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Data-Driven Maintenance: Combining Predictive Maintenance and Mixed Reality-supported Remote Assistance

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Abstract

Predictive Maintenance and Mixed Reality are two enabling technologies, which enable effective ways to support future maintenance work in factories. Predictive maintenance techniques are designed to help determine the condition of machines and machinery parts in order to estimate when maintenance should be performed. Mixed reality describes ways to merge digital (or virtual) information with real environments, where both worlds can interact in real-time. Both technologies show potential to support workers in industrial settings to accomplish their tasks more effectively. Especially the field of remote assistance (or remote support) where workers are visually guided through maintenance tasks via smartphones or smartglasses and mixed reality-supported information, are described to be disruptive. In this paper, we describe our concepts and ideas to integrate both technologies into future learning factories. Following this idea, predictive maintenance algorithms trigger a specific maintenance task and inform a technician. If the technician needs further support at the component in need of a maintenance check, she can trigger a remote support call with an expert. Both can make use of anchored annotations to discuss and solve the problem. We present our current research, as well as a design proposal to combine both technologies in future learning factories.

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Keywords: Predictive Maintenance; Mixed Reality; Smart Manufacturing

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1. Introduction

Predictive Maintenance (PdM) and Mixed Reality (MR) are among the most intensively investigated topics in the scope of recent developments concerning the digitalization of production industry [1,2,3,4,5]. The idea of predictive maintenance, to plan maintenance tasks proactively based on a system's actual current and predicted future condition – in opposition to common reactive (i.e. break-fix) and preventive (i.e. periodical) maintenance strategies – promises great potential: Based on improved predictability of machinery degradation and breakdowns, maintenance can be triggered if necessary without redundancy, downtimes can be reduced which increases productivity and furthermore, the form of future maintenance contracts may significantly change [6]. By means of MR-based remote assistance (or remote support), a maintenance worker is visually guided through maintenance tasks via smartphones or smart glasses and augmented annotations. Both technologies are still in an early phase of development.

In our work, we present a design proposal to combine both technologies in real-world settings and learning factories. The first part deals with predictive maintenance and describes the schematic implementation concept for the future smart factories. Chapter 3 explains the concept of a MR-supported remote assistance tool based on PdM data and covers current challenges with regard to real-world usage.

2. Condition Monitoring Testbed

From a technical viewpoint, predictive maintenance requires to equip the system of interest with sensors and to analyze the emerging data stream in real-time with modern machine learning algorithms on high performance computing platforms, such that the production system's condition can be estimated or even predicted. With the advent of new technologies, such as the Industrial Internet of Things (IIoT) or Cloud Computing [2], and the continuing decline of costs for necessary hardware (cf. sensor equipment, computing resources), predictive maintenance is becoming more attractive for the whole production sector, not only for highly complex or secure areas, such as aircraft engine maintenance. However, similar to the situation of other trending technologies, such as mixed reality glasses, real-word implementations of predictive maintenance in industry are still quite rare, or only in a prototypic state. Based on the experience from our recent case studies, we identified several reasons for that, including

- a lack of viable measurement data and corresponding maintenance protocols,
- reservations concerning disruptive technologies on the part of domain experts, such as maintenance operators,
- a lack of application domain knowledge for successful algorithm selection and adaption on the part of researchers.

Nevertheless, companies are willing to invest in topics such as PdM and MR, and strive to reach a productive level with them ([3]). In order to address some of the detected barriers, we designed a PdM/MR testbed to show the technical feasibility and to provide a platform for discussions between domain experts and researchers concerning the possibilities of these technologies.

2.1. Testbed Design

The drafted PdM/MR testbed consists of several soft- and hardware components. The communication between these components follows the publisher-subscribe pattern and is handled by a central *Message Queuing Telemetry Transport* (MQTT) broker, as visualized in Fig. 1, representing the schematic implementation concept.

