A generic Approach for Reliability Predictions considering non-uniformly Deterioration Behaviour

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Abstract. Predictive maintenance offers the possibility to prognosticate the remaining time until a maintenance action of a machine has to be scheduled. Unfortunately, current predictive maintenance solutions are only suitable for very specific use cases like reliability predictions based on vibration monitoring. Furthermore, they do not consider the fact that machines may deteriorate non-uniformly, depending on external influences (e.g., the work piece material in a milling machine or the changing fruit acid concentration in a bottling plant). In this paper two concepts for a generic predictive maintenance solution which also considers non-uniformly aging behaviour are introduced. The first concept is based on system models representing the health state of a technical system. As these models are usually statically (viz. without a timely dimension) their coefficients are determined periodically and the resulting time series is used as aging indicator. The second concept focuses on external influences (contexts) which change the behaviour of the previous mentioned aging indicators in order to increase the accuracy of reliability predictions. Therefore, context depended time series models are determined and used to predict machine reliability. Both concepts were evaluated on data of an air ventilation system. Thereby, it could be shown that they are suitable to determine aging indicators in a generic way and to incorporate external influences in the reliability prediction. Through this, the quality of reliability predictions can be significantly increased. In reality this leads to a more accurate scheduling of maintenance actions. Furthermore, the generic character of the solutions makes the concepts suitable for a wide range of aging processes.

1. Introduction
Using predictive maintenance systems, one is able to predict the health state of machines and therefore to optimize maintenance actions. It is guessed that applying predictive maintenance systems can save up to 1/3 of the total maintenance costs. In the USA this means for example a total saving of about 60 Billion US-dollars per year [1].

Figure 1 shows a workflow which is valid for most of the state of the art systems in the area of predictive maintenance.
Figure 1. Workflow for Predictive Maintenance (based on [2]).

During the data acquisition phase useful data from target systems is collected and stored. Usually, this data consist of condition-data (e.g., sensor measurements) and event-data (higher level information).

In the phase of data selection, data which is relevant for the following steps is selected. An overview of methods for this purpose can be found in [3][4].

The data processing phase is manifold. In general, data cleaning is the first step here. This is important as data usually contains errors like outliers. Next the data is analyzed. In terms of predictive maintenance, the objective here is to determine models which are suitable to recognize the health state of a machine. For this purpose, many state of the art techniques are available [3][5][6][9].

Another input for this step are breakdown statistics. They are important in order to correlate the condition data with breakdown information. Some techniques are even exclusively based on those statistical data. For example many maintenance policies are based on the so called Mean Time Between Failures (MTBF) [1]. In order to predict the health state of a machine, many approaches define a parameter which correlates with the likelihood of a breakdown of the concerned machine [10]. In this paper, the term aging indicator refers to such a parameter. A closer look on the state of the art brings to light two problems.

1. The most of these techniques are very specific and are therefore not easy applicable to another technical system. Therefore, a lot of effort has to be done determining a health state model for every single target system.
2. There are process-dependent changes such as different production steps influencing machine data. In literature, the resulting fluctuations in the data are often averaged in order to minimize them [1]. Other techniques just ignore this problem [1]. Both approaches usually lead to a bad model quality [1].

The last phase is the trend analysis/prediction. Thereby, the previous defined aging indicator - which is given by a time series - is predicted in order to make assumptions about the health state of a machine at a future point in time. In literature, many techniques are available for trend analysis such as ARIMA - Models, exponential smoothing, and regression [11][12]. Unfortunately, there are often external influences which determine the aging behavior of a technical system [7][8]. For example in [8] an example of a milling process is shown. Thereby, the abrasion of a milling tool is dependent on the workpiece materials each of them with a specific degree of hardness. The harder the workpiece material, the faster the process of abrasion of the milling tool is. In the present paper, these influences are referred to the term aging contexts. Although, this problem is often ignored in literature, there are modelling approaches which can be used for this concern such as ARX-Models [13] (Auto Regressive models with eXogenous influences). A problem appears when trying to find a global time series model for a specific aging context.

