SMART MAINTENANCE LIFECYCLE MANAGEMENT: A DESIGN PROPOSAL

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ABSTRACT
Given the latest trends toward the implementation of Industry 4.0 principles, the proposed research work combines human assistance technologies such as Virtual and Augmented Reality with advanced data analysis techniques and tools to develop a comprehensive strategy for Predictive Maintenance planning and execution. On one hand, using Augmented and Virtual Reality technologies, workers are effectively assisted during maintenance operations towards better performances and lower error rates. On the other hand, Predictive Maintenance entails strategies for maintenance planning based on machines' current conditions to avoid unnecessary overhauls.
Thus a seamless integration of Virtual and Augmented Reality with Predictive Maintenance is envisaged to bring substantial advantages in terms of productivity and competitiveness enhancement for manufacturing systems and represents a step ahead toward the real implementation of the Industry 4.0 vision.

Keywords: Industry 4.0, Virtual / Augmented Reality, Data Stream Analysis, Predictive Maintenance, Symbolic Regression

1. INTRODUCTION

Industry 4.0 is characterized by an unprecedented interconnection of things over the Internet, which brings the physical and the virtual world together. Cyber-Physical Systems (CPS) integrate physical devices (i.e. sensors) with software components, thus providing the availability of an immense amount of sensor data describing the condition of products, machines etc. The challenge for manufacturing companies is to obtain substantial benefits from analysis of the collected data in various application areas such as production planning, quality management, maintenance and so on.
Predictive Maintenance (PdM) means strategies to plan maintenance actions based upon a machine's current condition instead of reacting to breakdowns (corrective maintenance) or following fixed empirically intervals (preventive maintenance) as stated by Li, Wang and He (2016). Therefore, sensors, attached to a machine, keep track of its behavior over the time and a subsequent analysis component evaluates the resulting data stream in order to prognose factual maintenance needs and determine an optimal moment to trigger correcting actions. Hence, PdM aims at preventing machine breakdowns without performing unnecessary overhauls, leading to higher productivity and increased predictability.
Using Augmented Reality (AR) / Virtual Reality (VR) technologies, workers are effectively assisted during maintenance work – all the more so as using a common data base for PdM and assistance systems in maintenance. Wang et al. (2017), for example, propose a cloud based approach for PdM. Closing the loop of the maintenance life cycle leads to increased productive time of machines and thus contributes positively to productivity and competitiveness of manufacturing companies.
This work proposes a blueprint of how such a life cycle could look alike for real-world implementations, by combining cutting-edge data analysis and assistance technologies.

2. VIRTUAL / AUGMENTED REALITY TECHNOLOGIES FOR SMART OPERATORS

In the context of smart manufacturing systems, operators play a crucial role for the optimal integration of virtual and real assets. It is mainly due to the fact that, operators are expected to be fit from the knowledge generated by and within CPS while providing valuable inputs/feedbacks that are likely to drive CPS toward higher levels of intelligence.
In this perspective the smart operator concept is considered an enabling factor for a practical implementation of the Industry 4.0 vision. Smart operators are endowed with a superior knowledge of the working environment deriving not only from the abilities they acquire while executing daily tasks but

also from the interaction with high value-added contents/tools that contribute to enhancing his ability to perceive, understand and act in the workplace. Such contents/tools are mainly attributable to virtual and augmented reality. As a matter of facts, virtual and augmented reality contents are able to provide different levels of immersion and therefore to engage operators in unique experiences where real and digital objects are intertwined. As well known, augmented reality technologies allow keeping the actual view of real objects/systems while adding further contents levels on top of them whereas virtual reality allows recreating digital twins and highly interactive objects. These basic features make AR and VR well suited to achieve an optimal integration between real words objects and cyber resources in Industry 4.0 environments. Hence, within the scope of this research work, a substantial effort has been done toward the definition of an application methodology/approach that leverages on AR and VR as enabling factors for smart operators in smart factories with a special focus on maintenance operations. In particular, the basic idea behind the proposed approach/methodology is to support operators in complex, real time man-machine interactions that usually occur during maintenance operations providing visual, self-explanatory information on how to execute a specific task/procedure as well as demonstrating the best interaction patterns. The main building blocks of the proposed approach include:

