

# DESIGNING PREDICTIVE MAINTENANCE FOR AGRICULTURAL MACHINES

*Research paper*

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## Abstract

*The Digital Transformation alters business models in all fields of application, but not all industries transform at the same speed. While recent innovations in smart products, big data, and machine learning have profoundly transformed business models in the high-tech sector, less digitalized industries—like agriculture—have only begun to capitalize on these technologies. Inspired by predictive maintenance strategies for industrial equipment, the purpose of this paper is to design, implement, and evaluate a predictive maintenance method for agricultural machines that predicts future defects of a machine's components, based on a data-driven analysis of service records. An evaluation with 3,407 real-world service records proves that the method predicts damaged parts with a mean accuracy of 86.34%. The artifact is an exaptation of previous design knowledge from high-tech industries to agriculture—a sector in which machines move through rough territory and adverse weather conditions, are utilized extensively for short periods, and do not provide sensor data to service providers. Deployed on a platform, the prediction method enables co-creating a predictive maintenance service that helps farmers to avoid resources shortages during harvest seasons, while service providers can plan and conduct maintenance service preemptively and with increased efficiency.*

*Keywords: Predictive Maintenance, Agriculture, Data-driven Service, Design Science Research*

## 1 Introduction

Agricultural production is subject to heavy seasonal variations in workload and adverse weather conditions. For farmers, agricultural machines (e.g., tractors and combine harvesters) are particularly vulnerable to unforeseen downtimes in high seasons. For service providers, harvesting periods often come with severe resource shortages, which constrain the availability of service technicians and spare parts. One strategy to prevent these shortages is to avoid machine downtimes preemptively, as targeted by various predictive maintenance approaches (Mobley, 2002) in other industries—especially fostered and established in the ongoing Digital Transformation.

Digital Transformation—a topic of strategic importance for organizations (Henriette et al., 2016)—refers to the application of digitization and digitalization techniques on an organizational level in combination with innovative digital technologies (Priyadarshy, 2017). Thus, Digital Transformation enables organizations to establish new business models based on data-driven services and, thereby, to offer new value propositions for their customers. Digitization is the binary conversion of analogous information into a digital format (Hess et al., 2016, 2016; Tilson et al., 2010), whereas digitalization refers to a socio-technical process of applying digitization to a broader (social or institutional) context (Tilson et al., 2010).

Predictive maintenance is an example for such new data-based services but extant research is currently focused on industrial production and manufacturing. In this area, application scenarios require high data availability and sophisticated systems integration. Particularly, information systems for predictive

maintenance rely heavily on sensor data to monitor a machine's condition and predict defects and downtimes of equipment. For the predictive maintenance of agricultural machines, this design knowledge is insufficient, because sensor data are often unavailable in this scenario (Liu et al., 2016). However, extant design knowledge on maintaining industrial equipment can be subjected to an exaptation (Gregor and Hevner, 2013), to enable the implementation of predictive maintenance strategies for agricultural machines.

At a closer inspection, differences between industrial and agricultural production are rooted in unavailable and scattered data. First, digitalization in agriculture is all but starting, and onboard communication in agricultural machines has not been standardized, yet (Liu et al., 2016). Also, machines are non-stationary and cannot be connected by wire, while wireless communication is often difficult due to limited network coverage in rural areas. Both factors impede the availability and accessibility of machine and sensor data (Liu et al., 2016)—the type of data which most current predictive maintenance concepts are built on. Second, unlike industrial settings, data on the capacity and utilization of agricultural machines are not documented in Enterprise Resource Planning (ERP) systems (Lokuge et al., 2016). Third, agricultural production is subject to rough territory and adverse weather conditions, requiring the integration of external data—such as weather and geographic data—into predictive maintenance services. These data are semi-structured, so analyzing them requires special databases and substantial data preparation activities. Fourth, agricultural machines and their components are seldom managed in Enterprise-Asset-Management (EAM) systems, leading to incomplete and inconsistent data on a machine's condition, maintenance, and state of construction. Following Lokuge et al. (2016), the lack of information system usage in agriculture is caused by a low maturity of IT infrastructure, low level of IS acceptance, lack of specialized systems for the agricultural sector, the reluctance of IT consulting in the agricultural sector, and the high investment costs of implementing IT.

As regards organizational issues, maintenance activities for agricultural machines involve many stakeholders, whereas, in industrial production, the entire lifecycle of a machine is often governed by the same company. In agricultural production, farmers operate machines, detect defects based on gut feelings or identify defects after their occurrence, and reactively schedule inspection appointments with their local service companies. These service companies possess service records on the maintenance events they conduct, including structured and unstructured data. Manufacturers, on the other hand, have access to specific machine data (e.g., bill-of-materials or even sensor data), but lack access to service records and, therefore, possess limited data on a machines' condition and state of construction after its warranty period has expired. In these distributed settings, data on agricultural machines are scattered, leading to an insufficient digital representation of the machines that render current predictive maintenance concepts insufficient for the agricultural sector.

In an exaptation and extension of predictive maintenance strategies from industrial settings, we design a predictive maintenance method for agricultural machines. Deployed on a platform, the method enables service providers and farmers to preemptively conduct maintenance activities to avoid machine downtimes in high seasons. The method is the first IT artifact that exclusively predicts defects of machine components based on service records since sensor data on agricultural machines is insufficient.

The paper unfolds as follows. In Section 2, we discuss related research on predictive maintenance. In Section 3, we explain and justify how we performed the exaptation of existing design knowledge on predictive maintenance services for industrial equipment, to design a method for predictive maintenance of agricultural machines. In Section 4, we report on the design, demonstration, and evaluation of our IT artifact. Section 5 concludes the paper and motivates further research on this topic.

## 2 Related Research on Predictive Maintenance

Just like in other industries, digital technologies, big data analytics, and the Digital Transformation as a whole now leave their mark on the traditional agricultural sector, which has started to undergo a tremendous transformation (Pham and Stack, 2018). However, unlike other sectors, Digital Transformation in agriculture is accompanied faintly by scholarly research (Carbonell, 2016). While recent research efforts put forward smart farming (e.g., Lantzoz et al., 2013; Kruize et al., 2016; O'Grady and O'Hare, 2017),

Digital Transformations' impact on the domain has only recently started to be discussed. Kamilaris et al. (2017) provide a literature review on big data practices in the agricultural sector and conclude that despite “data analysis is leading to advances in various industries, it has not yet been widely applied in agriculture.” (Kamilaris et al., 2017, p. 23). To embed our research into extant theory, we, therefore, build on recent research and IT artifacts for predictive maintenance in other industries, including the high-tech sector.

## 2.1 An Overview of Maintenance Strategies

In industrial production and manufacturing, maintenance and repair of machines and equipment are done following one of three strategies—reactive maintenance, preventive maintenance, or predictive maintenance (Mobley, 2002). In reactive maintenance, machines and equipment are operated until a defect or malfunction occurs, which is then fixed (Mobley, 2002). For this strategy, maintenance is not planned or scheduled and components are used as long as possible, which minimizes costs for spare parts, but makes machines vulnerable for downtimes (Mobley, 2002). In preventive maintenance, equipment is replaced before a defect occurs. The interval of usage is usually defined regarding operating hours, based on experience or maintenance intervals pre-specified by manufacturers (Mobley, 2002). Thus, components might be replaced before the end of their lifetime has been reached, increasing costs compared to reactive maintenance. Conversely, preventive maintenance avoids or reduces downtimes since maintenance activities can be scheduled before a defect occurs. In predictive maintenance, repairs are scheduled based on the condition of a machine or component (Mobley, 2002). Machines or components are used as long as possible, but are replaced proactively before a defect is predicted (Nadj et al., 2016). Usually, a machine's condition is monitored and analyzed based on sensor data (Carnero, 2006), while some approaches additionally use data from Enterprise-Resource-Planning (ERP) systems to predict downtimes (Groba et al., 2007). Predictive maintenance allows scheduling maintenance activities efficiently and simultaneously reduce costs for spare parts. Importantly, each maintenance and repair strategy can be the best choice to maintain a machine or component, to minimize total costs (see Figure 1.).

