a PdM prototype usually starts at trying to model ”normal” system behavior and detecting changes in the continuously analyzed data stream – so-called concept drifts, which may represent degrading machinery condition. Further tasks can include the prediction of certain error states (i.e. *In which direction does the system drift?*) or the estimation of remaining useful lifetime, but come along with higher requirements regarding the quality of available data.

Regardless of the pursued approach's characterization, a fair share of PdM implementations employ machine learning methods, a subdomain of artificial intelligence [9] for analyzing the machinery data. Among the most popular associated methods are Support Vector Machines [28], Artificial Neural Networks [34] and Random Forests [7]. In addition to these very popular machine learning methods, our approach includes the white-box modeling method symbolic regression and classification [1]. In contrast to most of the before mentioned model types, their genetic structure, a mathematical syntax tree, is easy to read. The opportunity to discuss data analytics results with domain experts, not only considering model phenotype, such as accuracy or false positive rate, but also regarding the inner workings of a model, adds credence to the found solution. Furthermore, traditional statistic models including autoregressive forecasting models [12], Hidden Markov models [8], or Bayesian networks [16], are studied in PdM research, also in combination with machine learning models, as in [12] or [36].

In the stated work [36], we propose a novel regression based concept drift prediction algorithm, similar to the classification based approach in [12]. The algorithm forecasts several seconds of raw sensor time series in parallel, using autoregressive models with a rolling horizon. With a second, offline trained, multi-variate machine learning model the next value of a sensor variable, which is representative for a machinery's condition, is estimated. A drift towards abnormal system behavior can be predicted, if the estimation of the machine learning model, using the new time series as input, differs too much from the forecasted value. An added case study on industrial radial fans confirmed the feasibility of our approach and revealed promising results. However, it also raised further research questions regarding, the possibility for detecting more complex and hidden system changes, which we addressed in a subsequent paper [37]. Also this work pursues the idea of PdM by aiming for concept drift prediction in continuous sensor data streams. This time however, the focus was not on a specific, condition-representative sensor, but instead on the dependencies between all available sensor streams, which may change over time, for instance due to wear and tear of the monitored system. Besides successfully revealing the searched dependency drifts, the developed online evaluation of so-called variable interaction networks also granted a closer look at the possible root causes for drifts.

Apart from concept drift prediction, in other use cases we have been tasked to predict specific, critical error states – usually causing high costs – for which sample data already has been collected. To support these and future use cases we developed a data stream evaluation framework on the base of the open source software HeuristicLab [30]. The implemented machine learning approach aims at continuously classifying the monitored machine's condition by preprocessing and evaluating the provided data stream partition-wise with a sliding window. Although the pursued approach worked promisingly well on provided test data sets and hence, matched the results of similar, published state-of-art PdM research work, the eventual deployment on real-world data was only partly successful. From a technical viewpoint, the data stream processing performed as intended and its feasibility could be proven. However, our approach failed at finding a proper tradeoff between reaction speed and prediction confidence, such that in our case studies either alarms were triggered too late or too often. The following section summarizes our findings regarding this discrepancy between theoretical approach and real-world deployment, as well as further PdM case study experience.

4.2. Results and Findings

According to a review of recordings regarding working hours and corresponding, categorized tasks from the most recent PdM case studies we have worked on together with corporate partners, the time, spent on specific tasks, roughly distributes as follows: 10% problem and goal definition together with stakeholders and data acquisition; 60% data merging and preprocessing; 15% machine learning based experiments and evaluation; 15% result preparation and discussion with domain experts of corporate partners. Since data analytics projects follow an iterative and incremental problem solving process, several tasks are repeatedly executed, overlap with others and thus, can not be strictly separated. Considering this and the limited number of analyzed projects, the stated percentages represent an estimation of our own recent workload distribution, which may vary for others, differently situated PdM use cases. Nevertheless, we want to highlight that for instance, the ratio between time spent on data preprocessing and the presumable main task to perform machine learning experiments, match fairly accurate with results of a survey conducted in 2016 with about 80 data scientists [23] regarding their workload distribution. As for other data analytics applications, problems regarding data availability and quality, which force to spend a lot of time on data preprocessing before moving on to data mining (i.e. machine learning experiments), are the key factors also decelerating PdM projects. However, in the scope of the processed use cases, we identified additional, more PdM specific challenges.