In the following the structure of this paper is described. In chapter 2 the determination of dynamic aging indicators based on static system models is shown. Therefore, first of all two different mechanisms influencing system characteristics are described. One is related to aging and one is related to normal process behaviour. Based on these mechanisms it is shown that static system models are suitable for the determination of aging indicators. Afterwards, five steps for the determination of aging
indicators are introduced. Each step is explained and finally evaluated using data from an air ventilation system.

While the concept shown in chapter 2 is able to model fluctuations related to normal process behaviour, aging dependent fluctuations can still be problem. Therefore, chapter 3 shows a concept for the determination of reliability predictions considering aging related influences. The steps of this concept are described in detail and are finally evaluated using the same scenario of the air ventilation system already used in chapter 2.

Finally, a conclusion is given summarising the main aspects of this paper.

2. Determination of dynamic aging indicators based on static system models

As mentioned in the introduction, aging indicators are prone to fluctuations caused by changes in the underlying machine process. Consequently, the quality of predictions based on those aging indicators will be decreased. Therefore, it is necessary to determine aging indicators which are free of process-related fluctuations. This section will firstly introduce this problem in more detail. After that a concept is shown for the determination of aging indicators based on static system models. Finally, this concept is evaluated on machine data.

2.1. Description of Concept

The here described concept is based on the assumption that aging continuously changes the physical characteristics of a technical system. Consequently, system models (which determine these characteristics by modelling the relationship between input and output variables of a technical system) must be prone to aging as well.

It is important to realize that there are two different mechanisms that influence system characteristics. The first is related to normal process behavior triggered by process-related changes (such as different operating points which are reached by a machine during the production). The second is related to aging caused by the ageing of a machine. Figure 2 shows these two mechanisms schematically.

There the shift between different operating points correlates to normal process-behaviour, while the aging process leads to a shift of the characteristic curve itself. Therefore, the main idea of the here proposed concept is to observe the characteristic curve on a timely scale. In doing so, the shift cursed by aging will be visible in the shift of the model coefficients.

While the drift of model coefficients can be used as aging indicator, it is necessary to include all relevant process variables in the system model in order to avoid that process-related fluctuations influence the aging indicator. Figure 3 illustrates the problem of an insufficient number of process variables in a fictive example.
In the upper left corner, the system model is only based on an output variable. If the coefficient of the system model is determined at different points in time, it seems that the model parameter $c_0$ is jumping between different states. In the upper right corner, additionally one input variable is added. It can be seen that all samples are here located at the same characteristic curve. Consequently, the model parameters do not fluctuate. At the bottom, it is assumed that at a later point in time new values (red crosses) appear that do not fit accurately to the previously determined curve (the coefficients of the system model are fluctuating at different points in time). This indicates that there is probably another input variable not considered so far.

Based on the described issues a concept for the determination of aging indicators has been developed. The steps of this concept are shown in Figure 4 and described into more detail in the following.

![Figure 3. System models for different numbers of process variables.](image)

**Figure 3.** System models for different numbers of process variables.

First of all, relevant process variables need to be determined. Therefore, state of the art techniques can be used [3][4]. In the second step, a system model $f$ is determined containing all relevant process variables $x_i$ (input) and one output variable $y_1$ (see Figure 5).

![Figure 4. Steps for determination of an aging indicator.](image)

**Figure 4.** Steps for determination of an aging indicator.

Equation (1) shows the system model function $f$. The coefficients $c_i$ are determined using the least squares method (LSM) shown in Equation (2).

$$y = f(c_i)$$  \hspace{1cm} (1)

$$Z(c_i) = \min_{c_i} \left\{ \sum (y - f(c_i))^2 \right\}$$  \hspace{1cm} (2)
Thereby, a suitable system model must fulfill the following two requirements.

1. If the model coefficients are determined at different points in time, aging must be visible as drift of these model coefficients. If not, the input-output behaviour of the process variables considered so far is not prone to aging. In this case, either the structure of the system model must be adapted and/or it is necessary to go back to the previous step in order to identify missing process variables.

