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Availability-guaranteeing maintenance of series machine tools

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Abstract

Condition monitoring enables transparency, as for example irregularities are detected automatically and reported. A condition forecast, however, requires more. In contrast to AI black box methods, frequently used in this context, a combination of existing expert knowledge and classical statistics is used as a method for a reliable determination of the remaining component-lifetime. This works, if meaningful historical data are available in a sufficient quantity and quality. And this in turn requires a corresponding number of machines that are as identical in construction as possible and which must also be subject to a defined test regime, temporally closely monitored outside the production process. However, the quantity can be significantly smaller than the number of cases required for a prescient analysis of the correlations between a condition parameter and the wear condition of a specific component. The main target audience of the strategy presented here is therefore in particular manufacturers of series machines who wish to offer maintenance packages with corresponding availability guarantees and on-site support for maintenance personnel.

KEYWORDS

augmented reality, condition monitoring, condition-based maintenance, linked data, machine tool, predictive maintenance

JEL CLASSIFICATION

Applied science for engineering

1 | INTRODUCTION

In machinery and plant engineering, maintenance becomes more and more important since reliability of production systems is one of the factors relevant for competitiveness. For this reason, maintenance processes are required to result in an increased availability and service life of the production system. Furthermore, they need to be integrated into operational company processes.[1]

Maintenance is the combination of all technical and administrative measures serving to maintain or restore the intended functional condition.[2] Today, maintenance, inspection, and repair of machines and plants is performed either

reactive[3] due to failures or preventive[4] according to manufacturers' instructions, due to schedule (e.g., during company vacations) or based on personal experience (possibly slightly condition-dependent, but strongly staff-dependent).

Consequences of these methods include stochastic failure with machine downtimes, time-intensive, and costly search for errors, risk of uncontrollable damage extent due to consequential damage, high stock of spare parts, supply shortage, loss of sales caused by loss of production, waste of energy, and resources,[5] loss of reputation, legal consequences, and increased costs. Unplanned downtime caused by a poor maintenance strategy reduces a plants' overall productive capacity by up to 20% and costs around $50 Billion each year.[4] Considering the current situation, there is an urgent need for a **condition-oriented maintenance strategy.**[6]

A survey regarding the potentials of condition-oriented maintenance, which was conducted in 65 mainly medium-sized companies from the sectors of automotive engineering, machinery and plant engineering, and the food industry, states that the participating companies expect the following from implementing condition-oriented maintenance: 36% reduction in production losses, 31% decrease in downtimes, and 23% reduction of maintenance costs.[7]

However, often the technical prerequisites and qualified staff are missing to considerably apply condition-oriented maintenance. Furthermore, it is difficult to carry out a cost–benefit calculation since so far it has been almost impossible to predict the effects of technical defects of machines and plants on their life cycles and on consequential cost due to loss of production. Thus, companies often hesitate to implement condition-oriented maintenance. However, experience has shown that the effort is worthwhile for companies that frequently use the same type of machine, where machines fail more frequently, or for those companies that manufacture machines themselves and want to use condition-oriented and predictive maintenance not primarily for their own production, but for the machines they sell themselves.

2 | STATE-OF-THE-ART

Performing preventive maintenance at irregular intervals depending on the current machine condition is already state of the art in the processing industry (e.g., steelworks and rolling mills, paper production, chemical industry) and in wind power plants. There the processes run continuously and with nearly no changes over a large period of time. The corresponding condition monitoring systems are described in References 8 and 9. Thereby, for example, vibration measurements on components (e.g., bearings) are used for predicting the plant condition. The time when defined thresholds are exceeded can be estimated more or less accurately, by using simple trend observations.[10] However, if the machines and plants are used for frequently changing processes, load-dependent process variables such as speeds, forces, and torques do not occur continuously but rather in a time-variable manner in the same machine. This fact significantly complicates the assessment of the wear condition of assembly groups by means of native non-load-normalized parameters (e.g., oscillation amplitudes, temperatures, motor currents). In addition, a simple time-based extrapolation of the parameter trends until the wear limit is reached is usually too imprecise. It is necessary on the one hand to determine the most significant wear parameters, independent of the process, under standardized test conditions and, on the other hand, to cumulatively record the changing loads on the assembly to be monitored during the process in a suitable manner.

