# 1.4

# Foundations of Real Time Predictive Maintenance with Root Cause Analysis

Franz Wotawa<sup>1</sup>, David Kaufmann<sup>1</sup>, Adil Amukhtar<sup>1</sup>, Iulia Nica<sup>1</sup>, Florian Klück<sup>2</sup>, Hermann Felbinger<sup>2</sup>, Petr Blaha<sup>3</sup>, Matus Kozovsky<sup>3</sup>, Zdenek Havranek<sup>3</sup> and Martin Dosedel<sup>3</sup>

### **Abstract**

Research on cyber-physical systems comes to the fore with the increasing progress of applications in the field of autonomous systems. Therefore, there is a growing interest in methods for enhancing reliability, availability, and self-adaptation of such systems in safety critical situations. Hence, it is essential that autonomous systems are equipped with a detection system to observe faulty behaviour in real time or to predict failing operations to avoid safety critical scenarios, which may harm people. To bring or hold a system within healthy conditions, not only detecting a faulty behaviour is important, but also to find the corresponding root cause.

In this article, we introduce different methods which make use of detecting unexpected behaviour in cyber-physical systems, for the localization of faults. The first approach, *model-based diagnosis* uses logic to represent a cyber-physical system to perform reasoning for computing diagnosis candidates. A second promising approach deals with *simulation-based diagnosis* systems, using *digital twin models* to produce faulty behaviour data in advance, and to find correlations with the original cyber-physical system's behaviour, for diagnosis. For the third method the focus is set on artificial intelligence (machine learning and neural networks), where

<sup>&</sup>lt;sup>1</sup>Graz University of Technology, Austria

<sup>&</sup>lt;sup>2</sup>AVL List GmbH, Austria

<sup>&</sup>lt;sup>3</sup>Brno University of Technology CEITEC, Czech Republic

the goal is to utilize a huge amount of health and safety critical observations of the system for training to approximate the behaviour associated with faulty and safety critical states.

**Keywords:** model based diagnosis, model based reasoning, simulation based diagnosis, digital twin, AI based predictive maintenance, AI based diagnosis, abstract model, datacentre design, energy efficiency of datacentre, energy efficient metrics, datacentre carbon footprint computation.

# 1.4.1 Introduction and Background

Predictive analytics deals with forecasting the future progression of a situation and has a wide range of applications, including weather forecasting, epidemiology prediction, stock market prediction, and predictive maintenance. When implementing predictive maintenance, predictive modelling plays a major role. It aims to guarantee a robust prediction result, which can save considerable production downtime and either prevent or diminish economic loss. Considering information utilization and modelling mechanism, the predictive modelling techniques can be classified into three groups: *physics-based*, *data-driven*, and *model-based*.

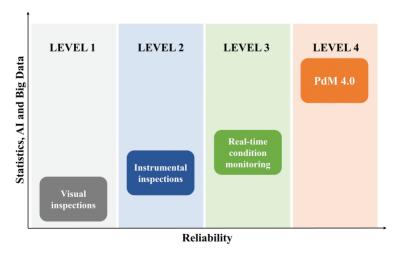
The *physics-based* approach describes the physical behaviour of a system using the first principle as a series of ordinary or partial differential equations according to the law of physics [1][6]. However, the construction of a physics model is usually difficult since it requires detailed and complete knowledge about the system. Still, this kind of model lacks extensive failure samples to determine the model parameters in practice.

The *data-driven* approach constructs a model representing the underlying relationship of a system based on data mining techniques. The *data-driven* approach could be grouped into two categories including statistical and machine learning based methods. The typical statistical method used, include the autoregressive model and its variations, linear regression, Wiener process, and Gamma process among others. Machine learning based methods include algorithms such as artificial neural networks, clustering techniques, extreme learning machines, fuzzy logic, and deep learning models. However, the performance of the *data-driven* model is sensitive to the size and quality of the collected dataset. It is important to note that *data-driven* models are extremely domain specific. Therefore, the selection of such models is a crucial part of the process.

The *model-based* approach takes advantage of established physical knowledge and collected data to enhance the prediction performance. It typically involves two steps including model construction and model updating [2]. First, analytical models are built based on the physical or empirical model representing the situation evolving in a quantitative manner. These models are then updated with newly acquired information to predict the future progression of the situation based on inference. Comparing with the *datadriven* approach, the *model-based* approach requires less historical data to construct the models. The predicted value is associated with a confidence level, resulting from the uncertainty involved in the prediction process [3].