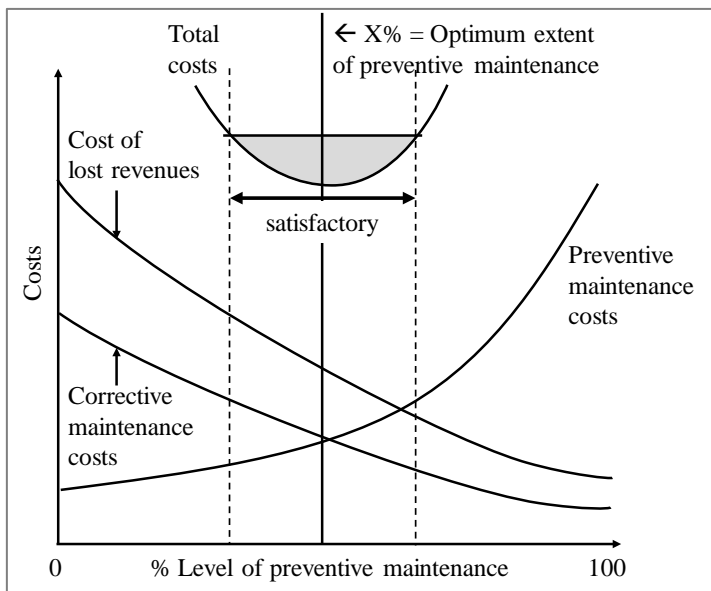


Figure 1. Total costs of maintenance, depending on the degree of prevention (Mobley, 2002)

## 2.2 IT Artifacts for Predictive Maintenance

Current research on predictive maintenance is interdisciplinary and focuses on different aspects. Amongst others, it addresses asset management and scheduling (Demoly and Kiritsis, 2012; Daily and Peterson, 2017), decision making and automation (Deshpande and Modak, 2003; Mourtzis et al., 2014), required technologies and infrastructure (e.g. wireless sensor networks and communication) (Akhondi

et al., 2010; Madni and Madni, 2008), processing huge amounts of data (Lee et al., 2015; Oneto et al., 2016; Daily and Peterson, 2017)), applying particular algorithms for data analytics (Niang et al., 2006; Unal et al., 2014), Internet of Things technologies and platforms (Bayoumi and McCaslin, 2016; Wortmann and Flüchter, 2015), frameworks and architectures for predictive maintenance (Groba et al., 2007; Sayed et al., 2015; Ramirez et al., 2013; Venkataraman et al., 2011), and the integration of existing information systems (López-Campos et al., 2013; Li and Roy, 2016). Additionally, some research focuses on new opportunities for organizations, e.g., the design of new or improved services and business models enabled by cyber-physical products (Herterich et al., 2015; Lee et al., 2014; Amberg et al., 2009).

The goals pursued with predictive maintenance also vary. Amongst others, approaches target the prediction of emerging defects (Woldman et al., 2015; Traore et al., 2015; Sayed et al., 2015; Peng et al., 2010), the Remaining Useful Life (RUL) of components (Prytz et al., 2015), the probability for exceeding a particular timeframe called prediction horizon (Prytz et al., 2015), and deriving decisions for maintenance actions (Galar et al., 2012; Ghosh and Roy, 2010; Huynh et al., 2015; Wang et al., 2010). As regards fields of application, next to industrial production predictive maintenance has focused aircrafts (Austin et al., 2003), railways (Umiliacchi et al., 2011), oil and gas operations (Nadj et al., 2016), military vehicles (Woldman et al., 2015), and electronic systems (López-Campos et al., 2013). Also, some first approaches in the agricultural sector are available but focus on different aspects than this paper, including predictive maintenance in greenhouses (Yu and Zhang, 2013) or the application of wireless sensor technologies (Ruiz-Garcia et al., 2009). The predictive maintenance approach of Liu et al. (2016) predicts the mean time between repairs for agricultural machines and is therefore related to our case. Their approach is based on service records without considering any technical components, but time series of failures of each machine. This means that they calculate the time between failures for an agricultural machine and predict the next time interval. The time interval between failures is very small compared to our case. Since for the case of Liu et al. (2016) defects occur between 1,431 and 2,082 minutes for one wheat harvester, whereas in our case the mean time between repairs of one machine is 62 weeks, the datasets deviate considerably. Also, Liu et al. (2016) do not consider the condition of components in a machine. Therefore, while repairs can be performed before a defect occurs, benefits for service providers are limited, since only the time of the repair can be scheduled, but spare parts cannot be ordered preemptively. Express deliveries for spare parts or tools might still be necessary, which leads to delays and additional costs for customers.

Prytz et al. (2015) predict required repairs for truck and bus compressors. Their approach is based on service records, but additionally considers Logged Vehicle Data—aggregated data reflecting the usage of the truck or bus—that was not available in our scenario. The purpose of their approach is to predict if a compressor survives a predefined time horizon (so-called prediction horizon). The prediction horizon is defined as a period between planned visits to a service station, which is 15 weeks on average for trucks and buses. Except during warranty time, farmers usually do not schedule visits at the service station proactively, but rather apply a reactive maintenance strategy, so that visits at the service station are notably less frequent than for trucks (62 weeks on average). Therefore, the prediction horizon in our case could not be defined as the time between planned visits at the service station. Instead, we defined the harvesting period as prediction horizon, since a defect during this time has particularly severe consequences for farmers and service companies.

Predictive maintenance approaches can be categorized based on the type of data they process and the methods they apply to make predictions (Figure 2.). As regards methods, Edwards et al. (1998) identify statistical-based and condition-based approaches. While statistical-based approaches use historical data of incidents to predict future failures, condition-based approaches use real-time sensor data to estimate the attrition of components (Edwards et al., 1998). Peng et al. (2010) and Prytz et al. (2015) sub-classify condition-based maintenance approaches based on real-time data into physical-model based approaches, knowledge-based approaches, data-driven approaches, and combined approaches. Contradicting Edwards et al. (1998), they view statistical-based approaches as a subset of data-driven methods, which include multivariate statistical methods, such as Principal Components Analysis or Bayesian Networks. According to Peng et al. (2010), data-driven approaches comprise approaches that apply artificial neural networks and similar artificial intelligence methods. "Physical model-based approaches usually employ

mathematical models that are directly tied to physical processes that have direct or indirect effects on the health of related components" (Peng et al., 2010, p. 299). Knowledge-based methods can further be divided into expert systems and fuzzy logic approaches (Peng et al., 2010). Expert systems use rules derived from domain knowledge of experts to solve a particular problem or gain new knowledge on a topic (Peng et al., 2010). Fuzzy logic approaches use fuzzy pattern recognition principles or fuzzy clustering for fault prognosis and self-learning processes (Peng et al., 2010).

