Digital Twin for Reliability Analysis During Design and Operation of Mechatronic Systems

Thorben Kaul, Amelie Bender, and Walter Sextro

Chair of Dynamics and Mechatronics, Faculty of Mechanical Engineering, Paderborn University, Germany.
E-mail: thorben.kaul | amelie.bender | walter.sextro@upb.de

As the emerging digitalization of technical systems offers immense opportunities to be exploited by means of big data analysis, ubiquitous computing and largely networked systems, the digital twin comes into focus to combine all these aspects to an attendant model of an individual system during design phase as well as during operation. Since state-of-art technical systems are growing increasingly complex due to inherent intelligence and increasing functionality, i. e. autonomous behavior so far, it becomes considerably challenging to ensure reliability for those systems. Many methods were developed to support a reliability focused design or reliability-by-design approaches to tackle this challenge during design process. In field, data-based methods, i. e. condition monitoring enabled by the rise of machine learning approaches, are exploited to ensure a reliable operation based on the current condition of the monitored system. In order to take advantage of existing models of system reliability during design phase and condition monitoring systems during operation, a method is proposed to combine both approaches in order to set up a digital twin with focus on system reliability. The base model of the digital twin is taken from the system reliability model from the design phase and is used during operation and therein updated to the current reliability based on the state estimation of the condition monitoring system. The approach is illustrated with a case study of a rolling bearing test rig.

Keywords: Condition Monitoring, Digital Twin, Integrated Model, Reliability, IoT, Data-based Diagnostics.

1. Introduction

The Digital Twin mirrors the physical system throughout the entire product lifecycle, during design, manufacturing, operation and disposal, and is perpetually edited to keep up with the evolving, physical system Grieves and Vickers (2017). Consequently, the digital twin incorporates a dynamic modeling approach, where the underlying model is updated based on sensor data or other observations. The digital twin is enabled by an emerging digitalization of technical systems, that has lead to interconnected, distributed systems with inherent intelligence. However, the development of a digital twin is only favorable and achievable if it is used in many phases of the product lifecycle, e.g. in design and operation, otherwise the potential benefits do not justify the efforts Rosen et al. (2015).

Since the digital twin is considered as a comprehensive virtual copy of the physical system, its ideal intention is to obtain at least the same information from the digital twin as from the physical system Grieves and Vickers (2017). In particular reliability analysis could significantly benefit from exploiting the digital twin for optimal maintenance operation scheduling, online diagnosis in case of unknown causes for system break downs and perpetually increase reliability, availability and safety.

Technical systems have become increasingly complex due to emerging use of machine learning methods and interconnectivity, which pave the way to autonomous systems. In order to increase reliability, and in addition availability and safety, existing modeling techniques could be extended to form a digital twin with focus on system reliability. In literature, several approaches are known to combine appropriate models for system reliability and sensor data of the physical system in order to monitor system reliability during operation.

In Sondermann-Wölke (2015) standard Bayesian Networks are exploited to perform diagnosis and prognostics on mechatronic systems, where component failures are detected based on sensor data. The current health condition of a component is not taken into account to update system reliability. In Zhao et al. (2013) an integrated prognostics method for gear remaining lifetime prediction with focus on fatigue crack growth is proposed. In the framework, stress, dynamics and damage propagation models are utilized and combined with condition monitoring data to update and analyze remaining lifetime. The framework is particularly developed for gears and hence cannot be applied to other sorts of systems. In Li et al. (2017) the remaining useful life for fatigue crack growth in airframe structural components is computed considering uncertainty

Proceedings of the 29th European Safety and Reliability Conference.
Edited by Michael Beer and Enrico Zio

Published by Research Publishing, Singapore.
ISBN: 978-981-11-2724-3; doi:10.3850/978-981-11-2724-3_0876-cd