2. If the model coefficients are determined at different points in time, they must not fluctuate. In case of strong fluctuations, there is either a bad structure of the system model or there are process variables not yet considered which need to be included in the model. In this case it is necessary to go back to the previous step and to identify missing process variables. Otherwise a better fitting model structure needs to be determined.

After a suitable system model has been determined, the size of a sliding time-window has to be defined. A good size covers most of the reachable operating points of the machine. In general, shorter windows lead to more noise in the data and longer ones tend to average the data.

Next the sliding window is iteratively shifted by one time index at a time. For each window the coefficients $c_i$ of the system model are determined. The results of these steps are time dependent coefficients $c_i(k)$. Their drift represents the aging process of the concerned machine.

In general, the system model consists of more than one coefficient $c_i$. In the here proposed concept, all coefficients but one are kept constant. The remaining (dynamic) coefficient is then defined as the aging indicator. Although, good results can already be achieved using this approach, more research is necessary on how to choose the right coefficients or even to handle different dynamic coefficients.

The so determined aging indicator fulfills two important requirements. It models the aging process while it does not contain process dependent fluctuations. Furthermore, as the here proposed method is very generic, it can be applied to a wide range of domains.

2.2. Evaluation

The Evaluation is based on an air ventilation system which is located in a building of the Technical University of Dresden (TUD). The objective of this air-ventilation system is to provide both fresh air and a constant air-pressure in the building. Therefore, a ventilator which is electrical driven controls the amount of air which flows through an aerating pipe. Furthermore, an air filter is used to keep the air clean. Physically, the aging process is given by the continuous pollution of this air filter. Thereby, the degree of pollution influences other process variables such as the difference pressure of this filter. In order to be able to repeat the experiments under different controllable conditions, this process was analysed and implemented as a simulation. Figure 6 shows the main input and output variables used in the following tests.

![Figure 6. Input and output variables of the air ventilation system.](image)

In order to illustrate the influence of an insufficient number of process variables which are included in a system model, a set of test runs were executed. In each test run, the coefficient $c_0$ of the system model was kept dynamic while all other coefficients of the same system model were kept constant.
In the first test run, only the output variable “difference pressure” was considered. A sliding window was applied on this data and the coefficient of the system model was determined for each iteration. The equation of the system model is shown in Equation (3).

\[ y = c_0 \]  
(3)

Thereby, \( y \) corresponds with the difference pressure and \( c_0 \) is the coefficient of the system model. Figure 7 shows the development of the coefficient \( c_0 \) over one week.

![Figure 7](image)

**Figure 7.** Development of a coefficient with no input variable.

It can be seen, that coefficient fluctuations occurs. Any attempt to make a reliability prediction based on this time series would lead to a bad prediction quality.

In the second test run another input variable, the air flow rate \( (x_i) \), was included in the system model. The resulting equation of the system model is shown in Equation (4).

\[ y = c_0 \cdot x_i \cdot c_1 \]  
(4)

Figure 8 shows the development of the coefficient \( c_0 \) with one input variable (Equation (4)) over a time of one week.

![Figure 8](image)

**Figure 8.** Development of a coefficient with one input variable.

It can be seen, that through the consideration of another process variable in the system model the corresponding coefficient drift is less fluctuating. Nevertheless, still some fluctuations are present.

In the third test run the process variable “air humidity \( (x_j) \)” was additionally included in the system model.

\[ y = c_0 \cdot c_4 \cdot x_1 \cdot \left( c_2 - c_3 \cdot x_2 \right) \]  
(5)

\[
\begin{align*}
    c_1 &= 1,76 \\
    c_2 &= 1,6 \\
    c_3 &= -0,01 \\
    c_4 &= 0,005344
\end{align*}
\]

Figure 9 shows the resulting development of the coefficient \( c_0 \) (Equation (5)) over a time of one week.
In conclusion, by including all relevant system variables in one system model, the coefficient drift is free of process depended fluctuations. Hence, it is suitable as aging indicator. Nevertheless, a closer look on the development of this time series reveals that it is still prone to some other fluctuations. Although, these fluctuations are not cursed by process behaviour they must be taken into account. The next chapter will describe the reason for such behaviour changes of the aging indicator and how to handle them in order to make accurate predictions.