However, predictions regarding the remaining life time of machine components that are subject to particular stress are based in practice on the subjective experience of the respective expert (e.g., Analyze MyMachine/Condition from SIEMENS[11]).

Besides the large IT companies, over the last years, a growing number of small and medium sized companies and start-ups offer tools and software for predictive maintenance. Some of these companies are specialists in their field and focus on industry applications, which are hardly adaptable to machine tools. One example is the start-up KONUX,[12] which enables railroad companies to perform predictive maintenance. Others are pure software providers such as IMMAVO,[13] RELAYR,[14] NEXOCRRAFT,[15] DEVICE INSIGHT,[16] or IS PREDICT,[17] some of which rely on artificial intelligence and self-learning systems. Furthermore there are end-to-end solution providers, such as PETASENSE,[18] which offers its own wireless vibration sensor, cloud software, and machine learning analysis, or AUGURY,[19] which uses noise detection and analysis in real time to detect deviations on machines. A description of the systems and also reference installations can be found on the websites listed in the reference directory.

In References 20 and 21 a cloud-based platform for condition-based preventive maintenance, supported by a shop-floor monitoring service and an augmented reality (AR) application, is proposed as a product-service system (CARM2-PSS). A similar architecture is also described in Reference 22. The knowledge required for a maintenance planning is to be obtained here with the aid of relevant AI algorithms.

However, none of the applications mentioned above, according to our research, is able to quantitatively determine a remaining lifetime, which is based on measured condition parameters and within which the availability of the assembly or machine is guaranteed with a specified statistical certainty.

Therefore, the core research goal comprised the design of a scalable system which monitors wear-related condition parameters of commonly used process-critical machine assemblies and calculates an availability guaranteeing prognosis for their remaining lifetime under specific process conditions. Since the diagnostic data required for this from machines located all over the world are recorded decentrally (on the shop floor) but must still be comparable, standardized diagnostic tests must be used under standardized test conditions at defined time intervals. Based on this, there the need to centrally manage and evaluate the collected data is deduced. And last but not least it is necessary to clearly communicate back the current condition, the remaining lifetime, and the possibly resulting maintenance instructions of a selected machine via a web-based front-end application that can also be used in the field on portable devices.

3 | SCIENTIFIC TECHNOLOGICAL APPROACH

In order to better plan the inevitable machine downtime, the necessary spare part orders and the deployment of maintenance personnel, it should be possible to retrieve the currently still available wear stock (remaining lifetime until the threshold is reached).

With regard to production machines, it is advisable to focus on particularly stressed components or assemblies, especially from an economic point of view. These are subject to increased wear and therefore have to be replaced or serviced more frequently and thus account for a relatively high proportion of the operating costs incurred for the machine. In machine tools, this particularly affects the drive components for axes and tool spindles (e.g., bearings, toothed belts, ball screws, and guides).

The evaluation of the wear behavior of such components can always be carried out with the help of statistical approaches or by applying analytical models (see Figure 1). Which method is chosen depends on various factors. While the successful application of statistical methods requires the existence of a relatively high number of machines that are as identical as possible, analytical models, due to their high complexity, usually only work with regard to very specific assembly elements.

For example, a very detailed analytical wear model exists for rolling bearings. The main factors influencing their service life are the axial and radial forces acting on the bearing. This standardized lifetime calculation is the fatigue theory by Lundberg and Palmgren.[23] However, modern bearings can significantly exceed the values calculated in this way under defined operating conditions. Ioannides and Harris[24] developed a theory on the fatigue in rolling contact, which extends the work carried out by Lundberg and Palmgren, and better describes the performance of state-of-the-art bearings.

Targeting a complete machine tool axis, were bearings are only one component among others, using the analytical approach would need a tremendous initial expenditure to develop the wear model. Therefore it was decided to use the statistical approach.

