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Foundations of Real Time Predictive Maintenance with Root Cause Analysis

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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

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 *data-driven* 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

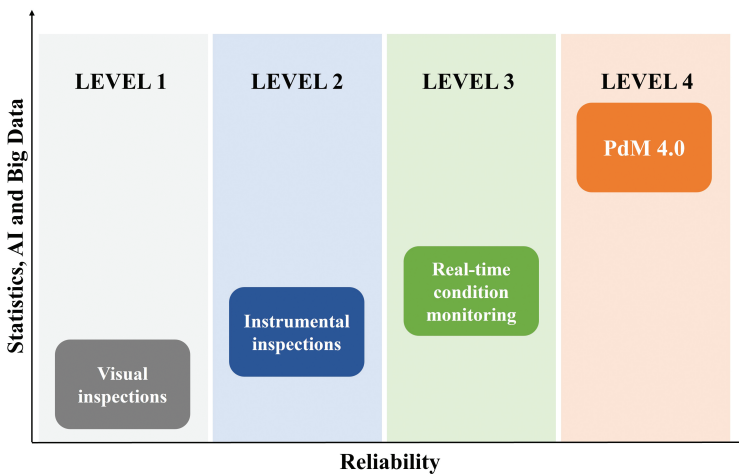


Figure 1.4.1 Four levels of maturity in predictive maintenance.

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

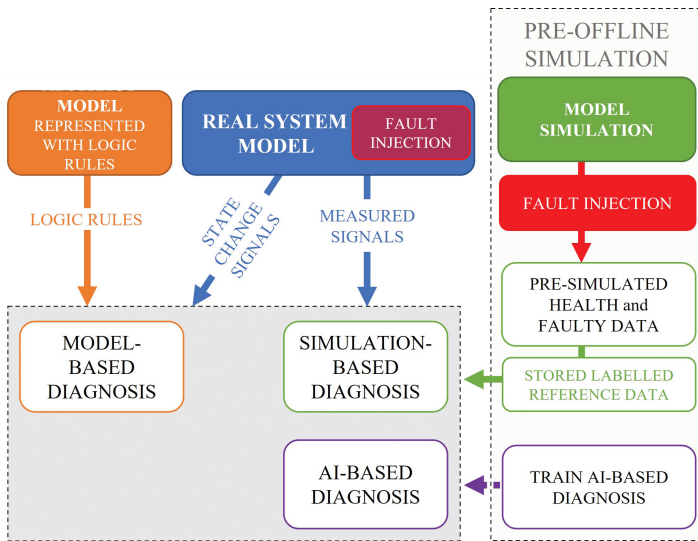


Figure 1.4.2 Diagnosis system architecture.

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 OBS for 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 (minority 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 condition-driven maintenance program that monitors the mechanical condition, system efficiency, and other indicators to determine the system's actual mean-time-to-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.