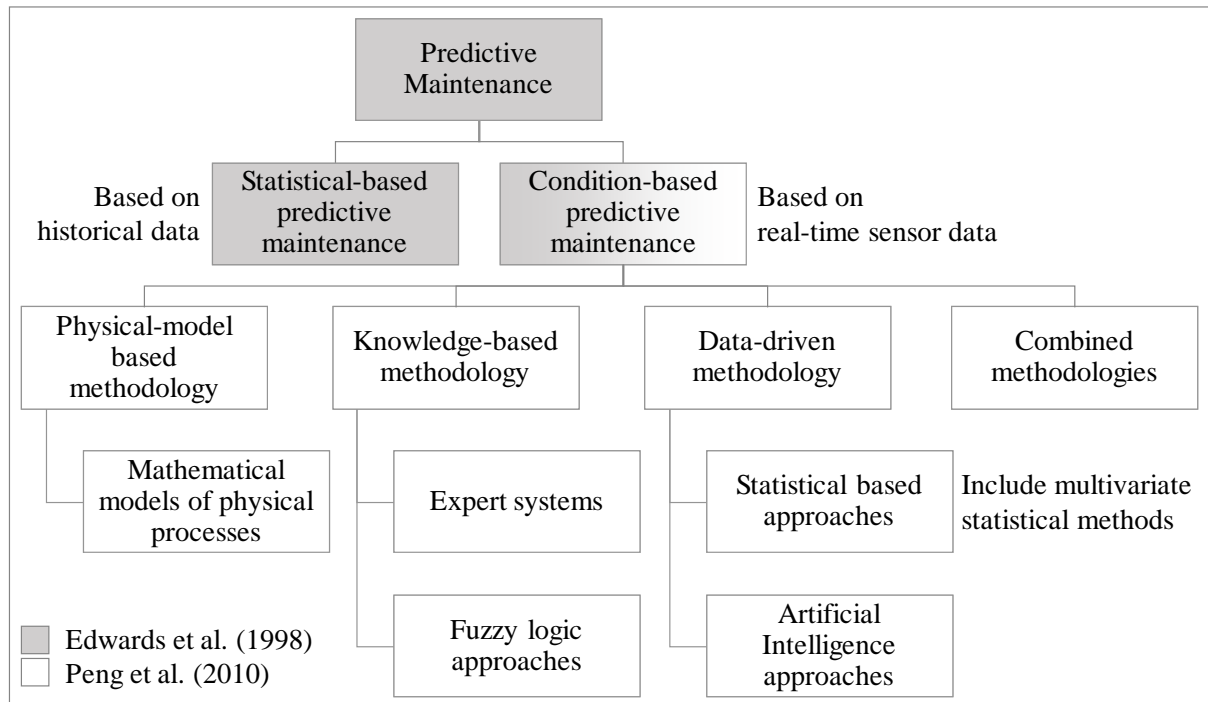


Figure 2. Systematizing predictive maintenance approaches

Against this backdrop, our approach can be categorized as a combination of a knowledge-based expert system and a statistical-based approach, as defined by Edwards et al. (1998). The knowledge-based expert system is based on position data designed to predict the harvesting period and required workloads until and during harvesting. The statistical-based predictive maintenance approach is based on historical service records to predict defects of critical parts in an agricultural machine.

### 3 Research Method

The purpose of our paper is to develop a theory for design and action to specify how IT artifacts for the predictive maintenance of agricultural machines ought to be designed. Design science research is on a dual mission (Sein et al., 2011) to solve problems relevant to an application domain by designing IT artifacts, while simultaneously offering generalized theories for design and action (Gregor and Jones, 2007; Gregor and Hevner, 2013). The core of our IT artifact is a method for predicting defects of critical components and estimating if the components will hold long enough to prevent downtimes in the next critical period (i.e., harvesting period) in which agricultural machines must be operational.

The design process is built on an exaptation of IT artifacts that have been designed to enable predictive maintenance strategies in the high-tech industries. In line with Gregor and Hevner (2013), an exaptation is focused on re-utilizing design knowledge from one field (here: predictive maintenance of industrial equipment), to solve a relevant problem in another field (here: predictive maintenance of agricultural machines). The core of the exaptation fits the IT artifact to the particular technological and organizational context that constitutes the maintenance of agricultural machines. In particular, agricultural machines often lack the amounts and structure of data that applies in industrial settings, rendering current IT artifacts useless to predict defects of agricultural machines. On the other hand, statistical methods

used for computing the predictions themselves can be applied without major changes, since from a statistical point of view, both problems exhibit the same structure.

To design and implement a predictive maintenance approach, we applied the design science research method, as proposed by Peffers et al. (2007). The design process took a problem-centered initiation that focused overcoming current deficiencies in agricultural machinery service. The design goal was two-fold, (1) improving the current maintenance service for customers by reducing downtimes and (2) making service providers' operations more efficient by preventing resource shortages and optimize spare part handling in high seasons. We cooperated with a large agriculture company, which performs maintenance activities on behalf of most manufacturers of agricultural machines. Importantly, while some of these companies collect sensor data on their machines from the remote, these data are not being made available to the service company, for strategic reasons concerning access to the customer interface.

Following the advice of Shearer (2000) on how to set up a data mining model, we first analyzed current predictive maintenance systems' properties and modeled business processes of the as-is and to-be maintenance service, including roles and resources. Thus, we identified service processes, the business context, and the data available on machines. To populate the prediction method, we used real service records that were provided by the company. We enriched the dataset with external data to set up a data model to be accessed by our prediction method. Just like external data sources, the internal data sources were only partly integrated. Therefore, we prepared the data, including joining separate data tables, harmonizing data, and concatenating service records. Also, data quality was checked, to assess if analyzing the data yields meaningful predictions. Since components that are part of routine checks might be preventively replaced during a check and therefore before a defect occurs, the actual defect would not be contained in our data. Thus, considering components that are part of routine checks might lead to false predictions (Susto et al., 2015). Because of this constraint and weak data quality and data availability (i.e., missing sensor data), we focused the predictions on critical machine components that can potentially cause downtimes and are not part of routine checks performed on a machine. Subsequently, we first designed a knowledge-based expert system to predict the next harvesting season and the required workload, and second designed a data-driven model to predict if critical components will defect.

We demonstrate our artifact by implementing the prediction method. We evaluated our prediction method with 3,407 real-world service records on agricultural machines. In line with approved techniques to classify the performance of data mining models (Fawcett, 2006), we calculated Receiver Operating Characteristic (ROC) graphs and confusion matrices to assess the accuracy of our predictions. Since the stakeholders in our scenario were not data scientists, we designed a graphical web-interface on which farmers and service providers can access all data on their machines, along with the predictions that were computed by the method we implemented.

## **4 A Predictive Maintenance Method for Agricultural Machines**

### **4.1 Problem Identification**

In the initiation, we identified the problem of seasonal resource shortages—especially during harvesting time—from two perspectives. Farmers' revenues are highly dependent on efficient and effective harvesting, such that the breakdown of their machine is a worst-case scenario in that period (Kusumastuti et al., 2016). For service providers, a standstill of machines for a long or unpredicted period is critical for customer satisfaction. Service providers need to have service technicians available on standby duty and work overtime during harvesting periods to work through farmers' service requests. Also, out of stock spare parts have to be ordered on short notice and might even be transported in express delivery, which causes severe scheduling problems and additional costs.

The breakdown of machines, maintenance strategies, and countermeasures are not exclusive to the agricultural sector but approaches that are discussed in different domains often lack applicability in this sector. While many approaches implemented in the industry rely on live-tracked sensor data, agriculture is subject to a lack of sensor data, divergent data-formats, and distributed data ownership. Others have

observed that the agricultural sector is characterized by old-fashioned IT, leading to a gap between innovative tools on the market and their exploitation and application in agriculture (Antle et al., 2017).

Kusumastuti et al. (2016) categorize six types of problems in crop-related agriculture, three of which have to leave their mark on predictive maintenance services. First, agriculture is a seasonal business (Salin, 1998; Tsubone et al., 1983) that is constraint by short time windows, e.g., for harvesting. Deviation from these time windows can have severe adverse effects since it directly influences product quality, subject to the crops seeded (Arnaout and Maatouk, 2010; Bohle et al., 2010; Higgins et al., 1998). Second, resource limitations are particularly strong (Kusumastuti et al., 2016) and effect all steps in the supply chain. Third, in harvesting times, the availability and operability of agricultural machines are crucial. Adverse weather conditions can suddenly have severe implications, e.g., on a harvest season's length (Allen and Schuster, 2004) and crop maturity time (Tan and Çömnden, 2012), leading to high complexity in the management of agricultural supply chains (Kusumastuti et al., 2016).