about different model parameters, e.g. prevailing load, current crack length, and observations made on these parameters. Again, this method is only suitable for certain systems, i. e. airframe structures. These approaches are either restricted to specific systems and failure modes, i. e. fatigue crack growth, or lack a sophisticated integration of component health conditions. Besides these approaches, digital twins often lack a useful synchronization between virtual and physical world and the capability to gather and process large data sets Schleich et al. (2017). The maintenance of complex technical systems relies on health monitoring of critical components, which are identified during design, and thus, neglecting the remaining components in predictive maintenance operations, for which mostly reactive maintenance operations are scheduled. A combination of sophisticated reliability models, taken from design process, and condition monitoring of critical components during operation is able to close this gap. In previous work Kaul et al. (2015), the authors proposed an integrated modeling approach for dynamics and reliability of mechatronic systems, that uses Bayesian Networks as system reliability models and supports their synthesis by an automated translation method. Bayesian Networks are used in the present work to establish a link between system reliability models from design process and condition monitoring systems used during operation. The system reliability, which is modeled with Bayesian Networks, can be updated by observations made on the current health state of particular components based on the condition monitoring at runtime. This combination offers a more accurate analysis of system reliability during operation and supports maintenance scheduling as well as operations, e.g. performing probable cause analysis in an event of system failure.

The objective of the proposed method is to develop a digital twin, which integrates in an existing framework of the integrated modeling of reliability and dynamics during design Kaul et al. (2015) to enable for extensive reliability analysis during operation. The digital twin is considered as a model of an individual, physical system, that is kept up with the physical system throughout the entire product lifecycle with focus on design process and operation with the aim to optimize maintenance operations, i. e. optimal scheduling and diagnosis in an event of failure.

The remainder of the paper is structured as follows: the successive section briefly introduces the mentioned approach for reliability analysis during design and discusses methods to ensure reliability during operation as basis for the proposed digital twin in Sec. 3. In Sec. 4, the proposed method for a digital twin with focus on system reliability is illustrated on a rolling bearing test rig. The last section discusses the proposed digital twin, the method, and its results and ends with a conclusion.

2. Reliability During Design and Operation

The model-based development process of mechatronic systems provides models of system behavior on which different methods set up in order to perform software supported reliability analysis. Theses models deteriorate when the system is set to operation and condition monitoring systems are developed to estimate reliability or the remaining useful lifetime based on the current condition of the monitored component or system.

2.1. *Reliability Model*

The increasing complexity of state-of-the-art mechatronic systems makes the design process of such systems more prone to errors, e.g. common mode failures are major threats to reliable systems Grieves and Vickers (2017). Thus, ensuring reliability becomes considerably challenging and has to be taken into account in early design phase using a model-based approach. To overcome these issues, the integrated modeling of system behavior and reliability was introduced Kaul et al. (2015) to support the design process by offering an automated synthesis of a reliability model.

The integrated modeling of dynamic behavior and reliability in system development delivers a model-based approach for reliability investigation by taking into account the dynamic system behavior as well as the system architecture at different phases of the development process. This approach features an automated synthesis of a reliability model out of a behavior model, enabling for the closed loop modeling of degradation of the system components and its (dynamic) behavior. It is based on standard models used in model-based development methodologies, i. e. SysML, Matlab/Simulink, Dymola and MSC ADAMS. To each component in the model of system dynamics, a lifetime estimator is added which estimates component reliability for prevailing loads obtained from the system dynamics model. The components reliability distributions are used as a priori knowledge in system reliability analysis. A Bayesian Network (BN) is used as system reliability model. For further reading about the integrated modeling approach, please refer to Kaul et al. (2015).

A Bayesian Network is a directed acyclic graph (DAG) model with its nodes representing a set of n variables $\nu = \{X_1, X_2, ..., X_n\}$. Each variable of ν represents a set of a finite number of states and is endowed with a conditional probability distribution (CPD). A Bayesian Network, that is set up for ν specifies a unique joint probability distribution $P(\nu)$ given by the product of all CPDs:

$$P(\nu) = \prod_{i=1}^{n} P(X_i \mid \mathrm{Pa}(X_i)), \qquad (1)$$

where X_i represents node i and $\mathrm{Pa}(X_i)$ is the entity of its parent nodes. Parent nodes are all nodes, whose edges are directly or by intersecting other nodes pointing to the current node X_i. Perpetually, $P(X_i \mid \mathrm{Pa}(X_i))$ refers to the probability, that X_i occurs for given knowledge about its parent nodes $\mathrm{Pa}(X_i)$. To obtain the marginal probability $P(B)$ out of the joint probability distribution $P(\gamma)$, all probabilities that quantify the influence of other events x on X_i are taken into account:

$$P(X_i) = \sum_{x \in \gamma} P(\gamma). \qquad (2)$$

Assume another discrete set of variables $\gamma = \{A, B, C\}$ which is shown in Fig. 1. It can be represented by a set of conditional probability tables (CPT), which lists the probabilities that a child node B takes on each of its states for each combination of states of its parent nodes $P(B|\mathrm{Pa}(B)) = P(B|A, C)$. The probability table of a root node $P(A)$ (node without parents) includes a priori knowledge, i. e. component reliabilities $R_A(t)$ and $R_C(t)$.