Over the past 30 years, predictive maintenance has been evolving from predicting failures based on periodic visual inspections to continuous real-time monitoring of assets and external data with alerts based on statistical techniques such as regression analysis for at least one important asset. Furthermore, the advent of Industrial Internet of Things (IIoT) technology has significantly optimized industrial operations management by connecting industrial assets with information systems and, hence, with business processes. Predictive Maintenance 4.0 (PdM 4.0) or simply Maintenance 4.0, is among the major focus points of IIoT. In [4] the authors identify four levels of maturity in predictive maintenance, depicted in Figure 1.4.1.

Many companies are combining the capabilities of IIoT and Big Data to predict equipment malfunctions. The accuracy of the forecast is further



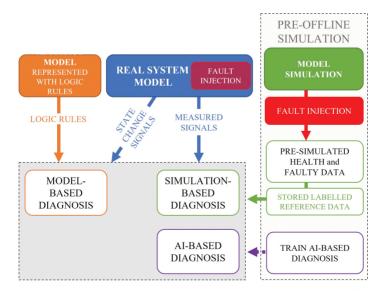
**Figure 1.4.1** Four levels of maturity in predictive maintenance.

getting more precise with improved Artificial Intelligence (AI) techniques and machine learning tools.

As depicted in [5], Maintenance 4.0 forms a subset of smart manufacturing systems which are autonomous in their operation, capable of predicting failures and triggering maintenance activities. These systems consist of smart equipment in form of embedded or cyber-physical systems forming the digital twin of physical assets. To achieve near-zero defects, near-zero downtime and automated decision making based on condition monitoring, top diagnosis and prognosis techniques need to be implemented.

Finally, the most advanced form of maintenance is prescriptive maintenance which builds on PdM and provides further guidance on the maintenance task, including diagnosis capabilities. Prescriptive maintenance strategies extensively use advanced data processing and visualization techniques such as graph analysis, simulations, neural networks, complex event processing, heuristics, and machine learning. These tools can calculate the timing and the effect of failure, thus, deciding on the priority and urgency of the maintenance activity.

In Figure 1.4.2, we depict a simplified system architecture, showing how the different approaches contribute to diagnosis of systems. Simulation-based diagnosis as well as AI-based diagnosis, utilize models that are obtained in a pre-offline phase, depicted on the right. Model-based diagnosis makes use of



**Figure 1.4.2** Diagnosis system architecture.

mainly abstract models for diagnosis directly not requiring an offline phase. In the following, we discuss the different approaches and their foundations in more detail.

#### 1.4.2 Foundations

In the following, we discuss the foundations behind the diagnosis. i.e., the detection of failures and the identification of its root causes in the context of predictive maintenance. In particular, we focus on methods from artificial intelligence considering model-based diagnosis, machine learning, and specifically neural networks. Instead of a detailed discussion of the foundations, we briefly introduce underlying ideas and provide references to related literature for the interested reader.

## 1.4.2.1 Model-based Diagnosis

Model-based diagnosis or reasoning from the first principle has been developed in the 80s of the last century as an answer to challenges arising when using logic reasoning as a basis for applications like configuration and decision support. Instead of formalizing the knowledge-base in a way from observations to causes such that diagnosis can be directly derived using ordinary deduction, the idea was to formalize knowledge either in form of relations or as rules where causes imply their effects. Instead of deduction abduction or in a more general setting non-monotonic reasoning was used as an underlying reasoning mechanism (see [19], [20], [21]).

The idea behind model-based diagnosis is to take a model of a system, which is usually called a system description SD, and observations OBSfor diagnosis computation. In this setup, SD comprises the structure of the system comprising interconnected components, and the behaviour of the components. For the latter, we explicitly introduce health states for components like working abnormally (ab), or correctly (i.e., not abnormal  $(\neg ab)$ ). For example, the correct behaviour of components can be formalized using an implication, i.e.,  $\neg ab(C) \rightarrow behav(C)$ , where C is a component and behav(C) the behaviour of C. Whenever the component works as expected the behaviour is determined. However, if we assume C to be wrong, the implication does not allow us to determine behaviour. Hence, the component may work appropriately even when considered to be faulty. Note that this modelling allows also to specify a behaviour for any incorrect health state if required.