The statistical approach is based on the assumption that the remaining life time of a machine tool axis or spindle on fairly identical machines with fairly the same work load are subject to a certain statistical distribution. For this purpose, it is necessary to quantitatively evaluate the current degree of wear of the corresponding assembly in a suitable manner. In order to reduce the time required for training the AI methods commonly used in the predictive maintenance environment
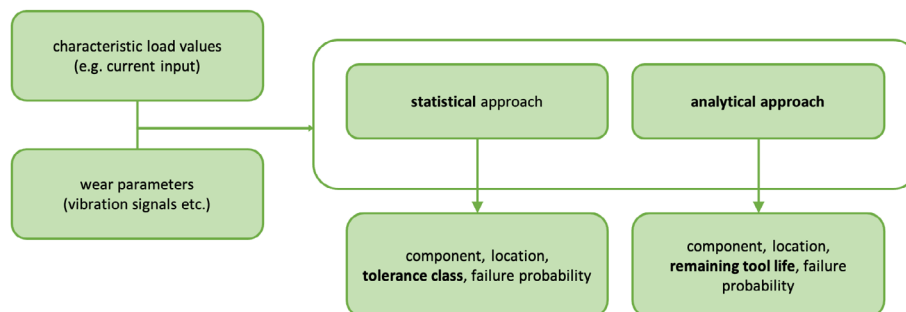

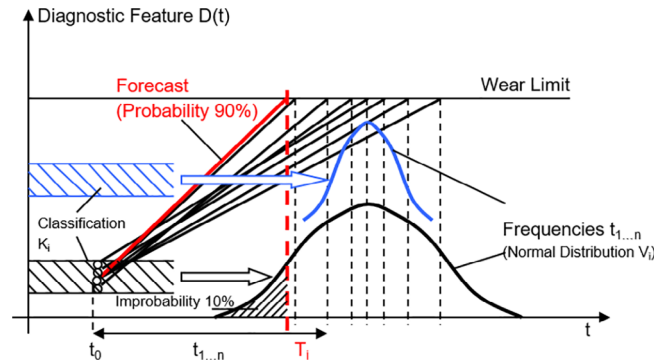**FIGURE 1** Diagram for calculating the remaining lifetime

FIGURE 2 Statistical approach for calculating the lifetime

(advanced data analytics, data mining, machine learning), existing expert knowledge in the field of early detection of machine failures was used here. In this way, it was possible to draw on already known relationships between the degree of wear of a machine tool axis or a spindle and the so called condition features $D(t)$. The procedures for determining the diagnostic features that appear useful for machine tool axes/spindles and the monitoring tests required to determine them are described in detail in Section 4. At this point, however, it is sufficient to consider $D(t)$ as a time series of an initially abstract quantity that can be used to describe the degree of wear of the mentioned assemblies as well as possible (see Figure 2).

For the following statistical considerations, however, a classification of $D(t)$ is still necessary. This means that for each $D(t)$, 10 classes K_i ($i = 0 \ldots 9$) must be formed. For this purpose the possible value range of the diagnostic features (reaching from the value expected at delivery up to the value marking the wear limit) is divided into 10 intervals of equal size (see also end of Section 4).

The remaining life time t_j (j is the machine no.) is defined as the time span between the time t_0 at which $D(t)$ is assigned to a certain class K_i for the first time and the time at which $D(t)$ exceeds the defined wear limit. If all t_j assigned to a class i ($\{t_j\}_i$) are considered, it is assumed that they will be subject to a certain statistical distribution.

If the type as well as the parameters of the distribution v_i (mean value M_i and standard deviation S_i in case of normal distribution) are known, a statistical probability can be assigned to any defined/assumed time interval t_j. Conversely, a time T_i can be calculated for any given probability or improbability.

The central limit theorem (CLT) states, when independent random variables are added, the properly normalized sum tends toward a normal distribution (bell curve), independent of their specific type of distribution. Since the lifetime of a component, and even more of an assembly of components, depends on many small independent influencing variables, we adopt the theorem for the lifetime calculations without further proof.

Thus, if in Figure 2 $D(t)$ falls into a class K_i, the remaining operation time T_i of the corresponding machine tool axis or spindle will be calculated with a certainty of 90% concluding it will fail before the predicted time T_i with a probability of only 10% (designated as "improbability" in next Figure).