1) Develop geometric models recreating real objects such as machines and equipments in the working environment;
2) Build Virtual environments recreating a typical or particular manufacturing system;
3) Dynamical integration of geometric models within the relevant virtual environment;
4) Identify and recreate each object dynamical behavior;
5) Set up interconnections with real-time data sources (such as sensors networks) to recreate within the virtual word the operational conditions of the real word system;
6) Procedures mapping, analysis and 3D reconstruction.
7) Knowledge resources digitalization and organization.
8) Dynamic binding of knowledge digital assets to real objects in the workplace for AR / VR contents delivery.

The practical implementation of the proposed methodology turns out into a working tool whose main features/functionalities can be summarized as follows:

- let operators be immersed and interact with a cyber space where they can gain meaningful insights, based on virtual and augmented reality, about man-machine interaction procedures for maintenance operations compliant with safety standards and principles;
- exploit virtual and AR resources for operators' preliminary training on high risk tasks in maintenance operations;
- support operators providing information that is usually not available in the workplace (i.e. expected maintenance operations, warning on unexpected dangers, risks that are likely to occur, suggestions on how to increase productivity, etc) as well as operator's training;
- send warning messages about the outcomes of improper operations (i.e. what happens if a maintenance operation is not performed, if the operator fails, etc).

Keeping in mind the need to preserve operational efficiency without hindering operators' workability, the many possibilities offered from wearable technologies have been investigated to detect the most suitable system configurations. As a consequence it can be deployed and integrated with different fruition technologies such as: tablets, headsets, interactive whiteboards, monocular eyewear, smart glasses, armbands and gesture recognition technologies as shown in Figure 1 and Figure 2.

Figure 1: Augmented reality contents delivered through mobile devices


Figure 2: Augmented Reality contents delivered through monocular eyewear

3. DATA BASED PREDICTIVE MAINTENANCE

Real world data series, collected in a PdM scenario as depicted in Section 1 are presumably quite complex to analyze. Some of these generated features might have correlations to others, which leads to redundancies and could bias analysis results. Moreover, it is most likely that not all relevant system aspects are covered by sensors, which also complicates a reasonable analysis. Another challenge refers to the high volume of a data stream, which is updated e.g. every second to represent a system's inner workings correctly (Gubbi et al. 2013), but therefore, computationally demanding to analyze. Furthermore, sensor values can go missing or get skewed while they're transferred from one to another component in a PdM setup as proposed in Section 4. In addition, fault system behavior might not be manifestable in single sensor series, but in their changed interplay (Saxena et al. 2008). Hence, the transgression of sensor thresholds, might not suit as a trigger for maintenance in a robust decision support system, since these thresholds only deal with one system dimension at a moment.

In order to address these considerations, first a preprocessing component, consisting of filters and routines for missing value handling, signal smoothing and feature extraction has to be setup. Based on the preprocessed series the actual stream analysis is performed in a second component downstream, which models the inner workings and output of the monitored system. Recent works on smart maintenance solutions, propose machine learning methods like Random Forests (Scheibelhofer et al. 2016) and Hidden Markov Models (Cartella et al. 2015) to build models in order to identify a tracked system's behavior as close as possible.

In this work we focus on Symbolic Regression models, developed with Genetic Programming (GP), a method applicable to machine learning. Symbolic Regression models suit well to describe systems which incorporate biological or physical processes, like the industrial production plants in a PdM implementation. The models are mathematical functions, combining terminals like variables and constants with a broad palette symbols, such as arithmetic, trigonometric or conditional operators. The GP algorithm develops a population of these functions, which are usually represented as syntax trees, following evolutionary concepts like parental selection, crossover and mutation, in order to find a good estimator for the observed system. One major advantage of Symbolic Regression models compared to other representations is that they are interpretable for domain experts, which might enable them to gain deeper insights (Affenzeller et al. 2009).

