SYSTEMATIC REVIEW

Industry 4.0 solutions for preventive engine maintenance: a systematic review [version 1; peer review: awaiting peer review]

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Abstract

Background: Industry 4.0 is about to revolutionize engine maintenance and support systems with predictive and analytical technologies. Available academic research probes into different expert technologies but lacks a comprehensive overview of available standards and their interaction.

Methods: The study conducts a systematic review based on the PRISMA Concept 2020 to provide a systematic overview on articles empirically analyzing technologies for maintenance and repair using industry 4.0 technologies.

Results: The review identifies four key development fields of industry 4.0 solutions for preventive engine maintenance and repair: sensor equipment, digital networks, technology integration and augmented behavior. All four technologies can be intertwined to implement industry 4.0 based solutions in the industry shopfloor. A cycle model illustrating this is derived.

Conclusions: Industry 4.0 based maintenance and repair in the shopfloor is a promising technological development field but further research is required to utilize the individual technologies consistently and integrate them into a comprehensive digital shopfloor environment.

Keywords
Industry 4.0, maintenance engineering, preventative maintenance, shop floor control, smart factory
Introduction
The integration of digital intelligence into products, machines, and equipment in the form of cyber-physical systems requires the adaptation and reconfiguration of production processes (BMI, 2020). Industry 4.0 is an umbrella term applied to the intelligent networking of machines and industrial processes with the aid of information and communication technology (BMI, 2021) and has been formulated as a catchword for industrial development programs of the German government and OECD (OECD, 2017). The autonomous, computer-assisted interaction and communication of industrial machinery, in brief, smart factory designs, promise to dynamize and modularize production, optimize logistics, monitor and control production processes, individualize outputs to customer requirements and define sustainable product lifecycles (BMI, 2021).

Predictive industrial maintenance refers to all processes of monitoring, analysis, and amendment applied before machinery or digital processes fail to retain and grant their full functionality (Zhong et al., 2017; Oztemel and Gursev, 2020). To integrate digital self-optimizing industry 4.0 elements in industrial production processes a paradigm shift of the maintenance and support process chain is required. At the same time industry 4.0 technologies promise to revolutionize maintenance and repair systems for industrial production (Reinhart, 2017, 409). To avoid downtime and bottlenecks in autonomous production networks, preventive maintenance is mandatory, intelligent digital technologies could enable industrial production systems to self-organize and self-implement their maintenance processes (Oztemel and Gursev, 2020).

Industry 4.0 is also, undoubtedly, a fashionable buzzword and a series of publications in preventive industrial maintenance use it (Sony & Naik, 2019; Bongomin et al., 2020). However, a comprehensive overview of relevant preventive maintenance approaches does not yet exist. Integration of the fragmented digitalized solutions for preventive maintenance as postulated by the industry 4.0 principle, is outstanding. Earlier reviews (Zhong et al., 2017; Oztemel and Gursev, 2020; Çınar et al., 2020; Bueno, Filho, and Frank, 2020) in industry 4.0 technologies are more general, i.e. not specialized in preventive maintenance and accordingly provide no in-depth data on the above points.

Methods
This study uses a systematic review of empirically proven technologies to develop an integrative model of preventive maintenance applicable and adjustable to diverse industries using industry 4.0 standards.

First eligibility criteria for study consideration have to be specified: The review includes publications in English language in academic peer-reviewed journals, as well as conference papers published since the initial public discussion of the term industry 4.0 in 2017. Studies published as working papers or final theses in a university context as well as books and book contributions are excluded since these are not peer-reviewed. Publications in languages beyond English and publications not available in full text have to be excluded, to ensure a detailed analysis of the content.

Second information sources the considered articles are retrieved from, have to be specified: to ensure the academic focus of results the study focuses on academic databases. Three major academic data bases are searched for relevant contributions: Web of Science, Scholar Google and Ebscohost. The search was done in June 2021 and the review thus considers publications until 2021.

A homogenous research strategy is applied across all three databases. It uses the following uniform keyword combination to retrieve appropriate studies: “industry 4.0” AND “preventive maintenance” OR “preventive repair” AND empirical. The research is limited to the period 2017 to 2021 to ensure topicality of results in the dynamically evolving field of research. Only studies discussing the issues of preventive maintenance or preventive repair in an industry 4.0 context and within the framework of an empirical study are retained for further evaluation. The titles of the initially retrieved 127 studies are screened manually for relevance to the review. After removal of 52 duplicate or not eligible studies 75 studies remain. Based on a scan of study abstracts 22 studies are deselected for content reasons. 53 studies remain to be sought for retrieval but only 25 studies are openly available in full text from the databases. Textual analysis is done for these studies. Due to lacking applicability four further studies are excluded, six evaluated studies contain no new information. A total of 15 studies were included in the final review. Figure 1 shows the PRISM flowchart (Fauska, 2022).