When assuming a model of a system comprising components COMP and observations, we are able to compute diagnoses. Informally, a diagnosis explains a faulty behaviour. In the case of model-based diagnosis, we are interested in assigning a health state to every component in COMP such that the observations are not in contradiction with the components' behaviour. Hence, diagnosis becomes searching for health states. In order to be applicable in practice, diagnosis reasoning often utilizes simplifications like searching only for diagnoses where one component is considered to be faulty, and all others are working as expected. Alternatively, diagnosis search may focus on parsimonious diagnoses, i.e., health assignments to components unequal to  $\neg ab$ , where we are not able to switch a component from being faulty to working correctly.

Model-based diagnosis computation in general is hard and requires a lot of computational resources. However, considering today's hardware, most recent algorithms, and the availability of fast theorem provers, diagnosis can be computed within a reasonable amount of time, i.e., within a fraction of a second even for larger systems (see [22]). For a more detailed discussion on model-based diagnosis, modelling, formal definitions, and its application to self-adaptive systems we refer to [23] and most recently [24].

# 1.4.2.2 Machine Learning Based Diagnosis

Machine learning algorithms have shown promising solutions and improved decision-making processes by analysing an enormous amount of data. The use of these algorithms has grown rapidly in the recent years which helps systems to act intelligently without being explicitly programmed [7]. Machine learning techniques are often used to detect faulty behaviours of the system [8], [9]. For example, [10] used Support Vector Machine (SVM), a machine learning algorithm to model linear and non-linear relationships, to model 9 fault states of the modular production system with different kernel functions namely Sigmoid, RBF, polynomial and linear kernel functions. The work presented a 100% classification rate on all kernel functions except for the sigmoid kernel (52.08% classification rate).

Machine learning algorithms are mainly divided into four categories explained below:

• *Supervised*: This type of learning typically learns a function based on the sample input and output pairs. The goal of the function is to classify/map a new input instance to the respective output [11]. Please note that the data samples provided during the training are labelled.

- Unsupervised: Unsupervised learning involves understanding the distribution of the data given the data is unlabelled [11]. These types of algorithms are mostly used for feature generation, dimensionality reduction, extracting hidden patterns, clustering/grouping data points, and exploratory analysis.
- Semi-Supervised: Data points could be rarely labelled in real world [12]. For example, in the fraud detection problem, there could be few occurrences of fraud transaction leaving too much non-fraud detection data. Thus, semi-supervised learning comes into play by generating new instances from the less seen (minatory output), often called synthetic data generation. It's a hybridization of "supervised" and "unsupervised" where the goal is to model better predictions given the data is highly unlabelled.
- Reinforcement: Reinforcement learning is an area of machine learning in which an agent is trained to learn the optimal behaviour for a given environment [13]. The goal of reinforcement learning is to find the best possible actions such that reward is maximized and the risk is minimized. Reinforcement learning is mostly useful for automation e.g., autonomous driving.

Based on the application, nature of the data and learning outcome, various machine learning algorithms can be chosen for fault diagnosis in complex systems. For this case study, we model the fault diagnosis problem with one of the supervised machine learning algorithms called Bootstrap Aggregation (Bagging).

# 1.4.2.3 Artificial Neural Networks for Diagnostics

Machine learning as well as deep learning techniques are very popular in many areas of engineer's work. The connection of the AI approach and technical diagnostics especially in the field of predictive maintenance of machines [14] is a very actual problem and directly addresses the Internet of Things as well as Industry 4.0 topics [15]. Big data processing algorithms, necessary for modern AI techniques application, are overviewed in, e.g., [16], standard machine learning approaches, mostly containing statistical algorithms [17] like SVM, k-NN, PCA, Mahalanobis-Taguchi strategy etc., are commonly used, but mainly using of powerful and very popular neural networks is currently growing. There exists a lot of NNs types used for diagnostics of the machines, but the convolutional neural network is one of the most recommended and also used types [18]. Mostly, NN algorithms

run on the dedicated and powerful hardware designed especially for such purposes.