4. SMART MAINTENANCE

Based on current research for innovation of maintenance in industrial applications, using human assistance technology on one end and data analysis on the other, the idea of joining these two approaches towards a smart PdM adaption arose.

4.1. Related Work

In the current movement of Industry 4.0, several recently presented projects deal with modernizing maintenance towards PdM. In the work of Li, Wang and He (2016) the interdependencies of *IoT*, *Cyber-Physical Systems* and *Big Data Analytics* in the context of Industry 4.0 are highlighted and a PdM setup, using these technologies and methods, is briefly outlined. Sayed, Lohse and Madsen (2015) present a component based reference architecture for PdM implementations, using a very similar mix of IT, in greater detail. The work presents the overall architectural approach and describes all employed components on a software level, down to activity diagrams. Furthermore, Wang et al. (2017) present a mobile agent based paradigm for PdM, including implementation details and an experimental study on induction motors.

The potentials of AR-based knowledge sharing in industrial maintenance are explored in Aromaa et al. (2018). Here a field study has shown positive users' experiences as well as a good level of acceptance of AR systems. Similarly Uva et al. (2017) evaluate the effectiveness of augmented reality for conveying technical instructions. A seven-task maintenance procedure on a motorbike engine has been considered as case study and the outcomes of the study confirmed a performance improvement and lower error rates especially for difficult tasks.
Interesting applications can be found in Alam et al. (2017) where a AR/VR IoT prototype for maintenance tasks in complex working environments is introduced; in Kranzer et al. (2017) where in Intelligent Maintenance planner to provide augmented reality information are designed; in Jayaweera et al. (2017) that propose an AR wearable system to enhance the capabilities of machine operators and repairmen; in Akbarinasaji and Homayounvala (2017) that present an optimized framework which combines context-awareness and AR for training and assisting technicians in maintaining equipment to improve field workers effectiveness in an industrial context; and many others.

A state of the art on AR in maintenance can be found in Palmarini et al. (2018) highlighting also the areas where AR technology still lacks of maturity that are mainly related to reliability and robustness.

Although data analysis for PdM as well as AR/VR have been addressed in several projects in the context of industrial maintenance, to the best of our knowledge there is none proposing an architecture to combine them. Even if an interesting attempt to merge PdM and AR can be found in Mourtzis et al. (2017) that consider condition-based preventive maintenance supported by augmented reality and smart algorithms. However, unlike the approach we propose in this research work, little attention is paid to VR contents and the system is devised to work real-time with no possibility to be used for off-line training.

4.2. Maintenance Lifecycle

This work aims at proposing a general concept of how data analysis methods and AR/VR technologies could be employed beneficially to develop a comprehensive smart maintenance strategy. Starting with a monitored industrial production plant, Figure 3 illustrates how information, initially in form of sensor data, is transferred and transformed by cloud services to analysis software on a high performance cluster. Based on this system's output, concrete tasks are derived and sent to tablets and head mounted virtual/augmented reality glasses used by maintenance operators. These people close the depicted cycle when performing the generated instructions on the real-world plant. Thus, the figure presents how the pathway of data from acquisition, over digital transformation to its physical reintegration can be designed. We refer to this proposed design as *Smart Maintenance Lifecycle*.