## 4.2 Definition of Objectives

The main objective implemented by our IT artifact is to predict if a component will fail during harvesting times. Critical components are essential for a machine's operation and—if they fail—cause an entire machine to stop. Therefore, the prediction method of future defects is the core of a predictive maintenance service that can be provided on a web-based platform. If a critical component is predicted to fail during harvesting season, the farmer has to be notified by a mobile application. The service platform enables a farmer to make an ad hoc maintenance appointment for the replacement of defective components before the critical period starts and consequently to reduce harvesting losses due to machine failures. The prediction of defects also enables a service provider to plan a specific maintenance action and to order required spare parts proactively. Thus, the service provider can plan all resources in advance and increase the efficiency of the maintenance service.

## 4.3 Design and Development

Our method consists of two steps. Since the service records only contain information of a defect that already occurred and sensor data are not available, we cannot analyze the circumstances leading to a defect. Instead, we identify several features from the service records to predict, if a component has to be replaced during a maintenance appointment at the service station. Since this is no prediction for a future point in time but an existing service record, we need to create future service records containing the machine state during harvesting time and predict, if these generated service records will contain defect components. Therefore, in a first step, we implement a knowledge-based approach to identify the next period for harvesting and estimate the workload until and during the next harvesting period. This information is used to generate future service records since all varying information of the service records can be extracted from the expert system. In a second step, a data-driven approach is applied to predict the defects of critical components in the generated service records. If the defect of a critical component is predicted, it needs to be replaced before the harvest starts to prevent downtimes.

To identify the harvesting period and estimate workloads, we designed a knowledge-based expert system based on position data of the machines. Since an estimation of future working hours until and during harvesting time is required, the operating time of a machine needs to be analyzed. In an industrial context, a production plan could be used to estimate future operating hours of the machine. However, a production plan or a similar datum does not exist in agricultural production. In contrast to Prytz et al. (2015), who determined the RUL of truck compressors, operating hours of agricultural machines are typically not as steady as for trucks (except for agricultural contractors). Due to a missing integration with the service company's Customer Relationship Management (CRM) system, we had to identify harvesting periods otherwise. Therefore, we took advantage of the seasonality of field work. We assumed that the time horizon and required working hours for harvesting can be estimated based on the cultivated type of crops and the average working hours performed on a field. For this, we analyzed location data and timestamps of one agricultural machine and designed a knowledge-based method to predict the

harvesting period and required workloads for one particular customer. This method is an expert system based on the following rules:

1. Cultivated fields can be identified by clustering position data points that are nearby.
2. For each cultivated field, working hours can be analyzed to identify periods with a high workload.
3. The harvesting period for each cultivated field can be estimated based on comparing periods with a high workload on a particular field to reference calendars for seeding and harvesting. The identified harvesting period is defined as prediction horizon.
4. The average workload of former harvesting periods is considered as the required workload for the prediction horizon. The required workload for the period between the last repair and the prediction horizon is estimated based on the average workload for cultivating the identified crops (rule 3).
5. If a farmer cultivates more than one field, the expected harvesting times for all fields are considered to determine the predicted time horizon.
6. If a defect of a critical component is predicted for the identified time horizon, a proactive exchange of the components is recommended to prevent downtimes.

The estimation of a prediction horizon is subject to constraints. First, our assumptions are not valid for agricultural contractors, since cultivated fields might change often and machines are scheduled to maximize their capacity. Second, we assume that historical data are available to identify if working hours on a field are related to seeding or harvesting based on cultivated crops and crop rotation.

To design the data-driven method for the prediction of defects, we applied the Cross-Industry Standard Process for Data Mining (CRISP-DM) reference method proposed by Shearer (2000). Following the steps of the reference method, we first modeled the current maintenance process with event-driven process chains (EPC) and identified the data generated in each activity. One of the main challenges was to understand the inter-organizational distribution of data—among manufacturers, farmers, and service companies. The service company for which we implemented the system had not integrated their ERP and CRM systems. Our prediction method, therefore, analyzes service records extracted from the service company's ERP system. We preprocessed the data, e.g., by joining separate data tables, harmonizing data, and concatenating service records that were distributed across multiple rows. Subsequently, we selected one exemplary critical component to be included in the analysis, based on the available records identified by service technicians. We identified all machine types that contained this critical component. As a result, we compiled a table containing all service records for the identified machine types. Since no real-time sensor data were available, our prediction focuses on whether or not the component will fail.

The resulting prediction method consists of six steps (Figure 3.). First, all service records that listed the critical component were labeled '1' in an additional column. Since service records are intermittent data, one service record only contains a specific amount of operating hours of one machine. Components usually do not defect at the same operating hour, so we assumed that predicting a failure based on clustered service records might improve our results. Additionally, we assumed that service records containing the defect component are more important to determine clusters of service records than functional components. Therefore, we filtered service records labeled with '1' (step 2) and clustered the records based on operating hours and year of construction of the maintained machine (step 3). Subsequently, the identified clusters were assigned to all service records (label '0' and '1') (step 4). In step 5, we applied a data mining algorithm for classification (Random Forest) (Coppersmith et al., 1999) to learn and predict the assigned clusters of the fourth step. This is necessary to obtain probabilities for the assignment to a cluster, which can be used as a feature for the prediction of defects in step 6. The probability for cluster assignment indicates the impact of the feature "cluster" for predicting defects. If the probability for the cluster assignment is low, the feature "cluster" should not have the same impact on the prediction of defects as if the probability for the cluster assignment is high. In step 6, we applied a classification algorithm (Gradient Boosted Trees) (Friedman, 2001) to predict if the considered critical component will defect. For this, the algorithm predicts the values of the column that contains the labels '0' and '1'.



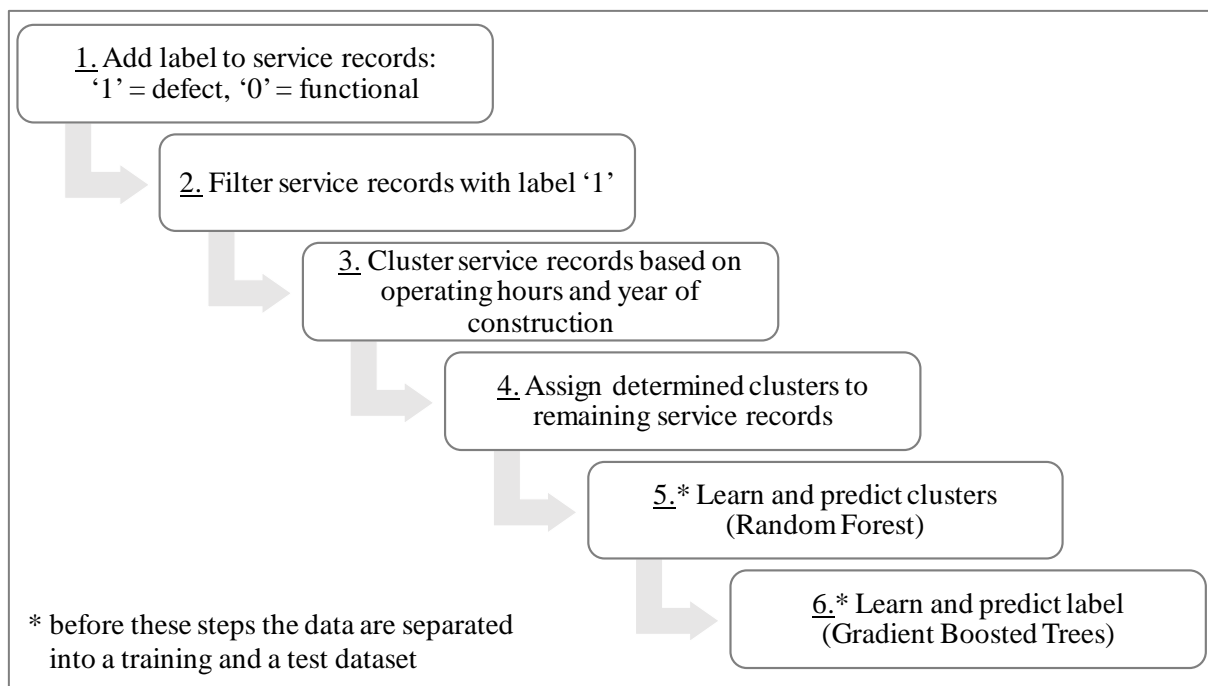


Figure 3. Data-driven predictions of critical components' defects

The designed method can predict the replacement of a defective component in service records. To predict defects during harvesting period, additional future service records are generated based on the results of the knowledge-based expert system. Our prediction method is then applied for these service records and if a component is predicted to fail, it has to be replaced proactively.