The shift from cloud AI processing to local intelligence architecture is described in [25]. According to that paper, AI has a strong potential for sensor solutions in the future. Reasons are the increasing complexity of sensors, the increasing amount of generated raw data, and the requirement for straightforward data fusion from several sensors. The integration of wireless communication capabilities in smart sensors makes them usable also as an IoT device [26]. This process must be accompanied by the integration of safety- and privacy-aware functions.

#### 1.4.3 Related Research

Predictive analytics intends to make predictions about future progressions, based on domain knowledge and historic data combined with physic-based, model-based or machine-learning modelling techniques. In the context of predictive maintenance (PdM), predictive modelling is used for failure prediction and prescription of operation and maintenance strategies. Here, the main objective is to obtain accurate and robust prediction results to avoid unexpected system downtime. Predictive maintenance is a conditiondriven maintenance program that monitors the mechanical condition, system efficiency, and other indicators to determine the system's actual mean-timeto-failure or loss of efficiency. Considering the definition from [27], the three key steps of a PdM program are data acquisition to obtain data relevant to system health, data processing to handle and analyse the data or signals collected and maintenance decision-making to recommend efficient maintenance actions or adoptions of the operation strategy. Techniques for maintenance decision support in a PdM program can be divided into two main categories [27]: diagnostics and prognostics. Fault diagnostics focuses on detection, isolation, and identification of faults when they occur. In contrast, prognostics attempts to predict faults or failures before they occur. Jardine [28] reviewed and compared several commonly used PdM decision strategies such as trend analysis that is rooted in statistical process control (SPC), expert systems (ESs), and neural networks. Wang and Sharp [29] discussed the decision aspect of PdM and reviewed the recent development in modelling PdM decision support.

Various model-based diagnosis approaches have been applied to fault diagnosis of a variety of mechanical systems such as gearboxes [30][31], bearings [32][33][34], rotors [35][36] and cutting tools [37]. Hansen et al.

[38] proposed an approach to more robust diagnosis based on the fusion of sensor-based and model-based information. Vania and Pennacchi [39] developed some methods to measure the accuracy of the results obtained with model-based techniques aimed to identify faults in rotating machines. Two practical successful applications of maintenance programs using model-based approaches are: (i) an integrated framework for on-board fault diagnosis and failure prognosis of a helicopter transmission component and (ii) the TIGER system [40] that combines several artificial intelligence technologies, including qualitative model-based reasoning to perform condition monitoring of gas turbines. Here, the diagnostic mechanism is based on a fault manager and the three independent tools KHEOPS [67], IxTeT [40] and CA-EN [69]. KHEOPS [41] is a high-speed rule-based system, used to express diagnostic rules in a classic rule-based formalism and allows the user to set pre-alarm limits for each parameter. IxTeT [40] is used to either describe the normal causal reaction or look for specific patterns resulting from known faults. CA-EN [42] is a model-based supervision system devoted to complex dynamic systems. CA-EN's representation formalism allows one to combine empirical causal knowledge and first principles of the domain.

The effectiveness of predictive maintenance depends on practical factors such as required planning time and implementation effort but especially on the achievable quality of condition monitoring, the behaviour of the deterioration process and system specific fault severity. For instance, vibration and oil debris monitoring is limited by the accuracy of the measuring instruments and can therefore be considered as imperfect [52]. In many cases, the imperfect condition information has been combined with deterioration processes, which were modelled as continuous stochastic processes. Kallen and Van Noortwijk [43] use a gamma deterioration process, Peng and Tseng [44] a linear trend with random coefficient plus a Brownian motion as a second random effect, Ye et al. [45] a Wiener process with positive drift, and Zio and Compare [46] a Randomized Paris-Erdogan fatigue crack growth model. Nevertheless, also here inspections have to be performed in order to obtain condition information. Given the effort and short comings, PdM should only be applied if the expected benefit outweighs the efforts and costs during the entire life cycle [47][48][49].

#### 1.4.4 Conclusion

Predictive maintenance mechanisms are the major key to improve the availability, reliability and safety of cyber-physical systems in relation to finding or predicting an unexpected behaviour before downtime, defects or harm to the environment occurs. In this article, we focus on different approaches for diagnosis, discuss their foundations, and also related research. However, there remains the questions which diagnosis methods to use and how to implement them to interact with a specific cyber-physical system. We elaborate on use cases in two separated articles of this book to answer these auestions.