In more pragmatic terms, this means, that the component or assembly remains failure-free with a probability of 90% if required maintenance is carried out by time T_i at the latest. If a normal distribution is assumed, T_i is calculated as follows:

$$T_i = t_0 + M_i(\{t_j\}) - 1.282 S_i(\{t_j\}) \tag{1}$$

If a smaller or even larger improbability is desired, the factor *1.282* in (1) must be adjusted accordingly. It is also expected that the closer the classification K_i gets to the wear limit, the smaller the standard deviation of the measured times $\{t_j\}_i$ will be (represented by the blue graph in Figure 2). This means the predicted time T_i approaches the time the wear limit is reached in reality.

But there is also another challenge. In practice, even similar machines at a single manufacturer never have the same work load due to, for example, different jobs or unexpected downtimes. For that reason, the measured operation time alone is not a sufficient basis for a statistical approach in that matter. A more general and reliable basis is the accumulated work acting on the drive components of the machine tool until the wear limit is reached. This work can be determined separately for each axis by measuring the specific axis drive current.

$$W_j = U \int_{t_0}^{t_0 + t_j} I(t) \mathrm{d}t \tag{2}$$

But then it is no longer the set of time spans $\{t_j\}$ that is normally distributed, but the set of recorded workloads $\{W_j\}$.

If required maintenance is carried out before the work acting on the drive components since t_0 exceeds the limit W_i, the machine axis component or assembly group remains failure-free with a probability of 90%. Analogous to (1), W_i is calculated as follows:

$$W_i = M_i(\{W_j\}) - 1.282 S_i(\{W_j\}) \tag{3}$$

The predicted remaining lifetime is calculated for the case that the machine is used as before, this means it was operated up to time t_0 with the same average power consumption P_i. Assuming that the work load has been recorded since the axis was put into operation at time $t = 0$ (time of delivery) until time t_0, P_i is calculated as follows:

$$P_i = \left(U \int_0^{t_0} I(t) \mathrm{d}t \right) / t_0 \tag{4}$$

This results in T_i:

$$T_i = t_0 + W_i / P_i \tag{5}$$

4 | DEFINITION OF SHOP FLOOR MONITORING TESTS

Besides characteristic values of bearing vibrations, mainly dynamically excited axial positions or motor currents are stored as "fingerprints" (nominal state, e.g., state of delivery). In the following they are measured and documented at certain intervals and under defined test conditions. In principle, it is suggested to perform each of the following tests once a week on the same day of the week and at the same time.

In each test usually several diagnostic parameters $P(t)$ can be formed. These are in some ways a precursor to the diagnostic features. At the end of this section it is described how the diagnostic features $D(t)$ are calculated from these parameters. In our opinion, only those parameters should be included for which there is a clearly recognizable linear correlation between the parameter value and the cumulative operating time. With regard to the correlation coefficient, the following should apply:

$$|K(P, t)| > 0, 5 \tag{6}$$

In the presence of a certain number N of fairly identical machines should apply:

$$\sum_{i=1}^{N} |K_i| > N/2 \tag{7}$$

It is proposed to eliminate all parameters for which condition (7) is not met after a start-up period of 6 months.

1. **Circular shape test:** Axis positions from the direct measurement systems (if they are present) of two geometric axes (e.g., x/y, x/z, y/z) are recorded during the axis perform a circular motion (each forward and backward movement, $r = 50$ or $100\,\mathrm{mm}$ / $v = 1000$ or $2000\,\mathrm{mm/min}$) in a time-consistent IPO cycle (interpolation cycle time of the CNC control, typically 4 ms). Feed in and feed out (each 180°) are to be eliminated in the evaluation.