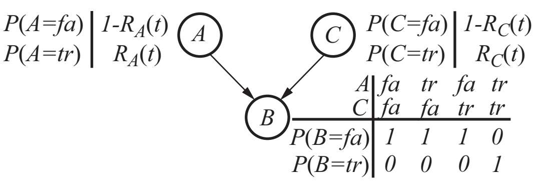

Fig. 1. Simple Bayesian Network as reliability model representing an OR-gate.

In previous work Kaul et al. (2015), a reliability model is proposed, where a Bayesian Network represents a set of components of the investigated system. Here it is assumed that all system components have *Boolean* states: true tr representing a component in operable state and false fa representing a component failure. Accordingly, the CPTs for system components A and C are shown in Fig. 1. Since component failures are assumed to occur independently if parent nodes are in operable state, the CPTs represent component reliability $R_A(t)$ and $R_C(t)$ as well as causal failure propagation implemented as binary table entries; B conditionally fails when a failure of A or C occurs. The probability distribution $P(B|A, C)$ (Eq. 1) can be obtained using Eq. 2 and is interpreted as system reliability $R_{\mathrm{Sys}}(t)$.

The knowledge, represented by a Bayesian Network can be updated with certain or uncertain observations called evidences. There are two types of uncertain evidences in Bayesian Networks: virtual evidences, which can be interpreted as the uncertainty about the observation, and soft evidences, which can be interpreted as an uncertain observation Peng et al. (2010). Soft evidences are represented as a probability distribution of one or more variables. In this work, the probabilistic results of a condition monitoring system are used to add evidences to single variables within a Bayesian Network. The condition monitoring gives only an estimate of the current health state of the observed component by a probability distribution and is not capable of providing a deterministic value, apart from an eventual component break down. This probability distribution is treated as soft evidence. The soft evidence is applied on only a single variable within the network in order to sufficiently illustrate the proposed method. Peng et al. (2010) proposed an efficient algorithm to incoorporate soft evidence on a single variable within a network. This algorithm, which is used in the proposed method of this work, convertes a soft evidence into a virtual evidences, making inference on the updated network more robust. For a detailled description of the algorithm please refer to Peng et al. (2010).

2.2. *Condition Monitoring*

Condition monitoring is nowadays implemented in different application areas to enable its advantages such as less unplanned break downs, a higher availability and in general a more reliable system. To reach these goals condition monitoring includes two techniques, in particular diagnosis and prognostics. Diagnosis is in the first step the detection of anomalies such as errors or failures of the system and in the second step the detailed identification of the anomaly. Whereas diagnosis is focused on the present, prognostics develops an estimate of the future. Therein, based on current measurements the next time step or even a long-term estimation are calculated. This work focuses on diagnosis, prognostics is neglected in this work. However, both techniques can be subdivided in two main kind of methods, data-based and model-based methods. While the former is only built on data of the monitored system, the later needs a defined model based on expert knowledge to achieve its aim. Nowadays, data-based methods experience huge regard due to their easy implementation and their adaptability to different systems. Especially, machine learning techniques are widely applied.

The condition monitoring process for data-based methods can be structured in three parts, namely training, testing and usage. During training the method learns a model based on the input data. Therefore, training data sets are necessary as input. That data set should contain all relevant information, e.g. the different errors or classes the monitored system experiences during its lifetime. The learned model is tested in the next step by a testing data set. Splitting the data set in these two parts is often done by cross validation. Regarding the model evaluation, performance metrics such as mean squared errors are used to estimate the error between the estimated class and the true class.

After the model is evaluated, it can be used during the third part of the condition monitoring process, the real usage or application. Therefore class estimation is executed based on new data of the same system. These classes are often called health states due to their internal meaning, they describe the current state of the monitored system regarding its functionality. So, the estimated health states correlate to the reliability of the mechatronic system.