In these articles, we decided to focus on different diagnosis approaches based on two systems, a simplified DC e-motor model and a dual three-phase permanent magnet synchronous motor supported with detailed acausal emotor model with the capability of fault injection. The use of model based and machine learning based approaches is demonstrated on a simplified DC e-motor model in the article "Real-Time Predictive Maintenance -Model Based and Machine Learning Based Diagnosis". The artificial neural network approaches are demonstrated on a dual three-phase motor diagnosis and on a diagnosis using smart vibration sensor which is described in article "Real-Time Predictive Maintenance – Artificial Neural Network Based Diagnosis".

In the mentioned articles, we discuss the applicability of diagnosis algorithms in real-time simulation environments by highlighting a specific case of how to implement the methods and perform diagnoses on unexpected behaviour. We obtained promising results encouraging for further research on the described diagnosis methods depending on the desired detection dimension, available resources, and model specifications. In addition, the diagnosis methods deliver the root cause affects which builds the basis for the research in self-adapting or self-healing systems to bring a system to a safe state if an unexpected behaviour is detected.

# **Acknowledgements**

This work is conducted under the framework of the ECSEL AI4DI "Artificial Intelligence for Digitising Industry" project. The project has received funding from the ECSEL Joint Undertaking (JU) under grant agreement No 826060. The JU receives support from the European Union's Horizon 2020 research and innovation programme and Germany, Austria, Czech Republic, Italy, Latvia, Belgium, Lithuania, France, Greece, Finland, Norway. The work was co-funded by grants of Ministry of Education, Youth and Sports of the Czech Republic, by the Austrian Federal Ministry of Transport, Innovation and Technology (BMVIT) under the program "ICT of the Future" between May 2019 and April 2022 (more information can be retrieved from https://iktderzukunft.at/en/). The work was also supported by the infrastructure of RICAIP that has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 857306 and from Ministry of Education, Youth and Sports under OP RDE grant agreement No CZ.02.1.01/0.0/0.0/17 043/ 0010085.

#### References

- [1] Wang, J., Liang, Y., Zheng, Y., Gao, R. X., and Zhang, F., "An integrated fault diagnosis and prognosis approach for predictive maintenance of wind turbine bearing with limited samples," Renewable Energy, vol. 145, pp. 642âĂS650, 2020. Available online at: https://www.sciencedirect.com/science/article/pii/S0960148119309371
- [2] Song, Z., Zhang, Z., Jiang, Y., and Zhu, J., "Wind turbine health state monitoring based on a bayesian data-driven approach," Renewable Energy, vol. 125, pp. 172âÅŞ181, 2018. Available online at: https://www.sciencedirect.com/science/article/pii/S0960148118302404
- [3] Wang, J., Wang, P., and Gao, R., "Enhanced particle filter for tool wear prediction," 2015.
- [4] Sept. 2018, SURVEY Predictive Maintenance 4.0 Beyond the hype: PdM 4.0 delivers results. Mainnovation.
- [5] Towards an open-standards based framework for achieving conditionbased predictive maintenance, Kaur, Karamjit & Selway, Matt & Grossmann, Georg & Stumptner, Markus & Johnston, Alan, (2018) Proceedings of the 8th International Conference on the Internet of Things.
- [6] Peng, Y., Dong, M., Zuo, M., "Current status of machine prognostics in condition-based maintenance: a review," 2010.
- [7] I. a. F. M. a. N. R. Sarker, "AI-Driven Cybersecurity: An Overview, Security Intelligence Modeling and Research Directions," SN Computer Science, vol. 2, 2021.
- [8] T. a. B. M. a. P. V. Ademujimi, "A Review of Current Machine Learning Techniques Used in Manufacturing Diagnosis," pp. 407-415, 2017.
- [9] M. a. D. F. a. K. M. a. M. O. Barakat, "Self adaptive growing neural network classifier for faults detection and diagnosis," Neurocomputing, vol. 74, pp. 3865-3876, 2011.