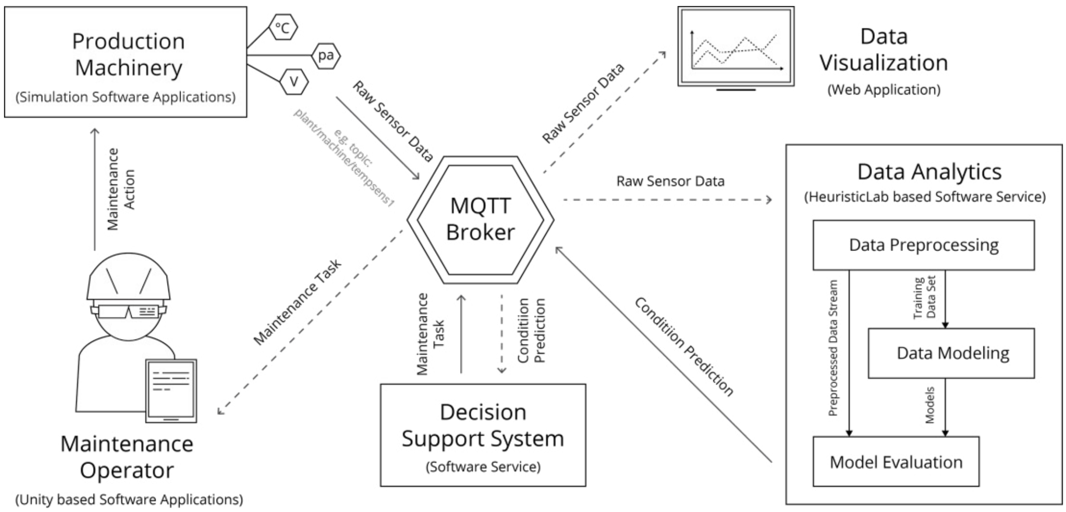

Fig. 1. Schematic implementation concept for the simulated smart factory (read clock-wise starting at "production machinery").

In order to simulate a sensor equipped production machinery, we use a software tool presented in previous work [7]. The tool enables to generate realistic seeming sensor data, which is continuously published (e.g. at every full second) via MQTT. Based on a configuration file, the characteristics of data streams are defined (mathematical function to generate data points, update interval, publishing route etc.). Concerning the simulation of a predictive maintenance showcase, the tool also allows configuring the dynamics of a stream. Therefore, conditions may be defined (e.g. "at a certain time", or "if a certain stream transgresses a certain threshold"), at which the data generation function is altered and hence, a change of system behavior (i.e. changing machinery conditions) is simulated. To improve the understanding of what the streaming application is currently doing, a web based data visualization application was developed, which subscribes to the published streams and visualizes them, using dynamically updated line plots.

The data analytics component subscribes to the raw sensor streams, processes them and finally estimates the current and future state of the simulation (e.g. "machinery 96% healthy"). The software service is implemented on the base of the open source framework HeuristicLab [8]. It is divided in an offline model learning and an online model evaluation phase. However, both phases perform data preprocessing tasks, such as consolidation of sensor streams, outlier filtering, feature selection, feature creation etc. before processing the data further on.

In the first phase, data points are collected for a certain period, subsequently preprocessed, labeled with the corresponding machinery condition and structured as follows: one column per feature (i.e. sensor) and one row per timestamp, including a corresponding condition label per row (i.e. a percentage value). In this testbed, the necessary condition information is mapped to the sensor data automatically by the streaming simulation. However, in a real-world use case usually domain experts would have to perform manual checks at the monitored system and hence, the information cannot be provided in real-time. Further, we use various machine learning algorithms, such as Random Forest, Support Vector Machine or Symbolic Regression to create so-called regression models based on this training data set. The models use the sensor values as input and the condition label as estimation target variable. Alternatively, the estimation horizon of models may be increased, by providing additional time-relevant information as synthetic features, such as the *moving average* or the *moving standard deviation* of sensor values. This way the models may be capable of performing predictions concerning a system's future condition to some extent. Since the correct condition at each time stamp is known in this *offline* phase, we are able to evaluate the models by computing the estimation error and hence, pick the most accurate model from this phase and persist it for the next one. In order to enable accurate model estimations, the training data has to cover various types of system behavior ranging from "healthy" to "worn out".

The second phase is performed *online*, meaning that each streaming update of sensor data, triggers an action of the analytics component. After passing the new data points to the same preprocessing routine as in the latter phase, the resulting data row is transmitted to the previously trained model, however, without a label regarding the system condition. The regression models output – the estimated system condition – is sent to the MQTT broker.

Since there is no real-time information concerning the actual machinery condition in a real-world scenario – which would make the whole data analytics component redundant – the machine learning using offline phase can be performed only with a certain time lag, after a manual condition evaluation by domain experts. Therefore, the offline phase is performed once in the beginning and iteratively in the background of the running online system (i.e. in parallel to the second phase) within defined intervals. This way, estimation models can adapt new long-term trends in the data stream. Based on the model estimations, a subsequent decision support component derives necessary maintenance tasks, if a certain condition threshold is undershot. Relevant data needed to complete the maintenance task is transmitted to the worker's device (e.g. smartphone), who is then directed to the component in need of servicing. The following Section describes our concept for MR-supported remote assistance.

3. MR-Supported Remote Assistance

According to Gartner's hype cycle [3], Mixed Reality (or "XR", covering the whole spectrum of AR, VR and MR technologies) is about to overcome the trough of disillusionment. Nevertheless, until MR can reach the plateau of productivity, various challenges have to be tackled until companies can make use of its full potential. Although concepts for MR usage in industrial context exist [4,5], only few companies use the technology in their daily work routine. Applications in this area (especially with a strong focus on 3D CAD data) are often developed in an ad-hoc fashion and the development does not follow predefined processes or methodologies [9].