3. Digital Twin Method

The digital twin for system reliability requires an appropriate system reliability model, which is capable of updating its beliefs with newly arriving sensor data. Bayesian Networks meet this requirement, because observations can be added to the system analysis by means of different forms of evidences, i. e. soft and virtual. The use of a particular synthesis method, e.g. previously introduced integrated modeling Kaul et al. (2015), is favorable, because it offers the opportunity to form a closed framework for a sophisticated analysis of reliability during design as well as during operation by means of condition monitoring and a digital twin.

Condition monitoring can be used for either diagnosis or prognosis, if applied to technical systems. Since prognosis aims at the estimation of the remaining useful life, it cannot easily incorporated into a probabilistic model, i. e. Bayesian Networks. In context of the digital twin, diagnosis is required to provide a probabilistic estimate on the current, discrete health state of the monitored component over operating time. Hence, condition monitoring provides a continuous health state estimate, see Fig. 2, to allow for a continuous update of system reliability over operating time. The health state estimations in this example are artificially generated to illustrate the method.

The Bayesian Network of γ in Fig. 1 is used as a simple system reliability model for a system B of two components A and C. For both components, the reliability functions $R_{A/C}(t)$ are known from the design process and in order to prepare for the use as a digital twin, component A is observed by means of condition monitoring. Assume, a trained condition monitoring model for component A is available and provides a continuous diagnosis on five health states over operating time as shown in Fig. 2. Thus, the condition monitoring gives observation $e(t)$ on component A with a state probability vector $(e_1(t), ..., e_5(t))$, where $e_{1,...,5}(t)$ refer to the probability of each health state in each monitored time step t. In the Bayesian Network, the health state are refered to as follows: normal (tr), faulty state 1/2/3 $(f1/2/3)$) and failed (fa).

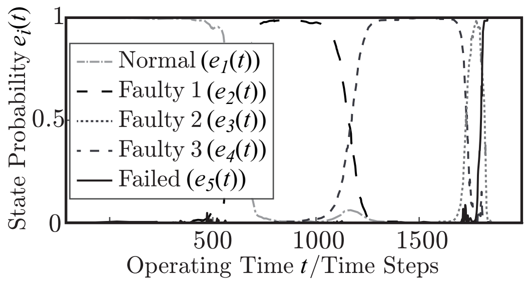

Fig. 2. Continuous probabilities of health states of rolling bearing.

To allow for an update of system reliability $R_{Sys}(t) = P(B = tr|e(t), C)$ for observation $e(t)$, the Bayesian Network has to be edited because the states of A used during design do not match with the identified health states of the condition monitoring. It is straight forward to edit states of A, while the editing of B requires additional information, because the influence of the health states on system reliability has to be defined. This can be achieved either by expert knowledge to judge on the influence or based on observations made on the system, which can be included during operation by means of evidences. In Fig. 3, the influence of an either normal, i. e. operational, (tr) or failed (fa) component A is considered as deterministic and thus modeled with binary values. The influence of $A = (f1, f2, f3)$

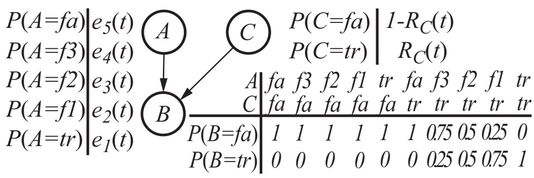

Fig. 3. Edited Bayesian Network with soft evidence in A and extended component B.

is uncertain and has to be estimated. The health states $f1, f2, f3$ refer to increasing severity level of damage of A, hence system failure caused by degradation of A becomes more likely.

The continuous observations $e(t)$ made by the condition monitoring of component A are added as soft evidence to the Bayesian Network. It is evaluated for each newly arriving evidence $e(t)$ at time step t and yields the system reliability $P(B = tr|e(t), C)$ in Fig. 4.

The results indicate the benefits of the digital twin, because the estimated and real system reliability can significantly differ, e.g. in this case for design model $R_{DM}(t = 200) = 62.84\%$ and for the digital twin $R_{DT}(t = 200) = 89.29\%$. This might be due to different reasons, e.g. no accurate

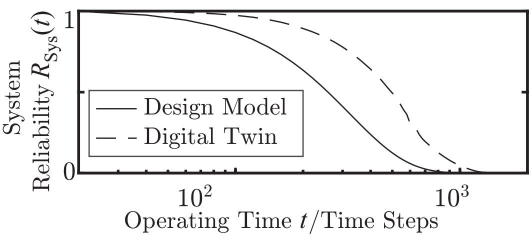

Fig. 4. Comparison between system reliability obtained from design model and from digital twin.

presumptions on the prevailing load on the system, unknown or unexpected operating conditions or operators who intentionally operate the system not regarding its specification. This might lead to an overly conservative prediction of system reliability during design or in the worst case a fairly overestimated prediction. The digital twin is able to cope with this risks by updating system reliability based on one or more current health estimates of monitored components.