#### 4.4 Demonstration

To demonstrate the proposed method, we implemented workflows using the open source software tool KNIME (KNIME.COM AG, 2018). A first workflow was implemented to estimate workloads and identify the harvesting period. First, we identified fields by clustering position data of one tractor using the density-based clustering algorithm DBScan (see the first image in Figure 4.). Applying this algorithm enabled us to identify fields with high accuracy, but also to identify roads (second image in Figure 4.). The roads were filtered manually, such that only clusters of fields remained in our dataset. Second, we analyzed working hours on one field and plotted them in a histogram to identify the crops grown on the fields and their harvesting times. The data used for this purpose were limited and did not cover a whole year. Nevertheless, we were able to identify calendar weeks with higher workload (see third image in Figure 4.) and we calculated the average working hours for one field. In this example, the highest workload was at the beginning of October. Due to a lack of historical data, it is unclear if the workload reflected seeding or harvesting activities. Reference calendars indicate that these activities could either represent harvesting of corn or green fodder, or seeding of winter crops.

For predicting defects in service records, we implemented an additional workflow using KNIME (KNIME.COM AG, 2018). As common in data-driven analytics, we cycled through several iterations to find the best prediction algorithm. We first implemented a workflow for predicting the defects of a critical component. According to our method, we initially labeled service records containing the considered component with '1' and remaining service records with '0'. For this purpose, we used a String Replacer node. By applying a Rule-based Filter node we filtered service records labeled with '1'. In the next step, we utilized a k-means-algorithm and assigned resulting clusters to all service records using the Cluster Assigner node. Next, we used an X-Partitioner node to divide our real-world dataset—consisting of 3,407 service records—into training and test datasets. The X-Partitioner node is the starting point for a cross-validation loop that is described in the evaluation section in more detail. We applied a stratified sampling since the number of defects in our dataset is very low (11.48%). The training dataset

(2,556 service records) was subsequently used to learn a Random Forest model, which was applied to predict the clusters assigned before. The resulting model was applied on the test dataset (851 service records). Before dividing these records again for the prediction of labels, we applied a SMOTE node to oversample the defects based on a technique called Synthetic Minority Oversampling Technique (SMOTE) developed by Chawla et al. (2002). As a result, the dataset contained nearly equal amounts of defective and operational parts. This step was necessary to improve the prediction to be conducted in the following steps. 80% (1,206 service records) were used to learn the model for predicting the labels, which was a Gradient Boosted Trees Learner here. With the remaining 20% (302 service records), the resulting prediction model was tested.

Resulting from the prediction method is a prediction model that is applied for incoming data on a web-based service platform. The platform website supports different views for farmers and service technicians. Farmers can access dashboards to analyze their whole vehicle-fleet or particular vehicles and — if required—schedule appointments before a defect occurs. Service technicians can plan and schedule maintenance activities based on future spare part demands resulting from the prediction.

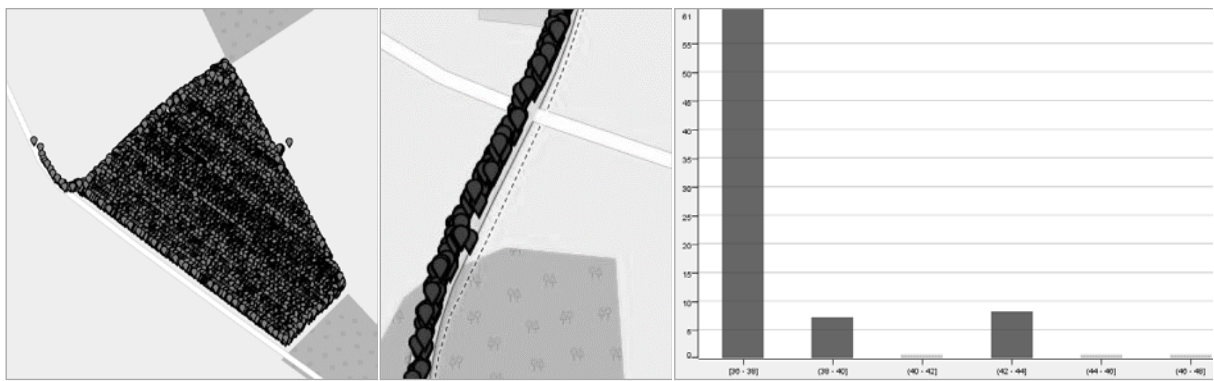


Figure 4. Field detection from clustered GPS data and activity duration analysis for one field

## 4.5 Evaluation

We evaluated our data-driven prediction method with established measures to assess the accuracy of cluster and regression algorithms (Fawcett, 2006). For cluster algorithms, we compiled a confusion matrix and a ROC curve, and calculated measures for precision, recall, and the algorithm's overall accuracy. As described before, we applied a cross-validation loop to validate our model and confirm our results. For this, the data were separated into four equal subsets of which three are used as training data and one is used as test data. The prediction workflow is executed four times. Each time another subset of data is used as test data. Small deviations in the results of the four executions indicate how good the model adapts to independent datasets as used in practice.

Since position data was not available for each maintained machine, the evaluation of the data-driven prediction method is done based on existing service records, while the additionally generated service records for the prediction of defects during harvesting time cannot be evaluated. We assume that the results for the generated service records will only deviate negligibly since all relevant features (e.g., operating hours, the age of a machine, and year, month and day of defect) can be extrapolated by applying the knowledge-based expert system.

Following the steps of the prediction method, we first evaluated the predictive accuracy of clusters. Since the overall accuracy is very high and does not vary substantially throughout the validation loops, we focus on the overall accuracy (see Table 1.) and do not report the confusion matrix here.

Measure	First partition	Second partition	Third partition	Fourth partition
Accuracy	0.9836	0.9941	0.9930	0.9906

Table 1. Accuracy of cluster prediction (step five)

Since we oversampled the data before predicting the labels, we evaluated both the results of the enriched dataset and a filtered dataset, which only included the original data. As shown in Table 2., the prediction of the labels performs well with 82.45%–89.40% accuracy (86.34% on average). Considering the classification in the first validation loop, 139 of 151 defects were predicted correctly, which leads to a recall of 92.05%. Additionally, 24 functional parts were predicted as defects. Therefore, 139 out of 163 predicted defects were true, which reflects the precision measure for the defect parts. The results of the four validation loops do not vary much, highlighting that our model adapts well to independent data.

Row ID	True Positives	False Positives	True Negatives	False Negatives	Recall	Precision	Accuracy
0	127	12	139	24	0.8411	0.9137	
1	139	24	127	12	0.9205	0.8528	
Overall							0.8808
0	125	27	124	26	0.8278	0.8224	
1	124	26	125	27	0.8212	0.8267	
Overall							0.8245
0	129	22	129	22	0.8543	0.8543	
1	129	22	129	22	0.8543	0.8543	
Overall							0.8543
0	133	14	137	18	0.8808	0.9048	
1	137	18	133	14	0.9073	0.8839	
Overall							0.8940

Table 2. Label prediction for the enriched dataset (step six)

Compared with the enriched data set, the original data set shows similar results except for precision (see Table 3.). The most conspicuous point is the difference in the precision measure for defect parts, which is nearly halved in comparison to the enriched data set. This is caused by the fact that for the first validation loop the true positives with label '1' were reduced from 139 to 20, but the false positives remain stable. While for the enriched data 139 out of 163 predicted defects were correct, for the original data set only 20 out of 44 predicted defects are correct, what reflects the identified difference in precision.