The data interpretation process is based on a methodology suggested by Webster and Watson (2002). No software is required for this method. First the studies are catalogued in table form in alphabetical order of authors in the form of a content matrix. It summarizes discussed technologies, fields of application, potentials, limitations, and success factors of the respective technologies (Box 1). The textual evaluation (presented in section “Results”) is then organized by order of technologies and adopt a classification described in Deloitte (2017) and Çınar et al. (2020). Ti includes the sections
“sensor equipment”, digital networks, technology integration and augmented behavior. Each section describes a technological subject field of predictive maintenance and repair. All four technological fields interact as shown in the section “discussion”.

The described review method avoids important biases of literature-based research, namely reporting, selection and interpretation biases by applying a coherent set of rules for study retrieval, selection and interpretation. However, some potential biases remain: Since there is only one coder in the person of the author, subjective biases and errors cannot fully be excluded. Further databases and key word combinations could deliver further results however cannot be considered here due to limitations in publication length.

Results
Predictive maintenance systems rely on predictive information to organize maintenance requirements (Jardine, Lin, and Banjervic, 2006), which is (1) gathered from decentral sensor equipment, (2) collected and integrated into digital networks, managed and evaluated in operation centred which rely on (3) technology integration and (4) augmented behaviour (Činar et al., 2020):

Sensor equipment
(1) Smart sensors collect machine-internal or external information to detect and inform on equipment status and status changes (Činar et al., 2020). Sensors collect maintenance information at the level of individual machines and dispose of usually wireless network connections, to feed in time series data on the central network (Jung et al., 2017;
Wang et al., 2020). Smart monitoring technology integrates various types of sensors and pieces of information to conclusive longitudinal data strands and profiles (Zhong et al., 2017).

Digital networks
(2) Digital (wireless) networks are applied to interconnect technological appliances, transfer and store data (Çınar et al., 2020). Smart machinery could shortly be able to survey its performance and repair status based on status and operation protocols and self-inform on repair requirements (Saxby, Cano-Kourouklis, and Viza, 2020). Big data i.e. time series data of smart sensor units are automatically collected, analyzed, and integrated to develop an action schedule (Lee et al., 2019; Powell, 2018).

Technology integration
(3) Technology integration refers to data management and accumulation in the Internet of Things and uses artificial intelligence to process and analyze data (Çınar et al., 2020; Leyh, Martin, and Schäffer, 2017). By integrating machinery data, a maintenance plan for the equipment is designed automatically which considers interdependencies and common maintenance requirements (Jung et al., 2017). Linear (regularly moving) assets place particular inspection and maintenance challenges that could be solved by automated robots operating digital data self-reliantly (Seneviratne et al., 2018). Degradation analysis is supported by contingent and reliable data streams (Zhong et al., 2017).

Augmented behavior
(4) Augmented behavior refers to virtual computing and service applications administring the machine-human interface (Çınar et al., 2020). Preventive maintenance and repair information provides a reliable data basis for operative human repair and exchange activities (Saxby, Cano-Kourouklis, and Viza, 2020). Chen et al. (2017) see the key action field for preventive maintenance to be the level of data application. The analysis of data gathered from diverse sensor networks is integrated using a data mining strategy and enable active maintenance processes. Augmented reality applications enable humans to understand and control maintenance processes (Longo, Nicoletti, and Padovano, 2017; Bueno et al., 2020).

Integrating these points and referring to the Total Quality Management “Plan – Do- Check- Act” cycle (Johnson, 2002) a circular model for the integration and use of industry 4.0 technology to preventive maintenance processes results:

Figure 2. Smart preventative maintenance cycle.
Discussion
In the following discussion the opportunities, limitations and success factors of preventive maintenance using industry 4.0 technologies are discussed controversially.