4. Case Study

The case study is carried out on a modular rolling bearing test rig, that is used to generate data sets for specific conditions of bearing health. In particular, the system was set up to obtain vibration and motor current data from worn or damaged rolling bearings Lessmeier et al. (2016), that are used as benchmark data sets with specific bearing health conditions for the development of condition monitoring systems.

Accelerated lifetime tests were conducted on another specifically designed test rig with the monitored bearings in order to provide pre-damaged bearings with known health conditions. The acceleration factor of the accelerated lifetime tests, used to map experiment duration to operating time under similar conditions, is not known.

In this work, a digital twin for system reliability is set up for the modular bearing test rig. The already conducted experiments and the acquired data sets are exploited to illustrate the proposed digital twin. The data sets represent different bearing health conditions, i. e. from new to severe pitting at the inner and outer ring. The worst level of pitting at the inner and outer ring indicates a failure.

Since the acceleration factors of the accelerated lifetime tests of the pre-damaged bearings are not known, it is not possible to link the data sets and their health states to the total operating time of the test rig. Thus, the use of these data sets rules out continuous degradation monitoring until system failure with the digital twin. However, the data sets show discrete health conditions of increasing severity and allow for updating of the system reliability model during operation.

4.1. *Test Rig and Data Aquisition*

The test rig consists of industrial equipment to generate condition monitoring data as close to industrial standard as possible, i. e. vibration and motor current signals. The test rig consists of several modules: an electric motor (1), a torque-measurement shaft (2), a rolling bearing test module (3), a flywheel (4) and a load motor (5), see Fig. 5. The ball bearings with different types of damage are mounted in the bearing test module to generate the experimental data. The rolling bearing module provides the possibility of using a test bearing under a constant radial load and to measure the vibration of the inner housing, which holds the test bearing in the main direction of the load. For a detailed description of the test rig please refer to Lessmeier et al. (2016). The vibration data used in the following sections is taken from the reference data set generated by Lessmeier et al. (2016).

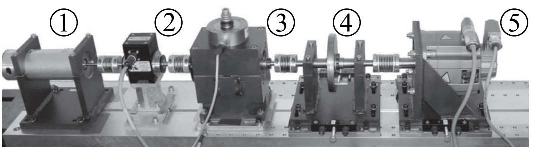

Fig. 5. Set up of the modular rolling bearing test rig according to Lessmeier et al. (2016).

4.2. *Reliability Modeling in Design*

The system reliability of the proposed test rig is analyzed with the integrated modeling approach for dynamics and reliability Kaul et al. (2015) during design phase. In order to analyze system reliability based on system dynamics and its influence on each individual system component, critical components are identified based on a failure mode effects analysis (FMEA). Clutches and structural components, i. e. bearing housings, flywheel and other supporting structures, are not found to be critical, since there is no notable degradation, and are hence neglected for system reliability analysis.

The drive and load motors are critical to system reliability and three different failure modes are taken into account for each motor, i. e. failure of one of the two rolling bearings and a failure of the wire coil insulation. The bearing failures are modeled using DIN 281, the lifetime estimation of the wire coil insulation follows an approach introduced by Brancato Brancato (1992). It is assumed that the occurrence of one of these failure modes directly leads to failure of the motor. The torque-measurement shaft, oil and housing temperature sensors are considered for the data acquisition system and modeled using simple models taken from Department of Defense (1995). The other rolling bearings, that are used in pairs in the flywheel and the housing for the monitored bearing, are also modeled based on DIN 281. The monitored bearing is also taken into account with a lifetime estimator based on DIN 281 during design and is intended to include the condition monitoring results to refine system reliability estimation during operation. The applied radial force to the monitored bearings is in average overall experiments $F_{\mathrm{r,aver}} = 700\mathrm{N}$ at rotating speed of $n = 1500\mathrm{min}^{-1}$. Thus, component lifetimes are calculated for these operating conditions of the test rig.