Row ID	True Positives	False Positives	True Negatives	False Negatives	Recall	Precision	Accuracy
0	127	3	20	24	0.8411	0.9769	
1	20	24	127	3	0.8696	0.4545	
Overall							0.8448
0	125	6	14	26	0.8278	0.9542	
1	14	26	125	6	0.7000	0.3500	
Overall							0.8129
0	129	5	16	22	0.8543	0.9627	
1	16	22	129	5	0.7619	0.4211	
Overall							0.8430
0	133	4	18	18	0.8808	0.9708	
1	18	18	133	4	0.8182	0.5000	
Overall							0.8728

Table 3. Label prediction for the original dataset (step six)

The ROC curve provides an overview of the quality of the classification. While a curve near to the diagonal corresponds to a random classification, the ideal curve starts vertically to the upper left corner and then continuous horizontally to the right. In addition to the graphical overview, the area under the curve can be calculated, which can obtain any value between 0 and 1, where 0.5 equals a random classification and 1 is a perfect classification. The ROC curves for the label prediction for the enriched and the original data set are reported in Figure 5. The ROC curves for our model reach high values of 0.8891–0.9710. Also, the variation between the enriched and the original data set can be neglected.

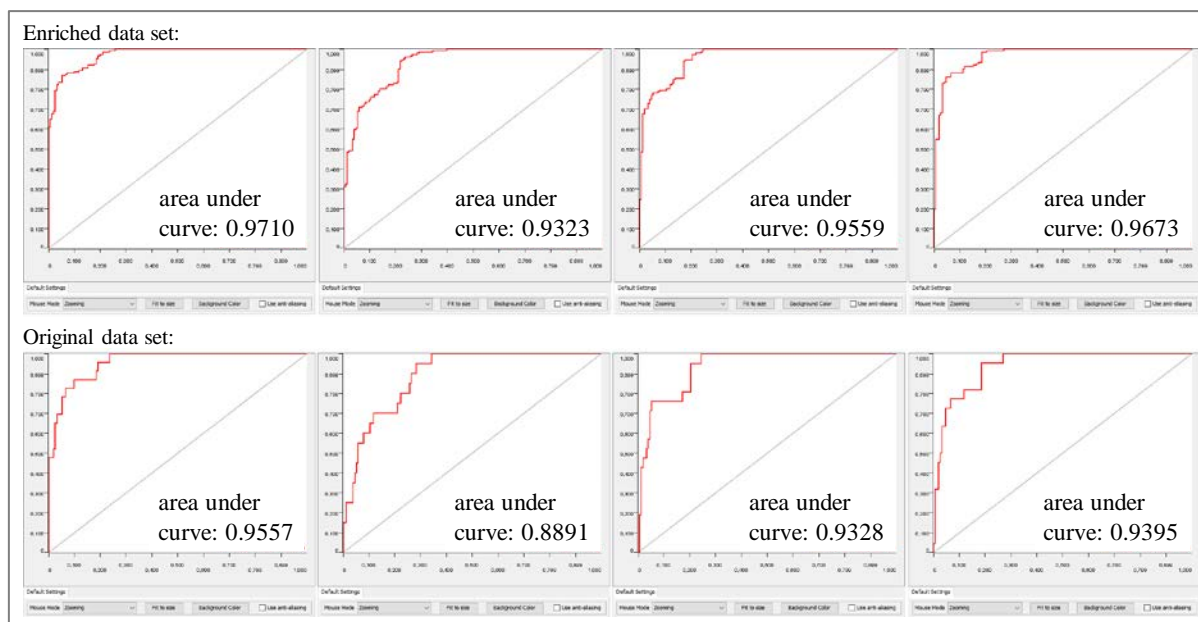


Figure 5. ROC curves for the enriched and original datasets

Our prediction method reaches a high overall accuracy and outperforms the current maintenance approach for the evaluated component. As described earlier, we evaluated a critical component that might lead to machine downtimes but is not contained in routine checks of the machine to prevent false predictions due to early replacements. This implies that the evaluated component is currently replaced on defect and not proactively. Applying our prediction method would, therefore, outperform the current approach, since about 86,34% of all defects can be identified in advance instead of replacing the component after the defect occurs.

## 5 Conclusion and Outlook

We designed, implemented and evaluated a predictive maintenance method for agricultural machines for predicting if a critical component exceeds an estimated prediction horizon, which represents a farmers' next harvesting period. The prediction method is based on real-world service records and position data provided by a large German agricultural service company, resulting in a prediction model that can be applied for analyzing incoming data and predicting future defects. We demonstrate that a predictive maintenance method in agriculture can be implemented with high accuracy based on service records and without sensor data. The evaluation of our prediction method shows that the mean overall accuracy for the prediction of defects is 86.34%, even though only few service records (11.48%) of the input data contained defects of the analyzed component.

Based on our results, the contribution of our paper is twofold. From a practitioner's perspective, on the one hand, our prediction method can be applied as the core of a predictive maintenance service. This service enables farmers to overcome the critical time of harvesting without a breakdown of agricultural machines caused by defect components—of course, it is not possible to predict accidents and human-caused breakdowns. Therefore, harvesting losses of farmers can be avoided. On the other hand, our prediction method allows a service provider to plan resources (i.e., personnel and spare part components)

proactively and by that provide their maintenance service more efficiently to customers. Our theoretical contribution is an exaptation of design knowledge on predictive maintenance from other domains to the agricultural sector. We show how this knowledge can be utilized and adapted to deal with special requirements and constraints in the agriculture sector. Furthermore, we present a generalized predictive maintenance method consisting of a knowledge-based expert system and a statistical-based approach that reaches a high prediction accuracy and can be used as a basis for further research on this topic. On the one hand, our method highlights the value of statistical-based methods for the design of predictive maintenance approaches for cases with no or limited access to sensor data. On the other hand, our method shows the value of using or integrating data from ERP systems for predicting defects.

Despite the overwhelmingly positive results in the evaluation of our prediction method, our research is subject to limitations. One limitation refers to the fact that the predictions made by our method are restricted to critical components. Our next step is to predict defects on a machine level. This implies differentiating equipment into critical and not critical components, regarding their impact on a machine level. For this approach, we need to determine dependencies of components as well as ascertain, if defects of several non-critical components could lead to critical issues when aggregated on a machine level. Both have to be considered in the prediction model to minimize faulty predictions and foster predictive maintenance services on a machine level. Another limitation is that the proposed method was evaluated with data on existing service records. An evaluation for generated future service records was not possible due to missing position data. To solve this problem, position data could be recorded by a smartphone app for our predictive maintenance service and applied in the prediction method. Even though the prediction model performs well, our results are dependent on the available data. On the one hand, service records containing similar information are usually available to other companies as well, which implies that a generalization of our results is possible to some extent. On the other hand, the accuracy of the prediction might vary if applied with different data. Further improvements of our method could avoid false predictions, which impede customers' trust in a service company's ability to keep machines operational.

In future research, we will include external data sources—such as weather and geological data—to further improve the method's accuracy. By considering weather data when estimating the prediction horizon, we assume to be able to narrow the timeframe for harvesting down to rain-free days. Geological data might improve the predictions for specific critical components, which are affected by different ground conditions. Since digitalization and standardization of onboard communication are only about to start in the agricultural sector, we expect further improvements for our method with the increasing availability of real-time machine data. Meanwhile, open data initiatives regarding the whole agricultural supply chain are fostered on a governmental level. For instance, the Global Open Data for Agriculture and Nutrition initiative (GODAN, [www.godan.info](http://www.godan.info))—an open data initiative in the food security sector run by the U.S. government, as well as by not-for-profit foundations, e.g. the Open Ag Data Alliance (OADA, [www.openag.io](http://www.openag.io))—serves to establish a secure data ecosystem for the entire agricultural industry, pursuing the goal of driving innovations to foster sustainable agriculture.