- [10] M. Demetgul, "Fault diagnosis on production systems with support vector machine and decision trees algorithms," The International Journal of Advanced Manufacturing Technology, vol. 67, 2012.
- [11] J. a. K. M. a. P. J. Han, Data mining concepts and techniques, third edition, 2012.
- [12] M. a. K. M. a. B. E. Mohammed, Machine Learning: Algorithms and Applications, 2016.
- [13] L. P. a. L. M. L. a. M. A. W. Kaelbling, "Reinforcement learning: A survey," Journal of Artificial Intelligence Research, vol. 4, pp. 237-285, 1996.
- [14] R. Liu, B. Yang and E. Zio: Artificial intelligence for fault diagnosis of rotating machinery: A review. Mech. Syst. Signal Process., vol. 108, aug 2018: p. 33–47, ISSN 10961216, doi:10.1016/j.ymssp.2018.02.016. URL https://linkinghub.elsevier.com/retrieve/pii/S0888327018300748.
- [15] A. Chen, F. H. Liu and S. D. Wang: Data reduction for real-time bridge vibration data on edge. In Proc. - 2019 IEEE Int. Conf. Data Sci. Adv. Anal. DSAA 2019, Institute of Electrical and Electronics Engineers Inc., oct 2019, ISBN 9781728144931, p. 602–603, doi: 10.1109/DSAA.2019.00077.
- [16] S. Yin, X. Li and H. Gao: Data-based techniques focused on modern industry: An overview. IEEE Trans. Ind. Electron., vol. 62, issue. 1, 2015: s. 657–667, ISSN 02780046, doi:10.1109/TIE.2014.2308133. URL https://ieeexplore.ieee.org/document/6748057/.
- [17] S. Zhang, S. Zhang and B. Wang: Deep Learning Algorithms for Bearing Fault Diagnostics A Comprehensive Review. IEEE Access, vol. 8, jan 2020: p. 29857–29881, ISSN 21693536, doi:10.1109/ACCESS.2020.2972859, 1901.08247. URL http://arxiv.org/abs/1901.08247
- [18] H. Qiao, T. Wan and P. Wang: An Adaptive Weighted Multiscale Convolutional Neural Network for Rotating Machinery Fault Diagnosis under Variable Operating Conditions. IEEE Access, aug 2019: p. 118954–118964, ISSN 21693536, doi:10.1109/ACCESS.2019.2936625.
- [19] Davis, R.: Diagnostic reasoning based on structure and behavior. Artificial Intelligence 24, pp. 347–410, 1984.
- [20] Reiter, R.: A theory of diagnosis from first principles. Artificial Intelligence 32(1), pp. 57–95, 1987.
- [21] de Kleer, J., Mackworth, A.K., Reiter, R.: Characterizing diagnosis and systems. Artificial Intelligence 56, 1992.

- [22] Kaufmann, D., Nica, I., Wotawa, F.: Intelligent agents diagnostics - enhancing cyber-physical systems with self-diagnostic capabilities. Advanced Intelligent Systems, 2021. DOI https://doi.org/10.1002/ai sy.202000218.
- [23] Wotawa, F.: Reasoning from first principles for self-adaptive and autonomous systems. In: E. Lughofer, M. Saved-Mouchaweh (eds.) Predictive Maintenance in Dynamic Systems - Advanced Methods, Decision Support Tools and Real-World Applications. Springer (2019). DOI 10.1007/978-3-030-05645-2.
- [24] Wotawa, F.: Using model-based reasoning for self-adaptive control of smart battery systems. In: M. Saved-Mouchaweh (ed.) Artificial Intelligence Techniques for a Scalable Energy Transition – Advanced Methods. Digital Technologies, Decision Support Tools, Applications. Springer (2020).
- [25] P. Jantscher: AI In Sensors For IoT [online] Cited 15.6.2021 Available from: https://siliconsemiconductor.net/article/106227/AI\_In\_Sensors For IoT.
- [26] S. C. Mukhopadhyay, S. K. S. Tyagi, N. K. Suryadevara, V. Piuri, F. Scotti and S. Zeadally: Artificial Intelligence-based Sensors for Next Generation IoT Applications: A Review, in IEEE Sensors Journal, doi: 10.1109/JSEN.2021.3055618.
- [27] A review on machinery diagnostics and prognostics implementing condition-based maintenance, Jardine, Andrew & Lin, Daming & Banjevic, Dragan, Mechanical Systems and Signal Processing, 2006.
- [28] A.K.S. Jardine, Optimizing condition based maintenance decisions, in: Proceedings of the Annual Reliability and Maintainability Symposium, 2002, pp. 90–97.
- [29] W. Wang, J. Sharp, Modelling condition-based maintenance decision support, in: Condition Monitoring: Engineering the Practice, Bury St Edmunds, 2002, pp. 79–98.
- [30] I. Howard, S. Jia, J. Wang, The dynamic modelling of a spur gear in mesh including friction and a crack, Mechanical Systems and Signal Processing 15 (2001) 831-838.
- [31] W.Y. Wang, Towards dynamic model-based prognostics for transmission gears, in: Component and Systems Diagnostics, Prognostics, and Health Management II, vol. 4733, Bellingham, 2002, pp. 157–167.