Learning factories provide a valuable playground to collect experiences with the advantages (and disadvantages) of current hardware and software solutions as well as implementation processes.

3.1. Challenges and Limitations

Remote support provides meaningful ways to assist workers in their daily work routine when unpredictable problems arise. The common approach up-to-date is to call an expert technician. Video calls simplify the process, but problems arise, when an expert wants to pinpoint a certain detail on a machine or machinery part. Mixed reality provides means to "anchor" annotations in the real environment, displayed on the worker's screen (e.g. smartphone or tablet) or in her field-of-view (on smart glasses, e.g. *Microsoft HoloLens*). What looks promising in many advertising and promotion videos, turns out to be a challenge in real-world usage. Commercial products in this area exist (like *Remote Assist* by *Microsoft* or *Chalk* by *Vuforia*), but these solutions are restricted to one specific device or ecosystem. Our goal was to implement an open-source and platform-open remote support solution for companies to provide a quick way to gain insight into the technologies potential.

Before starting the implementation of a MR remote-supported tool, four Austrian-based companies were asked to share their expectations and usage scenarios in their field. Following the research of [10], we organized semi-structured workshops (each lasting two hours) with the following goals:

- Define the field of activity and the current challenges with maintenance work.
- Define the preconditions of their work environment (e.g. safety regulations, hands-free work etc.).
- Define the expectations, hardware requirements and a specific use case for MR-supported remote assistance

Table 1 sums up the basic information for each company as well as the results of the workshops. The company sizes vary from small and medium-sized enterprises (company C, D) to large enterprises (company A and B). For each company maintenance work is an important field of work, both indoor and outdoor. 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 (such as mandatory hard hats, work gloves and safety glasses) play an important role in everyday's work life. Surprisingly, current smart glasses (even those with an explicit industry focus such as the *Epson Moverio* series or smart glasses by *Vuzix*) cannot fulfill these requirements, since they are not suitable for outdoor usage in rough weather conditions. In addition, gloves complicate the control of the devices (especially when they are equipped with touch input modules).

Table 1. Summary of the workshop results.

Company (Employees)	Field of activity	Maintenance Activity	Preconditions	Needs
A (20.000+)	Components for rail and commercial vehicles	A customer or a service technician triggers a support call. He scans a barcode to identify his position and requests support by an expert in the back office.	- Mainly indoor (railway carriage), sometimes outside - Rain and wind, no dirt, high noise level - Hardhats required	- Hands-free required - Access to documentation (images & diagrams) - documentation of maintenance steps
B (2500)	Industrial plant manufacturing	An employee with low experience level gets support by an expert. One expert can supervise various construction sites without being on-site.	- Dirt, high noise level, varying temperatures, varying lighting conditions - Hardhats and work gloves mandatory	- Hands-free required - Possibility to add content - Gamification mechanisms to reward sharing of expert knowledge
C (500)	Aerospace engineering	A device at the customer's site is defect. A service technician needs support and triggers the remote support call. The support staff can invite another expert to the call (3+ participants).	- Good lighting conditions, high noise level, varying temperatures, acid oil splash possible, - Hardhats or safety glasses not mandatory - Wi-Fi available	- Hands-free not required - auto-recognition of devices and parts - documentation of maintenance steps
D (100)	Surveying and information technology	A sensor on a tunnel-boring machine reports implausible data. A novice maintenance worker is sent out to check the sensor.	- bad lighting conditions, high noise level, dust, dirt, varying temperatures (-20°C up to +40°C), splash water - Hardhats mandatory - Wi-Fi available, but limited	- hands-free work required, - Access to documentation (images & diagrams), - documentation of maintenance steps, - offline feature

Based on these findings we started to implement a prototype for MR-supported remote assistance. We used *Unity3D* for visualization tasks, *WebRCT* to enable the audio/video communication between expert and worker (the person in need of assistance) and *ARFoundation* for anchoring annotations and tracking the environment. Since common smartphones and tablets are not equipped with depth-cameras, tracking relies on the 2D information of the device's camera image and a "*Simultaneous Localization and Mapping*" (SLAM) algorithm, which extracts feature points from the user's real environment. This approach works well for environments with distinct features, but fails for plain and monochrome surfaces (like white walls). In this case, anchored annotations do not stick to the anchored position and start moving when the perspective changes. Fig. 2 shows screenshots of this prototype. The worker (in this case equipped with a smartphone) triggers the call and establishes an audio/video connection to an expert. Both of them can pinpoint details in the real environment using various annotation tools. By now, the application provides the following features:

- Establish a video/audio call with a remote expert via smartphone, tablet and smart glasses (MS HoloLens)
- Set annotations in the live video image in both directions (expert and worker): arrows, text, simple drawings
- Low bandwidth mode and text chat: send texts and annotated still-images instead video streaming