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## References

- Akhondi, M.R., Talevski, A., Carlsen, S. and S. Petersen (2010). "The role of wireless sensor networks (WSNs) in industrial oil and gas condition monitoring". In: *4<sup>th</sup> IEEE International Conference on Digital Ecosystems and Technologies (DEST)*, pp. 618–623.
- Allen, S.J. and E. W. Schuster (2004). "Controlling the Risk for an Agricultural Harvest." *Manufacturing & Service Operations Management*. 6 (3), 225–236.
- Amberg, M., Holm, T., Koos, T. and K. Dencovski (2009). "Trends and challenges of industrial services: An empirical study." In: *Proceedings of the 12<sup>th</sup> International Business Information Management Conference (IBIMA)* Ed. by B. Johansson and F. Sudzina. IBIMA. Malaysia: Kuala Lumpur, pp. 476–483.
- Antle, J.M., Jones, J.W. and C. E. Rosenzweig (2017). "Next generation agricultural system data, models and knowledge products: Introduction." *Agricultural Systems*. 155, 186–190.
- Arnaout, J.-P.M. and M. Maatouk (2010). "Optimization of quality and operational costs through improved scheduling of harvest operations." *International Transactions in Operational Research*. 17 (5), 595–605.
- Austin, J., Jackson, T., Fletcher, M., Jessop, M., Cowley, P. and P. Lobner (2003). "Predictive maintenance: Distributed aircraft engine diagnostics." In: *The Grid* Ed. by I. Foster and C. Kesselman. Morgan Kaufmann. CA: San Mateo, pp. 69–80.
- Bayoumi, A. and R. McCaslin (2016). "Internet of Things – A Predictive Maintenance Tool for General Machinery, Petrochemicals and Water Treatment." In: *Advanced Technologies for Sustainable Systems* Ed. by Y. Bahei-El-Din and M. Hassan. Springer, pp. 137–146.
- Bohle, C., Maturana, S. and J. Vera (2010). "A robust optimization approach to wine grape harvesting scheduling." *European Journal of Operational Research*. 200 (1), 245–252.
- Carbonell, I.M. (2016). "The ethics of big data in big agriculture." *Internet Policy Review-Journal on Internet Regulation*. 5 (1), 1–13.
- Carnero, M. (2006). "An evaluation system of the setting up of predictive maintenance programmes." *Reliability Engineering & System Safety*. 91 (8), 945–963.
- Chawla, N.V., Bowyer, K.W., Hall, L.O. and W. Philip Kegelmeyer (2002). "SMOTE: synthetic minority over-sampling technique." *Journal of artificial intelligence research*. 16, 321–357.
- Coppersmith, D., Hong, S.J. and J. R. M. Hosking (1999). "Partitioning nominal attributes in decision trees." *Data Mining and Knowledge Discovery*. 3 (2), 197–217.
- Daily, J. and J. Peterson (2017). "Predictive Maintenance: How Big Data Analysis Can Improve Maintenance." In: *Supply Chain Integration Challenges in Commercial Aerospace. A Comprehensive Perspective on the Aviation Value Chain* Ed. by K. Richter and J. Walther. Springer International Publishing, Cham, pp. 267–278.
- Demoly, F. and D. Kiritsis (2012). "Asset Optimization and Predictive Maintenance in Discrete Manufacturing Industry." *IFAC Proceedings Volumes*. 45 (31), 1–6.
- Deshpande, V. and J. Modak (2003). "Maintenance strategy for tilting table of rolling mill based on reliability considerations." *Reliability Engineering & System Safety*. 80 (1), 1–18.
- Edwards, D.J., Holt, G.D. and F. C. Harris (1998). "Predictive maintenance techniques and their relevance to construction plant." *Journal of Quality in Maintenance Engineering*. 4 (1), 25–37.
- Fawcett, T. (2006). "An introduction to ROC analysis." *Pattern recognition letters*. 27 (8), 861–874.
- Friedman, J.H. (2001). "Greedy function approximation: a gradient boosting machine." *Annals of statistics*, 1189–1232.
- Galar, D., Gustafson, A., Tormos, B. and L. Berges (2012). "Maintenance decision making based on different types of data fusion." *Eksplatacja i Niezawodnosc-Maintenance and Reliability*. 14 (2), 135–144.
- Ghosh, D. and S. Roy (2010). "A decision-making framework for process plant maintenance." *European Journal of Industrial Engineering*. 4 (1), 78–98.
- Gregor, S. and A. R. Hevner (2013). "Positioning and presenting design science research for maximum impact." *MIS Quarterly*. 37 (2), 337–355.

- Gregor, S. and D. Jones (2007). "The anatomy of a design theory." *Journal of the Association for Information Systems*. 8 (5), 312–335.
- Groba, C., Cech, S., Rosenthal, F. and A. Gossling (2007). "Architecture of a Predictive Maintenance Framework." In: *6<sup>th</sup> International Conference on Computer Interaction Systems and Industrial Management Applications* Ed. by K. Saeed. IEEE Computer Society. USA: Minneapolis, MN, pp. 59–64.
- Henriette, E., Feki, M. and I. Boughzal (2016). "Digital Transformation Challenges." In: *Mediterranean Conference on Information Systems Proceedings*, Paper 33.
- Herterich, M.M., Uebernickel, F. and W. Brenner (2015). "Empowering Technical Customer Service by Cyber-Physical Industrial Equipment: Exploring Rationales, Opportunities, and Impediments." In: *Proceedings of the Pacific Asia Conference on Information Systems (PACIS 2015)*, Paper 42.
- Hess, T., Matt, C., Benlian, A. and F. Wiesböck (2016). "Options for Formulating a Digital Transformation Strategy". *MIS Quarterly Executive*. 15 (2), 123–139.
- Higgins, A.J., Muchow, R.C., Rudd, A.V. and A. W. Ford (1998). "Optimising harvest date in sugar production: A case study for the Mossman mill region in Australia. I. Development of operations research model and solution." *Field Crops Research*. (57), 153–162.
- Huynh, K.T., Barros, A. and C. Bérenguer (2015). "Multi-level decision-making for the predictive maintenance of k-out-of-n:F deteriorating systems." *IEEE Transactions on Reliability*. 64 (1), 94–117.
- Kamilaris, A., Kartakoullis, A. and F. X. Prenafeta-Boldú (2017). "A review on the practice of big data analysis in agriculture." *Computers and Electronics in Agriculture*. 143, 23–37.
- KNIME.COM AG (2018). "KNIME - Open for Innovation." URL: <https://www.knime.org/> (visited on 04/19/2018).
- Kruize, J.W., Wolfert, J., Scholten, H., Verdouw, C.N., Kassahun, A. and A. Beulens (2016). "A reference architecture for Farm Software Ecosystems." *Computers and Electronics in Agriculture*. 125, 12–28.
- Kusumastuti, R.D., van Donk, D.P. and R. Teunter (2016). "Crop-related harvesting and processing planning. A review." *International Journal of Production Economics*. 174, 76–92.
- Lantzós, T., Koykoyris, G. and M. Salampasis (2013). "FarmManager. An Android Application for the Management of Small Farms." *Procedia Technology*. 8, 587–592.
- Lee, J., Ardakani, H.D., Yang, S. and B. Bagheri (2015). "Industrial Big Data Analytics and Cyber-physical Systems for Future Maintenance & Service Innovation." *Procedia CIRP*. 38, 3–7.
- Lee, J., Kao, H.-A. and S. Yang (2014). "Service Innovation and Smart Analytics for Industry 4.0 and Big Data Environment." *Procedia CIRP*. 16, 3–8.
- Li, Y. and U. Roy (2016). "Challenges in Developing a Computational Platform to Integrate Data Analytics With Simulation-Based Optimization." In: *Proceedings of the ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*. American Society of Mechanical Engineers. USA: Boston, Massachusetts, pp. V01BT02A035.
- Liu, Y., Hu, Y., Zhou, R. and J. Wen (2016). "An Approach Based on Improved Grey Model for Predicting Maintenance Time of IPS 2." *Procedia CIRP*. 47, 204–209.
- Lokuge, S., Sedera, D., Atapattu, M. and D. Samaranyaka (2016). "Exploring the Role of IS in Agriculture. Creating an Agenda Towards Agri-Informatics." In: *PACIS 2016 Proceedings*, p. 200.
- López-Campos, M.A., Crespo Márquez, A. and J. F. Gómez Fernández (2013). "Modelling using UML and BPMN the integration of open reliability, maintenance and condition monitoring management systems. An application in an electric transformer system." *Computers in Industry*. 64 (5), 524–542.
- Madni, A.M. and A. M. Madni (2008). "Smart configurable wireless sensors and actuators for industrial monitoring and control." In: *3<sup>rd</sup> International Symposium on Communications, Control and Signal Processing*. St Julians, pp. 447–448.
- Mobley, R.K. (2002). *An introduction to predictive maintenance*. 2<sup>nd</sup> Edition. Amsterdam, New York: Butterworth-Heinemann.
- Mourtzis, D., Doukas, M., Vlachou, A. and N. Xanthopoulos (2014). "Machine Availability Monitoring for Adaptive Holistic Scheduling: A Conceptual Framework for Mass Customization." In: *Proceedings of the 4<sup>th</sup> International Conference on Through-life Engineering Services*. 25, 406–413.