3. Determination of context-sensitive prediction models by solving a nonlinear optimization problem

The result of the concept shown in the previous section is an aging indicator in form of a time series. Although this time series is free of process-dependent fluctuations, it obviously still contains behaviour changes. As mentioned in the introduction, these changes correlate with aging contexts. In order to achieve an accurate prediction, it is necessary to consider those contexts in the prediction model. In this section, a concept is described which is able to handle aging contexts and to determine context-sensitive predictions. Furthermore, the concept is evaluated on machine data.

3.1. Description of Concept

Figure 10 shows the main steps of this concept.

**Determination of a sequence of atomic contexts:**

The input for this step is a timely ordered list of aging relevant historical contexts $C(k)$. For each context, a finite set of $M_i$ context-characteristics $A$ exists. For example a context is given by the “work load” of a machine and the set of context-characteristics for this context consists of “low”, “medium” and “high”. The sets of contexts and context-characteristics are defined in Equation (6) and Equation (7).

$$C = \{c_i | i = \{1, 2, ..., N\}; N \in \mathbb{N}\}$$

$$A = \{a_{ij} | j = \{1, 2, ..., M_i\}; M_i \in \mathbb{N}\}$$

Figure 10. Steps for context-sensitive predictions.
State of the art methods can be used to identify relevant contexts [3][4]. A problem is that different contexts may influence the aging indicator simultaneously. Therefore, so called atomic contexts (ac) are determined. This is done by determining the set \( S \) of all simultaneously appearing contexts (Equation (8)) for all time series elements \( T \in \mathbb{N} \) of the aging indicator.

\[
S = \{ ac_j \} = \{ 1, 2, \ldots, U \}^U \ U \in \mathbb{N} \wedge U \leq T \tag{8}
\]

Specific for an atomic context is that it can be mapped to a unique behaviour of the aging indicator. By mapping atomic contexts to the aging indicator, a mapping between time series elements and atomic contexts can be made. Consequently, each time-series element is allocated to an atomic context. The timely order of atomic contexts is called sequence of (atomic) contexts.

Context-sensitive modelling:
Inputs for this step are the sequence of contexts and the time series of the aging indicator. The objective is to determine a time series model for each atomic context. Figure 11 shows three intervals of time series elements all influenced by the same atomic context \( ac_0 \). The data is taken from the air ventilation system over a period of time of about 33 hours.

![Figure 11. Three intervals of the aging indicator belonging to one atomic context.](image)

Between these intervals the aging indicator is influenced by other atomic contexts \( ac_x \). With current state of the art time series analysis techniques it is not possible to determine an accurate global model for such an atomic context consisting of a set of different intervals. Especially, as the location of the intervals in the global model curve is unknown. In the here proposed concept, regression is used to determine the coefficients \( c_i \) of the generic model function shown in Equation (9).

\[
x_{age}(k) = f(c_i, k) \tag{9}
\]

Thereby, \( x_{age} \) is the aging indicator and \( k \) the time index. Please note that the definition of a suitable model structure will not be discussed here. More information can be found in [11][12]. In order to solve the problem of shifted intervals (e.g., shown in Figure 11) a time-shift-parameter \( t_c \) (\( c = \) interval number) is included in the model function. Equation (10) shows the extended model function.

\[
x_{age}(k) = f(c_i, (k - t_c)) \tag{10}
\]

The coefficients of this model can be determined by solving Equation (11).

\[
Z(c_i) = \min_{c_i, t_c} \sum (x_{age} - f(c_i, t_c))^2 \tag{11}
\]
Equation (11) can be formulated as a non-linear curve fitting problem which can be solved by state of the art techniques like the Levenberg-Marquardt-algorithm. Figure 12 shows the result of the optimisation applied to the data shown in Figure 11 by means of the Levenberg-Marquardt-algorithm.

\[
y = 0.0089e^{0.05x} \\
R^2 = 0.9997
\]

![Figure 12. Result of optimisation including time shifted parameters.](image)

It can be seen that the three time-shift-parameters (one for each interval) are able to shift the intervals (the three clusters in figure 12) of the atomic context to the right positions in the model curve (green line) while the model parameters of the global model are determined. The model equation and the determined coefficients are visualised in Figure 12 as well.