- [32] D.C. Baillie, J. Mathew, Nonlinear model-based fault diagnosis of bearings, in: Proceedings of an International Conference on Condition Monitoring, Swansea, UK, 1994, pp. 241–252.
- [33] K.A. Loparo, M.L. Adams, W. Lin, M.F. Abdel-Magied, N. Afshari, Fault detection and diagnosis of rotating machinery, IEEE Transactions on Industrial Electronics 47 (2000) 1005–1014.
- [34] K.A. Loparo, A.H. Falah, M.L. Adams, Model-based fault detection and diagnosis in rotating machinery, in: Proceedings of the Tenth International Congress on Sound and Vibration, Stockholm, Sweden, 2003, pp. 1299–1306.
- [35] A.S. Sekhar, Model-based identification of two cracks in a rotor system, Mechanical Systems and Signal Processing 18 (2004) 977–983.
- [36] G.H. Choi, G.S. Choi, Application of minimum cross entropy to model-based monitoring in diamond turning, Mechanical Systems and Signal Processing 10 (1996) 615–631.
- [37] W. Bartelmus, Mathematical modelling and computer simulations as an aid to gearbox diagnostics, Mechanical Systems and Signal Processing 15 (2001) 855–871.
- [38] R.J. Hansen, D.L. Hall, S.K. Kurtz, A new approach to the challenge of machinery prognostics, Journal of Engineering for Gas Turbines and Power 117 (1995) 320–325.
- [39] A. Vania, P. Pennacchi, Experimental and theoretical application of fault identification measures of accuracy in rotating machine diagnostics, Mechanical Systems and Signal Processing 18 (2004) 329–352.
- [40] Dousson, C., Gaborit, P., & Ghallab, M. 'Situation recognition: representation and algorithms', Proc. 13th IJCAI, Chambery, France, 1993.
- [41] Ghallab, M., & Philippe, H. 'A Compiler for Real-Time Knowledge-Based Systems'. Proc. IEEE International Symposium on AI for Industrial Applications, 287-293, 1988.
- [42] Bousson, K., & Trave-Massuyes, L. 'Fuzzy Causal Simulation in Process Engineering'. IJCAI-93, Chambery, France. August-September 1993.
- [43] Kallen MJ, Van Noortwijk JM. Optimal maintenance decisions under imperfect inspection. Reliab Eng Syst Saf 2005;90(2–3):177–85.
- [44] Peng C-Y, Tseng S-T. Mis-specification analysis in linear degradation models. IEEE Trans Reliab 2009;58(3):444–55.

- [45] Ye Z-S, Wang Y, Tsui K-L, Pecht M. Degradation data analysis using wiener processes with measurement errors. IEEE Trans Reliab 2013;62(4):772-80.
- [46] Zio E, Compare M. Evaluating maintenance policies by quantitative modeling and analysis. Reliab Eng Syst Saf 2013;109:53-65.
- [47] Maintenance management of wind power systems using condition monitoring systems - life cycle cost analysis for two case studies, Nilsson J, Bertling L., 2007.
- [48] Asset life cycle management: towards improving physical asset performance in the process industry, Schuman CA, Brent AC, 2005
- [49] Two probabilistic life-cycle maintenance models for deteriorating civil infrastructures, Van Noortwijk JM, Frangopol DM, 2004.
- [50] Wang W, Christer AH. Towards a general condition based maintenance model for a stochastic dynamic system. J Oper Res Soc 2000;51(2): 145-55.