- Data merging: Apart from collecting and connecting all available resources, PdM applications require to label data sets with information from manual inspection regarding the monitored machinery's condition. If no automatic labeling system is available, maintenance protocols must be parsed and aligned to the monitoring data, otherwise generated models may not be able to distinct properly between "normal" and "erroneous" condition.
- Online applicability: Since PdM approaches aim at preventing breakdowns as fast as possible, data must be consolidated, preprocessed and analyzed online and in time, while the machine is running.
- Reactivity vs. false positive rate: Finding a breakdown prediction model, which reacts fast, yet precise during online data stream evaluation, is a cumbersome task, since it represents the search for a tradeoff between two concurring goals. One major reason therefore is that there are numerous possible errors for complex industrial machinery, which can be highly diverse, yet hard to separate from each other. This makes it especially hard to define proper training data sets, since new, previously unknown errors are always possible.
- Customer expectations and realistic objectives: Due to the already well established vision of Predictive Maintenance in the Industry 4.0 scope, as well as the success of artificial intelligence in other domains (e.g. voice and image recognition), expectations regarding data analytics methods are very high among industry managers and practitioners. Although scientific literature provides several examples of successful PdM implementations performing accurate remaining useful lifetime prediction on machinery [8, 13, 34], in our experience, most (unreported) use cases begin with similar goals, but end with less outcome. A close and continuous dialogue between all corporate stakeholders (innovation managers, machinery engineers and operators, maintenance personnel) and scientific partners, helps to define feasible objectives for any data analytics project. As the goals and characteristics of PdM applications can be so diverse, an early and clear understanding of the realistic potential of the targeted application domain and the available data is especially important.
- Lack of recorded breakdown events: Most PdM-considered breakdown events occur very seldom, such that there is simply not enough data to train any models or rules from.

Even facing these challenges, our preliminary results and the feedback from stakeholders, confirm the potential and interest regarding Predictive Maintenance. However, further research to facilitate the ongoing transition from concept to application is necessary.

5. Conclusion

Augmented Reality, Additive Manufacturing and Predictive Maintenance represent three major technological trends in the ongoing digital transformation of manufacturing industry. This work summarizes results and key findings regarding the maturity of these technologies for practical application, which have been gathered in the scope of a recent basic research project and added case studies.

In the case of Augmented Reality (AR), technology still needs to evolve. We see that current hardware still cannot completely fulfill industry requirements, especially when factors like rough weather conditions, noise, dirt and safety regulations (such as mandatory hard hats, work gloves and safety glasses) come into play. Nevertheless, our study has shown that the potential of AR-supported remote assistance is considered high. In this scenario, the customer is able to carry out a repair task, guided remotely by an expert located at the manufacturer's site. We see, that further studies are necessary to fully exploit this potential.

Laser Metal Deposition (LMD) is an additive manufacturing method, which stands for high flexibility and extensive performance. We think there are a lot of possible LMD applications which will lead to a further spread of the process in the next years. Nevertheless, we see the need for continuing process parameter related material investigations to increase the variety of available metal powders for the LMD process that help to set up new use cases.

Regarding Predictive Maintenance (PdM), we see that although current prototypical approaches using machine learning algorithms for data stream analysis are already quite successful, real-world implementations are still rare. Domain-specific problems such as the availability of labeled data and the tradeoff between breakdown prediction reaction speed and confidence, rank among the key factors, which currently hamper a successful transition from theoretical approach to deployment. Nevertheless, as the concept of predictive maintenance promises great potential to save time and material, it will continue to attract the interest of researchers and practitioners and with the maturing digitization of industry a growing number of real-world implementations is certain.

Although, each of the covered technological trends is capable to disrupt manufacturing industry and hence, currently witnessing a boom, we identified several major challenges to overcome before leveraging the technologies' full potential. Be it limitations regarding hardware, the need for more extended experiments, a lack of high quality data, or not fully developed methodology, both further basic and application oriented research is necessary.

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