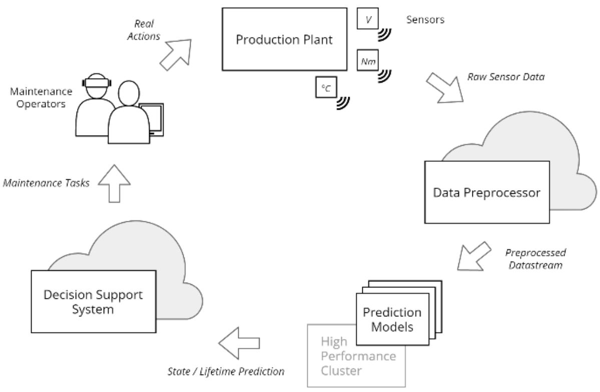

Figure 3: Smart Maintenance Lifecycle

Before the workflow incorporated by the presented lifecycle can be performed, all components have to be setup on the base of qualified test data series, each representing known states – i.e. normal and defective behavior – of the monitored system. During a second phase the installed filter rules, trained prognosis models and developed decision trees are evaluated on unseen sensor data stream. In the following, purpose and tasks of all components during these phases are described:

4.2.1. Production Plant

The production plant represents the maintenance lifecycle's start and end point. In the initial setup phase, it is equipped with condition monitoring sensors, which are generating data series in high frequency. As part of an IoT implementation, each sensor is individually connected to the cloud and continuously transferring the sensed values to the subsequent service. On the other end, the plant receives maintenance actions, performed by human operators, eventually on the base of its self-produced data. Hence, the production plant is source of digital information and sink for physical actions.

4.2.2. Data Preprocessor Service

This cloud service aggregates sensor data to a dense, equidistance stream, which makes it reasonably analyzable. The component filters outliers and signals with too many missing values, interpolates missing values, levels out the impact of noise and conclusively transfers the preprocessed data stream to the prediction models. Therefore a pipeline of rules and filters is developed in the initial phase.

4.2.3. Prediction Models

As outlined in Section 3 the model creation process is guided by the GP algorithm so that domain experts only have to provide qualified data sets. In our design approach we propose to employ a High Performance Cluster (HPC) for the initial training and the subsequent evaluation of Symbolic Regression ensemble models. These prediction models enable to analyze the preprocessed data stream considering two different aspects:

- Prediction of Remaining Useful Lifecycles (RUL) for the production plant's components (Saxena et al. 2008)
- Detection of abnormal or unknown system behavior and therefore, the need for checks and possibly maintenance

The emerging estimations are subsequently transferred to the cloud based decision support system for final reasoning. The necessity to deploy the model training algorithms on a HPC infrastructure origins from the complex task to analyze a great amount of high dimensional test data series. Furthermore, the infrastructure also speeds up the real-time evaluation of the created models in the second phase, especially when employing not only one, but large ensembles of models.

4.2.4. Decision Support System

Based on the previously made estimations regarding RUL and anomalies, this component reasons if, what and when actions should be triggered in order to prevent or correct an allegedly encountered defect. Hence, this component holds accountable for maintenance scheduling, which might not be a computational demanding task, but one, which is predestinated to run at the easy accessible and resilient position in the cloud. The decision support system consists of a set of hierarchically connected rules, formulated by domain experts. These *decision trees* evaluate the previous system's output so that the most proper concrete maintenance task is generated and textual and graphical content from a knowledge database to the subsequent system is forward.

4.2.5. AR/VR Technology and Operators

The maintenance operators, equipped with tablets and head mounted virtual/augmented reality glasses receive the decisions in form of instruction material from the

ISBN 978-88-97999-85-0; Affenzeller, Bruzzone, Jiménez, Longo and Piera Eds.

connected DSS cloud service. First, the operator is acoustically and visually informed about the issue and subsequently guided to the respective machine. The necessary maintenance actions, construction plans and (video-) tutorials etc. are displayed in order to support the service process optimally. The physical actions, which the operator performs, close the smart maintenance lifecycle. In greater detail, after contents are displayed, the operator can freely interact with them i.e. zoom in and zoom out of 3D representations, read text info, interact with virtual reality and/or augmented reality contents, etc.
Moreover, as mentioned above, operators have access to 3D animations explaining safety and maintenances procedures required along the period of operation. Each procedure is broken down into steps and each step is visually shown through an augmented 3D virtual animation and vocally explained (as shown in Figure 4). Along the explanation, visual and vocal messages draw the attention on potential dangers or risks the operator may incur.