In Fig. 6 the derived model of system reliability for the test rig is shown and analyzed for operating time $t = 1000\mathrm{h}$. The modeling and analysis was carried out using GeNIe Modeler and SMILE Engine[a]. The subsystem nodes are used to represent the system hierarchy and are implemented as OR-gates, i. e. every component failure leads to a failure of the subsystem.

The results of system reliability analysis are shown in Fig. 7. According to Fig. 6 at operating time $t = 1000\mathrm{h}$, the monitored bearing and the drive motor, which is mainly influenced by the included rolling bearings, are apparently already degrading, as long as the other components are still fully operational.

4.3. *Condition Monitoring for Bearing Health*

A couple of data-based condition monitoring methods exist for diagnosis in literature. For the purpose of this work, multi-class support vector machines (SVM) are suitable since they are proven to be a powerful classifier Kimotho (2016). Data of many real applications contain noise and are not lineary seperable into different classes. SVM is able to solve non-linear classification problems by transforming the input data into a higher dimensional feature space. Therefore a kernel function is necessary to construct a hyperplane in the higher dimensional space. So the classification is solved by separating binary classifications problems using hyperplanes, which are built by support vectors. For solving multi-classification problems, these problems are separated, treated as binary classification problems and solved individually. In the end, the binary classifiers are commonly combined by pairwise coupling method.

Another reason for the implemantion of SVM is its ability to estimate class probabilities which are used in the Bayesian Network. Moreover, the mentioned database encapsulates an optimized method SVM (SVM-PSO), that uses optimally tuned parameters. Usage of SVM requires at least two tuned parameters, the cost parameter and the kernel function parameter. In this work particle swarm optimization is used for tuning these intern parameters Kimotho (2016).

A condition monitoring system for the presented bearing test rig is developed. In the training phase features from time-, frequency- and time-frequency-domain are extracted from the vibration signals of each bearing. Fig. 8 illustrates the defined classes which are mapped to the corresponding bearing damage according to Lessmeier et al. (2016).

To avoid overfitting and to ensure a good classification, only the most relevant features are selected based on pairwise distance. In the next step, SVM trains a model using the selected features and the defined class labels. The trained models are evaluated by test data from the bearing test rig. The SVM results in class probabilities that assign a probability for each trained class to the input data, that can be used as evidences on the monitored bearing in the Bayesian Network.

4.4. *Digital Twin*

The digital twin is formed for the modular rolling bearing test rig based on the previously developed system reliability model and the condition monitoring system. The system reliability model has to be edited to match the identified classes of bearing health.

In the previous section, seven classes for bearing health conditions are defined, that represent different degradation states of the monitored bearing with increasing severity, i. e. pitting on the inner ring and on the outer ring. These classes have to be incorporated into the model of system reliability, so that an evidence can be set for the monitored component, which until now features only the binary states of the lifetime estimator used during design phase. The number of states for node MB is extended to include the seven classes. These classes do not clearly indicate component failure, hence the lifetime estimator used during design cannot be appropriately applied once the states are edited. Hence, a uniform distribution is assumed for the CPT of MB, representing the prior knowledge about the components state at an arbitrary time step during operation. However, this knowledge will be updated to certain time instances during operation by the condition monitoring system.

Since the classes identified by the condition monitoring do not include a class 'failure', the classes have to be interpreted within the reliability model to decide whether the component has failed or remains operational though already degraded. This is achieved by editing the child node BM and its CPT shown in Table 1, i. e. MB is considered as failed fa if the pitting in either inner

[a]GeNIe Modeler and SMILE Engine by BayesFusion, LLC, http://www.bayesfusion.com/