- Nadj, M., Jegadeesan, H., Maedche, A., Hoffmann, D. and P. and Erdmann (2016). “A Situation Awareness Driven Design for Predictive Maintenance Systems. The Case of Oil and Gas Pipeline Operations.” In: *ECIS 2016 Proceedings. Prototypes*, Paper 6.
- Niang, B., Adjallah, K. and P. Ndiaye (2006). “Characterization of Diagnosis Algorithms for Real-time Scheduling on Distributed Processors in Support to e-Maintenance Services.” In: *Proceedings of International Conference on Service Systems and Service Management*. IEEE. France: Troyes Cedex, pp. 626–631.
- O’Grady, M.J. and G. M.P. O’Hare (2017). “Modelling the smart farm.” *Information Processing in Agriculture*. 4 (3), 179–187.
- Oneto, L., Fumeo, E., Clerico, G., Canepa, R., Papa, F., Dambra, C., Mazzino, N. and D. Anguita (2016). “Delay Prediction System for Large-Scale Railway Networks Based on Big Data Analytics.” In: *Advances in Big Data. Proceedings of the 2<sup>nd</sup> INNS Conference on Big Data* Ed. by Angelov P., Manolopoulos Y., Iliadis L., Roy A., Vellasco M. Springer; Springer International Publishing. Cham, pp. 139–150.
- Peffers, K., Tuunanen, T., Rothenberger, M.A. and S. Chatterjee (2007). “A Design Science Research Methodology for Information Systems Research.” *Journal of Management Information Systems*. 24 (3), 45–77.
- Peng, Y., Dong, M. and M. Jian Zuo (2010). “Current status of machine prognostics in condition-based maintenance. A review.” *The International Journal of Advanced Manufacturing Technology*. 50 (1-4), 297–313.
- Pham, X. and M. Stack (2018). “How data analytics is transforming agriculture.” *Business Horizons*. 61 (1), 125–133.
- Priyadarshy, S. (2017). “Digital transformation essential for E&P industry to thrive in new economy.” *World Oil*, 66–67.
- Prytz, R., Nowaczyk, S., Rögnvaldsson, T. and S. Byttner (2015). “Predicting the need for vehicle compressor repairs using maintenance records and logged vehicle data.” *Engineering Applications of Artificial Intelligence*. 41, 139–150.
- Ramirez, A.S., Loendersloot, R., Jauregui, J.M. and T. Tinga (2013). “Design framework for vibration monitoring systems for helicopter rotor blade monitoring using wireless sensor networks.” In: *Proceedings of the 9<sup>th</sup> International Workshop on Structural Health Monitoring* Ed. by F.-K. Chang. DEStech publishing. USA: Stanford, CA, pp. 1023–1030.
- Ruiz-Garcia, L., Lunadei, L., Barreiro, P. and I. Robla (2009). “A review of wireless sensor technologies and applications in agriculture and food industry. State of the art and current trends.” *Sensors*. 9 (6), 4728–4750.
- Salin, V. (1998). “Information Technology in Agri-Food Supply Chains”. *International Food and Agribusiness Management Review*. 1(3), 329–334.
- Sayed, M.S., Lohse, N., Sondberg-Jepesen, N. and A. L. Madsen (2015). “SelSus: Towards a reference architecture for diagnostics and predictive maintenance using smart manufacturing devices.” In: *IEEE 13<sup>th</sup> International Conference on Industrial Informatics (INDIN)*. UK: Cambridge, pp. 1700–1705.
- Sein, M.K., Henfridsson, O., Puroo, S., Rossi, M. and R. Lindgren (2011). “Action design research.” *MIS Quarterly*, 37–56.
- Shearer, C. (2000). “The CRISP-DM model: the new blueprint for data mining.” *Journal of data warehousing*. 5 (4), 13–22.
- Susto, G.A., Schirru, A., Pampuri, S., McLoone, S. and A. Beghi (2015). “Machine Learning for Predictive Maintenance. A Multiple Classifier Approach.” *IEEE Transactions on Industrial Informatics*. 11 (3), 812–820.
- Tan, B. and N. Çömnden (2012). “Agricultural planning of annual plants under demand, maturation, harvest, and yield risk.” *European Journal of Operational Research*. 220 (2), 539–549.
- Tilson, D., Lyytinen, K. and C. Sørensen (2010). “Research Commentary —Digital Infrastructures. The Missing IS Research Agenda.” *Information Systems Research*. 21 (4), 748–759.



- Traore, M., Chammas, A. and E. Duviella (2015). "Supervision and prognosis architecture based on dynamical classification method for the predictive maintenance of dynamical evolving systems." *Reliability Engineering & System Safety*. 136, 120–131.
- Tsubone, H., Muramatsu, R. and M. Soshiroda (1983). "Designing an effective production system for processing agricultural products." *International Journal of Production Research*. 21 (1), 17–30.
- Umiliacchi, P., Lane, D., Romano, F. and A. SpA (2011). "Predictive maintenance of railway subsystems using an Ontology based modelling approach." In: *Proceedings of 9<sup>th</sup> world conference on railway research*, May, pp. 22–26.
- Unal, M., Onat, M., Demetgul, M. and H. Kucuk (2014). "Fault diagnosis of rolling bearings using a genetic algorithm optimized neural network." *Measurement*. 58, 187–196.
- Venkataraman, M., Chatterjee, M. and K. Kwiat (2011). "A dynamic reconfigurable routing framework for wireless sensor networks." *Ad Hoc Networks*. 9 (7), 1270–1286.
- Wang, Q., Yang, J., Liu, W., Yuan, Q. and H. Ma (2010). "Development and application of process industry equipment maintenance information system for intelligent decision-making." *Jixie Gongcheng Xuebao/Journal of Mechanical Engineering*. 46 (24), 168–177.
- Woldman, M., Tinga, T., van der Heide, E. and M. A. Masen (2015). "Abrasive wear based predictive maintenance for systems operating in sandy conditions." *Wear*. 338, 316–324.
- Wortmann, F. and K. Flüchter (2015). "Internet of Things." *Business & Information Systems Engineering*. 57 (3), 221–224.
- Yu, J. and W. Zhang (2013). "Study on Agricultural Condition Monitoring and Diagnosing of Integrated Platform Based on the Internet of Things." In: *Computer and computing technologies in agriculture VI*. Springer. Berlin, Heidelberg, pp. 244–250.