The above mentioned method must be executed for each atomic context. Finally, one global time series model, defined through a model structure and model coefficients, for each atomic context is available.

**Context-sensitive prediction**

Besides the context-sensitive models, the input for this step is a timely ordered list of future contexts. For these contexts, their future occurrence must be acquired. The sequence of future atomic contexts can then be determined using the same procedure described in the step: “Determination of a sequence of atomic contexts”.

Figure 13 shows how the context-sensitive prediction is realised.

![Figure 13. Steps for context-sensitive predictions.](image)
3.2. Evaluation

In order to evaluate the proposed concept for context-sensitive predictions, it was applied to the data of the air ventilation system described in section 2.2. For this test, machine data was acquired for the duration of about 240 day. Thereby, the sampling period T is 10 minutes. The aging indicator was determined using the concept described in section 2.1. It is given by the coefficient drift based on the system model shown in Equation (5). The time series of the aging indicator was then split into two parts each of a length about 120 days. The first part was used as training data. The second one was used as reference data in order to validate the quality of the prediction.

First of all, Figure 14 shows the development of the aging indicator until the point when the prediction starts (“start prediction”).

Starting at this point (“start prediction”) a prediction based on state of the art techniques (regression on an exponential function) is shown as well as the context-sensitive prediction. The dotted horizontal line indicated the threshold when a breakdown caused by an overload of the ventilation engine is most likely. It is visible that the difference between both predictions is about 28,5 days (4097 time series elements with a sampling period of T = 10 minutes). It shows that in contrast to the context-sensitive prediction, the “state of the art”- prediction is not able to handle changes in the context behavior visible as kink in the graph (in this case mainly caused by summer-holydays influencing the air ventilation system).

In order to validate the accuracy of the context-sensitive prediction, it was compared to the reference data of the aging indicator. As the matching is very good between these time series the reference data is not recognizable in Figure 14. Therefore, Figure 15 shows the reference data and the context-sensitive prediction in the interval (about one week) with the highest residuals between them. It can be seen that there are only marginal differences between the reference data (blue curve) and the context-sensitive prediction (red curve).

4. Conclusion

In this paper it has been shown that predictive maintenance has many advantages in order to save maintenance costs. Furthermore, it has been shown that there are a lot of state of the art concepts and tools available for the realization of predictive maintenance. Although, good progress has been made in this area some important questions are still open. Therefore, this paper has addressed two issues.
Firstly, it was shown that system models which are suitable to model system behavior can be used for the generic determination of aging indicators. This is done by the iterative determination of system model coefficients in order to acquire their drifts in a timely dimension. Thereby, it was shown that an insufficient number of included system variables leads to fluctuations of the coefficients and consequently to a decreased accuracy of reliable predictions based on those coefficients.

Secondly, this paper answers the question how external influences on aging indicators can be handled in order to determine context-sensitive predictions. Therefore, a concept was introduced that first decomposes external influences into a so called sequence of atomic aging contexts and then determines a time series model for each context by solving a non-linear curve fitting problem.

In the evaluation phase it could be shown that using this concept the prediction of aging behavior is much more accurate. Consequently, using this concept in real environments the scheduling of maintenance actions can be done more precisely and therefore costs can be avoided.

But still some problems are left. A system model usually consists of more than one coefficient. In the here shown tests only one of them was kept dynamic while the others were kept static. Furthermore, solving non-linear curve fitting problems in the context of this paper is not trivial. For example, some solutions determined by the used algorithms were sub-optimal (local minima or local maxima).

Hence, more research is necessary if and how different coefficients of the same system model can be modeled simultaneously and how non-optimal solutions can be avoided in terms of the determination of context-sensitive models.

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