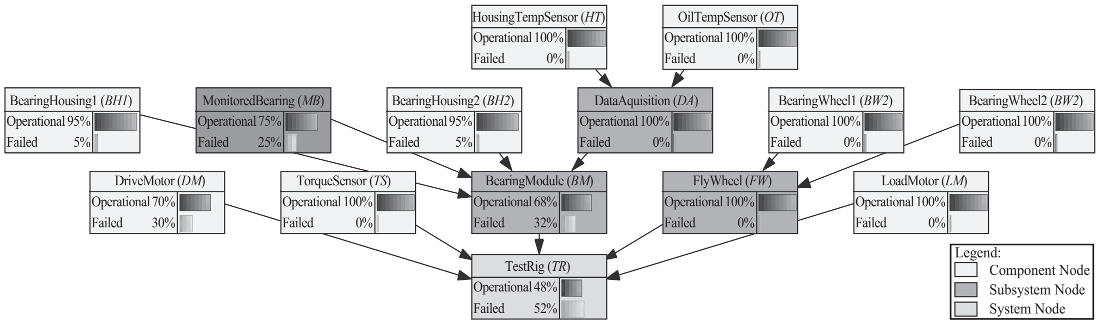

Fig. 6. Bayesian Network of the bearing test rig during design with system reliability $R(t = 1000\text{h}) = 47.61\%$.

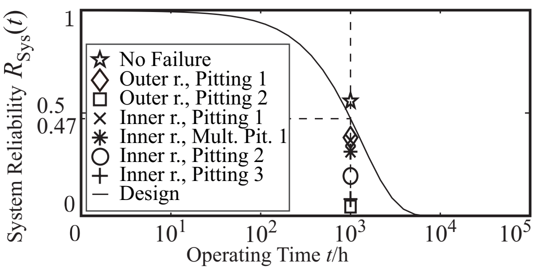

Fig. 7. System reliability of test rig during design with $R_{Sys}(t = 1000\text{h}) = 47.61\%$ and with updated results taken from Digital Twin.

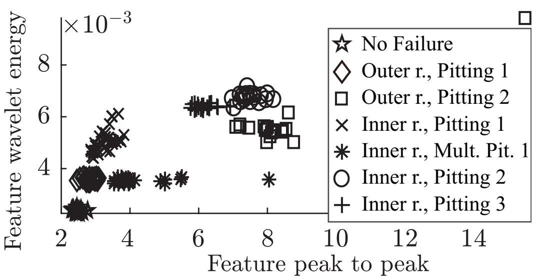

Fig. 8. Defined classes of rolling bearings by SVM.

or outer ring increases otherwise it is considered operational op. The probabilities $P(BM|MB)$ are chosen to consider the effects of degradation to the system reliability.

Table 1. Reduced representation of CPT of BM

MB	$BH1$	$BH2$	DA	$P(BM = op)$
$NoFailure$	op	op	op	1
$O.\,r., Pitt.\,1$	op	op	op	0.4
$O.\,r., Pitt.\,2$	op	op	op	0
$I.\,r., Pitt.\,1$	op	op	op	0.4
$I.\,r., M.\,Pitt.\,1$	op	op	op	0.5
$I.\,r., Pitt.\,2$	op	op	op	0.7
$I.\,r., Pitt.\,3$	op	op	op	0

Adapting the system reliability model to the requirements of the condition monitoring system, offers the possibility to compute system reliability based on the current state estimate of the monitored bearing. To allow for updating of system reliability, a soft evidence is added to the reliability model for each new estimate for bearing health of the condition monitoring. The chosen analysis tool is restricted to virtual evidences, so the approach of Peng et al. (2010) is used to convert soft evidence into virtual evidence.

4.5. *Results*

As previously stated, mapping the condition monitoring data sets to a particular total operating time of the test rig is not possible. However, the data sets represent degradation of the monitored bearings and one can easily imagine, that pitting evolves on the inner and the outer ring for ongoing operating time of the test rig. In order to simplify representation, let $K = \{BH1, BH2, HT, OT, BW1, BW2, DM, TS, LM\}$ refer to the remaining components with lifetime estimator within the system reliability model. The system reliability is considered as the conditional probability of the system node TR with $R_{Sys}(t = 1000\text{h}) = P(TR|e, K(t = 1000\text{h}))$ with evidence e as the estimate of current bearing health taken from the condition monitoring and $K(t = 1000\text{h})$ as the a priori probabilities of the remaining lifetime estimators for operating time $t = 1000\text{h}$. The operating time is chosen as $t = 1000\text{h}$ as evidence from the condition monitoring is added to the system reliability model to illustrate the effect of different health conditions of a single component on system reliability. Since only discrete data sets for particular bearing health conditions are available, a continuous computation of system reliability is not conducted. The results for the updated system reliability are shown in Fig 7. The results show, that for no detectable damage on the monitored bearing, the system reliability is with 55.71% even higher compared to the results obtained during design for $R_{Sys}(t = 1000\text{h}) = 47.61\%$. System reliability is significantly decreasing for severe degradation, i. e. Pitting 2 in outer ring and Pitting 3 in inner ring. The system remains operational for 4.5% respectively 8.06% in conditions, where it is considered to be failed. This is due to the uncertainty within the condition monitoring results.