Opportunities of smart preventive maintenance
Preventive engine maintenance offers huge technical and economic potentials: Smart machinery self-diagnoses emerging problems even on a remote basis (Oztemel and Gursev, 2020), provides decision support for operators (Oztemel and Gursev, 2020) and predicts system failure to design an immediate process of routine and extraordinary checks (Chen et al., 2017; Rosin et al., 2020). Real-time information gathering and monitoring enable timely intervention in case of failure risk and the planning ahead of routine maintenance jobs (Lee et al., 2019). Repair equipment and staff are ordered and organized regarding process flows. Maintenance intervals and life cycle management are optimized by structured scheduling (Zhong et al., 2017; Wang et al., 2020). Structured maintenance information helps to diminish production failure due to machinery shortcomings and increases productivity (Saxby, Cano-Kourouklis, and Viza, 2020).

Smart active repair prevents downtimes and organizes repair and maintenance processes so that process flows run undisturbed, which reduces the transaction costs of operation (Wang et al., 2020). Accident prevention becomes more effective due to early failure diagnosis (Wang et al., 2020). Technical replacement impacts and costs can be reduced by comprehensive intervention planning (Lee et al., 2019). Intelligent augmented reality systems could be applied to enhance human understanding of maintenance requirements and schedules (Longo, Nicoletti & Padovano, 2017; Powell et al., 2018).

Limitations of smart preventive maintenance
On the other hand, the technology requires further development: Expert knowledge is indispensable to adapt smart repair routines to complex production architectures individually (Chen et al., 2017). Initial capital investments are significant and usually, external experts are required to get and keep the system running (Lee et al., 2019; Seneviratne et al., 2018). Repair processes are frequently not possible without human interventions, e.g. when components must be changed physically (Longo, Nicoletti, and Padovano, 2017). Intersections between human activity and digital processes have to be designed (Longo, Nicoletti, and Padovano, 2017). Complex maintenance routines are prone to potential failure and human intervention could become difficult for lack of understanding of error causes and potential remedies. To date, test samples for preventive smart maintenance are small and available for individual industries and applications only (Lee et al., 2019). The net cost effects of smart preventive maintenance accordingly are not well documented and no general application standards are available (Saxby, Cano-Kourouklis, and Viza, 2020).

Success conditions of smart preventive maintenance
To develop sustainable preventive maintenance concepts in single factory industry 4.0 environments relevant data has to be identified and integrated into a database for machine learning models to gather the necessary information (Çınar et al., 2020). Workshop equipment has to be renewed and intense cooperation with IT experts is necessary (Jung et al., 2017). Businesses should document this knowledge carefully (Chen et al., 2017) to keep track of and monitor self-organizing routines and intervene in case of errors. Data security issues have to be considered for sustainable operationality (Çınar et al., 2020).

In the future, industry 4.0 maintenance applications could be augmented by cloud-based data, big data streaming and management systems (Sahal, Ali, and Breslin, 2020), which integrate information across various industrial units on share platforms, deselect redundant information and condense relevant data. These applications could provide reliable data sets to predict and plan maintenance processes for similar units (Zhong et al., 2017).

Conclusions
Huge initial investments into a comprehensive ICT grid are required to comprehensively collect all necessary repair and maintenance data and evaluate these data (Sahal, Ali, and Breslin, 2020) based on joint information models (Jung et al., 2017).

Further inter-industry research is desirable to augment knowledge on the efficiency of smart maintenance in an industry 4.0 environment and to develop general industry standards.

Data availability
All data underlying the results are available as part of the article and no additional source data are required.
## Reporting guidelines
FIGSHARE: PRISMA checklist and flowchart:

https://doi.org/10.6084/m9.figshare.20363727.v1 (Fauska, 2022)