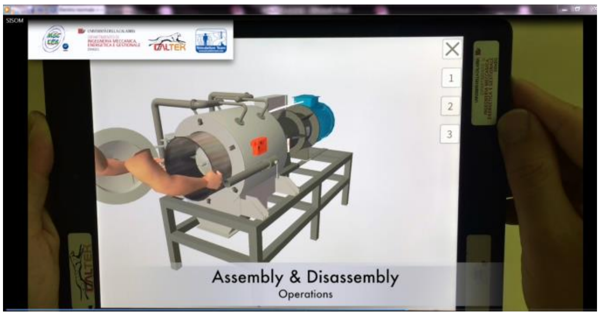

Figure 4: A sample of 3D animation for maintenance procedures

Besides, the operator can even search for additional contents typing keywords in a text search box.
This approach can be applied both real-time and offline for a variety of purposes:

- make available knowledge resources that usually may not be directly available in the workplace;
- be a consultation mean for operators' performances improvement thanks to easy and fast access to information contents;
- be an immersive and absorbing environment for preliminary training on new and/or complex procedures for maintenance operations;
- be an instrument for safety and security enhancement.

4.3. Continuous Adaption

In order to adapt current trends and to validate the applied maintenance actions and their effect, we propose to repeat the initial setup phase occasionally. Optimally, the phases work interleaved, so that single components are updated according to their performance. We propose to trigger an update if the quality of a component's output starts to decrease significantly. For instance, maintenance decision rules should be altered if the system triggered wrong or not necessary actions, or the adopted actions did not generated the expected results. On the other end, the preprocessing rules as well as the prognosis models should be updated after some cycles in order to react on changing conditions.

To detect the necessity for updates, a comprehensive maintenance validation workflow shall be employed: If the actions proposed by the decision support system do not fit the actual needs of the monitored plant, according to a hands-on analysis by a human operator, this information shall flow back and update the rule base automatically. We propose that the operator uses the assistance technology – i.e. tablets or AR/VR glasses – to respond her own impression by entering an estimation for the remaining useful lifecycles into a digital form or by using a voice recognition module. The modification of rules could be automated by penalizing poor decisions so that they are executed less likely. A gradual or more abrupt increasing frequency of such wrongful decisions might indicate, that the monitored system is under change. Hence, the decision support system should trigger the training of new prediction models on the base of more recently collected data series, if a certain threshold of a "poor-decision-counter" is exceeded. A similar routine could be applied to the preprocessor component. This continuous adaption process manages updating the components so that the maintenance lifecycle remains smart.

5. CONCLUSION

Within the scope of this research work, a substantial effort has been done toward the definition of an application methodology/approach that combines AR and VR technologies with data analysis methods as enabling factors for smart operators in smart factories to develop a comprehensive smart maintenance strategy. The practical implementation of such strategy turns out into a working approach that can be deployed at operational levels in order to:

- plan maintenance actions based upon a machines current conditions;
- deliver virtual and augmented reality contents on how and when procedures for maintenance operations are to be executed;
- exploit virtual and AR contents for operators' preliminary training and performance improvement with respect to high risk tasks in maintenance operations;
- support operators with information that is usually not available in the workplace (i.e. expected maintenance operations, warning on unexpected dangers, risks that are likely to occur, suggestions on how to increase productivity, etc)

ACKNOWLEDGMENTS

The work described in this paper was done within the projects:

"Smart Factory Lab" which is funded by the European Fund for Regional Development (EFRE) and the state of Upper Austria as part of the program "Investing in Growth and Jobs 2014-2020".

"SISOM" funded by the Italian National Institute for Insurance against Accidents at Work (INAIL) under the BRIC 2015 program.

"SG-ICT: Serious Game at Increased impact on Culture and Tourism" funded by Ministry of Education, Universities and Research (MIUR) under the StartUP program.

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