5. Discussion and Outlook

In a real application, the condition monitoring system works continuously, or at least in short intervals, and provides a diagnosis on the current monitored component health, which allows for a continuous updating of the digital twin. The case study provided access to few data sets, that allow for only discrete estimation of component degradation over operating time based on the given diagnosis data. However, the proposed approach for a digital twin focusing on system reliability could be illustrated based on the condition monitoring of one component. If more than one component is monitored and the results are intended to update the digital twin, another algorithm for incorporating multiple evidences into the Bayesian Network is required, i. e. extension to the iterative proportional fitting procedure (IPFP) Peng et al. (2010).

In this work, a method is introduced, that combines different methods of reliability analysis during design and operation of technical systems to a digital twin with focus on system reliability. The proposed system reliability model is taken from the design process and uses Bayesian Networks to exploit their capability to update system analysis with observations made during operation. These observations are taken from a condition monitoring system, that estimates the current health state of a monitored component, i. e. rolling bearing. The proposed method is illustrated with a case study of a modular rolling bearing test rig. From previous work, several data sets for different bearing health states are provided and used in this work. It was shown, that system reliability models from the design process can be combined with condition monitoring systems to be used as a digital twin during operation. Based on the digital twin, a more accurate estimation of system reliability during operation is possible compared to the lifetime estimators used during design.

The digital twin enables for optimal scheduling of maintenance operations not only for monitored bearing, but for the entire system, because the lifetime estimators of the remaining components can indicate possible unobserved failures.

Acknowledgement

The authors would like to thank D. Zimmer, C. Lessmeier and the Chair of Design and Drive Technology at Paderborn University for providing access to the reference data set of bearing damages and to the modular test rig.

References

Brancato, E. L. (1992). Estimation of lifetime expectancies of motors. *IEEE Electrical Insulation Magazine 8*(3), 5–13.

Department of Defense (1995). Military handbook reliability prediction of electronic equipment: Mil-hdbk-217f notice 2.

Grieves, M. and J. Vickers (2017). Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In *Transdisciplinary Perspectives on Complex Systems*, pp. 85–113. Springer.

Kaul, T., T. Meyer, and W. Sextro (2015). Integrated model for dynamics and reliability of intelligent mechatronic systems. In Podofillini et al (Ed.), *European Safety and Reliability Conference (ESREL2015)*, London. Taylor and Francis.

Kimotho, J. K. (2016). *Development and performance evaluation of prognostic approaches for technical systems*. Aachen: Shaker Verlag. Dissertation: Universität Paderborn.

Lessmeier, C., J. K. Kimotho, D. Zimmer, and W. Sextro (2016). Condition monitoring of bearing damage in electromechanical drive systems by using motor current signals of electric motors: A benchmark data set for data-driven classification. In *Proceedings of the European Conference of the Prognostics and Health Management Society*, pp. 05–08.

Li, C., S. Mahadevan, Y. Ling, S. Choze, and L. Wang (2017). Dynamic bayesian network for aircraft wing health monitoring digital twin. *AIAA Journal 55*(3), 930–941.

Peng, Y., S. Zhang, and R. Pan (2010). Bayesian network reasoning with uncertain evidences. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems 18*(05), 539–564.

Rosen, R., G. von Wichert, G. Lo, and K. D. Bettenhausen (2015). About the importance of autonomy and digital twins for the future of manufacturing. *IFAC-PapersOnLine 48*(3), 567–572.

Schleich, B., N. Anwer, L. Mathieu, and S. Wartzack (2017). Shaping the digital twin for design and production engineering. *CIRP Annals 66*(1), 141–144.

Sondermann-Wölke, C. (2015). *Entwurf und Anwendung einer erweiterten Zustandsüberwachung zur Verlässlichkeitssteigerung selbstoptimierender Systeme*. Aachen: Shaker Verlag. Dissertation: Paderborn University.

Zhao, F., Z. Tian, and Y. Zeng (2013). Uncertainty quantification in gear remaining useful life prediction through an integrated prognostics method. *Reliability, IEEE Transactions on 62*(1), 146–159.