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### Appendix

### Box 1. Overview of reviewed studies.

<table>
<thead>
<tr>
<th>Industry 4.0 technologies for preventative maintenance in smart factories</th>
<th>1st Author</th>
<th>Year</th>
<th>Industry/application</th>
<th>Potentials</th>
<th>Limitations</th>
<th>Success factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Human-machine task allocation Production scheduling Intelligent planning Plant process scheduling</td>
<td>Bueno</td>
<td>2020</td>
<td>REVIEW Smart production planning and control</td>
<td>No consensus on the meaning of industry 4.0</td>
<td>Self-organization of order and maintenance processes Avoidance of downtimes</td>
<td>Lacking expert knowledge in applying companies External expert knowledge required Individual adaptation knowledge documentation</td>
</tr>
<tr>
<td>Self-organization of order and maintenance processes</td>
<td>Chen</td>
<td>2017</td>
<td>Maintenance processes at the data application level</td>
<td>Proactive maintenance</td>
<td>Data security Identification of required data</td>
<td>Development of generally applicable machine learning algorithms for maintenance</td>
</tr>
<tr>
<td>Proactive maintenance</td>
<td>Çınar</td>
<td>2020</td>
<td>REVIEW Predictive maintenance by machine learning for higher sustainability</td>
<td>Integration of information at design and control level</td>
<td>High investment costs Expert knowledge scarce</td>
<td>Comprehensive ICT network required Individualized information model for all facilities</td>
</tr>
<tr>
<td>Integration of information at design and control level</td>
<td>Jung</td>
<td>2017</td>
<td>Factory design &amp; improvement activity model</td>
<td>Low maintenance efforts Self-adapting systems</td>
<td>Time management</td>
<td>Comprehensive Sensor grids Real-time monitoring</td>
</tr>
<tr>
<td>Time management</td>
<td>Lee</td>
<td>2019</td>
<td>Quality management model for smart factories</td>
<td>Low maintenance efforts Self-adapting systems</td>
<td>Integration of information at design and control level</td>
<td>Comprehensive ICT network required Individualized information model for all facilities</td>
</tr>
<tr>
<td>Integration of information at design and control level</td>
<td>Leyh</td>
<td>2017</td>
<td>Lean production in industry 4.0 factory</td>
<td>Time management</td>
<td>Integration of information at design and control level</td>
<td>Comprehensive ICT network required Individualized information model for all facilities</td>
</tr>
<tr>
<td>Integration of information at design and control level</td>
<td>Longo</td>
<td>2017</td>
<td>Smart operators in industry 4.0</td>
<td>Integration of information at design and control level</td>
<td>High investment costs Expert knowledge scarce</td>
<td>Comprehensive ICT network required Individualized information model for all facilities</td>
</tr>
<tr>
<td>Integration of information at design and control level</td>
<td>Oztemel</td>
<td>2018</td>
<td>REVIEW Industry 4.0 technologies</td>
<td>Decision support for operators Rapid intervention in case of eminent failure</td>
<td>Integration of information at design and control level</td>
<td>Comprehensive ICT network required Individualized information model for all facilities</td>
</tr>
</tbody>
</table>
Box 1. Continued

<table>
<thead>
<tr>
<th>1&lt;sup&gt;st&lt;/sup&gt; Author</th>
<th>Year</th>
<th>Industry/application</th>
<th>Potentials</th>
<th>Limitations</th>
<th>Success factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Powell</td>
<td>2018</td>
<td>Industry 4.0 production standards</td>
<td>Big data analytics for maintenance, improve man-machine interaction</td>
<td>Case study data only, no generalizable solutions</td>
<td></td>
</tr>
<tr>
<td>Rosin</td>
<td>2020</td>
<td>Lean principles in industry 4.0</td>
<td>Continuous information flows</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sahal</td>
<td>2020</td>
<td>Big data for predictive maintenance use cases</td>
<td>Integrate inter-industry data to derive generalizable information</td>
<td>Data selection and redundancy issues</td>
<td>Develop common interchange formats</td>
</tr>
<tr>
<td>Saxby</td>
<td>2020</td>
<td>Lean management method for industry 4.0</td>
<td>Production failure reduction, productivity enhancement, self-monitoring of smart machinery</td>
<td>No defined industry standards, only small-scale implementation studies</td>
<td>Larger trials and inter-industry collaboration</td>
</tr>
<tr>
<td>Seneviratne</td>
<td>2018</td>
<td>Smart maintenance &amp; inspection of linear assets</td>
<td>Use of autonomous robots for inspection tasks</td>
<td>Linear movement of assets, dynamic status and traits</td>
<td>Young emerging technology, investments necessary</td>
</tr>
<tr>
<td>Wang</td>
<td>2020</td>
<td>Preventive maintenance for complex equipment</td>
<td>Preventive health-status analysis, more accurate lifetime prediction, reduction of maintenance costs, higher sustainability</td>
<td></td>
<td>Integration of information from several sensors and checkpoints</td>
</tr>
<tr>
<td>Zhong</td>
<td>2017</td>
<td>REVIEW Intelligent manufacturing in industry 4.0 context</td>
<td>Optimized maintenance intervals and life cycle management, reduce maintenance costs</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

References


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