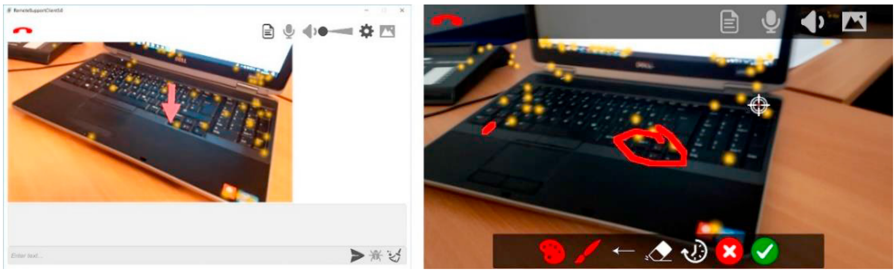

Fig. 2. (a) Remote assistance prototype, expert view on a desktop PC, a virtual arrow was anchored to the real-world scene; (b) client view on a smartphone screen, an annotation was drawn with a free-hand drawing tool.

First test sessions in laboratory environment with students show that the prototype works from a technical point of view. The companies mentioned in Table 1 tested the prototype on smartphones in their real working environment for maintenance tasks. Altogether, interview data of four participants was collected and analyzed. The results show that the current solution is still not (or only partially) useable, since current hardware devices (especially smart glasses) cannot fulfill the requirements for industrial usage (like dirt, moisture or safety regulations). In addition, the smartphones' battery lifetime and computing power (in our case *Samsung Galaxy S7* smartphones) was not sufficient to be able to operate the application for longer than 15 minutes. Nevertheless, the tool provides a first approach to demonstrate the potential of MR-supported remote assistance.

4. Conclusion and Future Work

With the presented concept, we aim to combine and enhance the described PdM- and MR-components in order to provide a comprehensive smart maintenance testbed. The implementation of the concept shall lead us to an immersive simulation, in which the breakdown of a production machinery – simulated by synthetic sensor streams – results in a maintenance task, including the necessary support information. Predictive Maintenance and MR-supported remote assistance are intensively investigated topics in the scope of digitalization of production industry. Both technologies still need to evolve, especially when it comes to the integration into complex production environments. We see challenges in the areas of data preparation, diversity of data formats and acceptance of current hardware solutions (especially smartglasses).

In our work, we presented a design proposal to combine both technologies in real-world settings and learning factories. This proposal serves companies and researchers as a basis to understand the requirements of data-driven maintenance activities in future factories.

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References

[1] S. Selcuk, Predictive maintenance, its implementation and latest trends. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 231.9 (2017), 1670-1679.

[2] F. Civerchia, S. Bocchino, C. Salvadori, E. Rossi, L. Maggiani, M. Petracca, Industrial Internet of Things monitoring solution for advanced predictive maintenance applications. Journal of Industrial Information Integration, 7 (2017), 4-12.

[3] Gartner Inc., 5 Trends Emerge in the Gartner Hype Cycle for Emerging Technologies. https://www.gartner.com/smarterwithgartner/5-trends-emerge-in-gartner-hype-cycle-for-emerging-technologies-2018. Accessed: 2019-12-06.

[4] R. Palmarini, J. A. Erkoyuncu, R. Roy, H. Torabmostaedi, A systematic review of augmented reality applications in maintenance, In *Robotics and Computer-Integrated Manufacturing*, 49 (2018), 215-228.

[5] N. Zenati-Henda, A. Bellarbi, S. Benbelkacem and M. Belhocine, Augmented reality system based on hand gestures for remote maintenance, *2014 International Conference on Multimedia Computing and Systems (ICMCS)*, Marrakech, 2014, pp. 5-8.

[6] R. Roy, R. Stark, K. Tracht, S. Takata, M. Mori, Continuous maintenance and the future – Foundations and technological challenges, CIRP Annals, 65(2), 2016, 667-688.

[7] J. Zenisek, J. Wolfartsberger, C. Sievi, M. Affenzeller, Streaming Synthetic Time Series for Simulated Condition Monitoring. IFAC-PapersOnLine, 51.11 (2018), 643-648.

[8] S. Wagner, M. Affenzeller, Heuristiclab: A generic and extensible optimization environment. Adaptive and Natural Computing Algorithms. Springer, Vienna, (2005), 538-541.

[9] I. Seidel, M. Gärtner, J. Froschauer, H. Berger and D. Merkl, Towards a holistic methodology for engineering 3D Virtual World applications, *2010 International Conference on Information Society*, London, 2010, pp. 224-229.

[10] I. Fernández del Amo, J. A. Erkoyuncu, R. Roy, S. Wilding, Augmented Reality in Maintenance: An information-centred design framework, *Procedia Manufacturing*, 19 (2018), 148-155.