   Note: Since the circular shape is evaluated via the internal measuring systems of the machine, it is not possible to assess the actual geometric accuracy of the machine. However, an evaluation of the axis dynamics shall be performed here. The following diagnostic parameters $P(t)$ are calculated for each axis involved (see Figure 3):

- **CW**: Circular form deviation with movement in clockwise direction
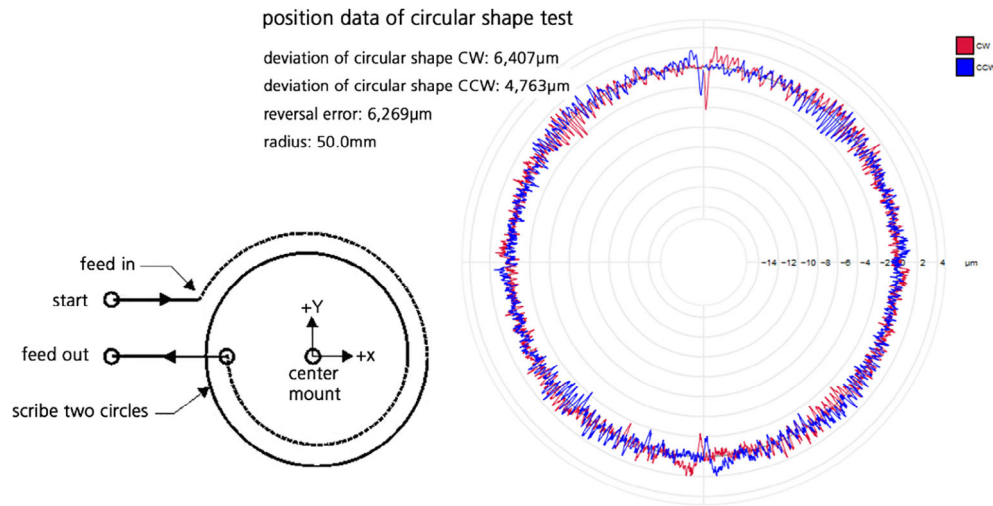- **CCW**: Circular form deviation when moving in counterclockwise direction

FIGURE 3 Circular shape test in X/Y plane

- **RE1**: Reversal error axis 1
- **RE2**: Reversal error axis 2 (in Figure 3 only an average value of RE1, RE2 is given)

- Equability axis test: Axis positions from indirect and direct measurement systems are compared to the motor current (proportional to the torque) during the travel of an axis (travel distance is axis-specific, $v = 1000$ mm/min) in a time-consistent IPO cycle. The acceleration and the breaking at the beginning and the end of the travel path are to be eliminated in the evaluation. Figure 4 shows the motor current as a function of the axis position and the diagnostic parameters determined from this.

    The analysis of the equability axis test points out errors or interference resistance of feed axis elements. The course of the stored values shows at which axis position the interference is located. For axes that possess an additional direct measurement system, the difference between the two position values can also be used to display the course of the overall stiffness over the axis position (no pictorial representation of this is included). The following diagnostic parameters are formed here for each axis involved:

- **MCF**: Maximum value motor current forwards
- **ACF**: Average value motor current forwards
- **MCB**: Maximum value motor current backwards
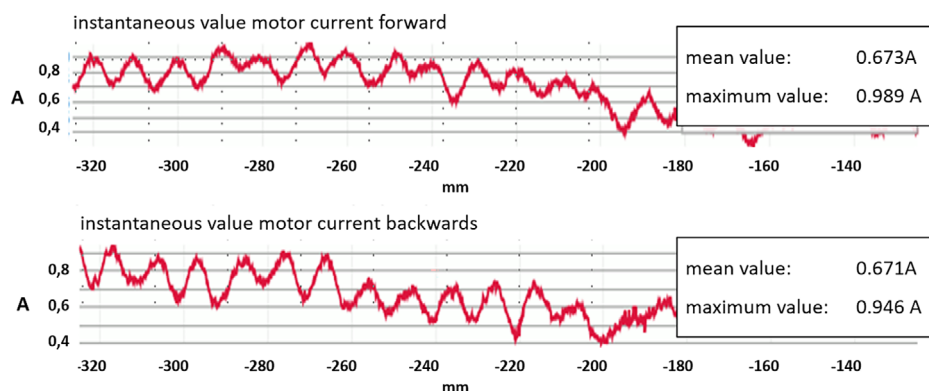- **ACB**: Average value motor current backwards

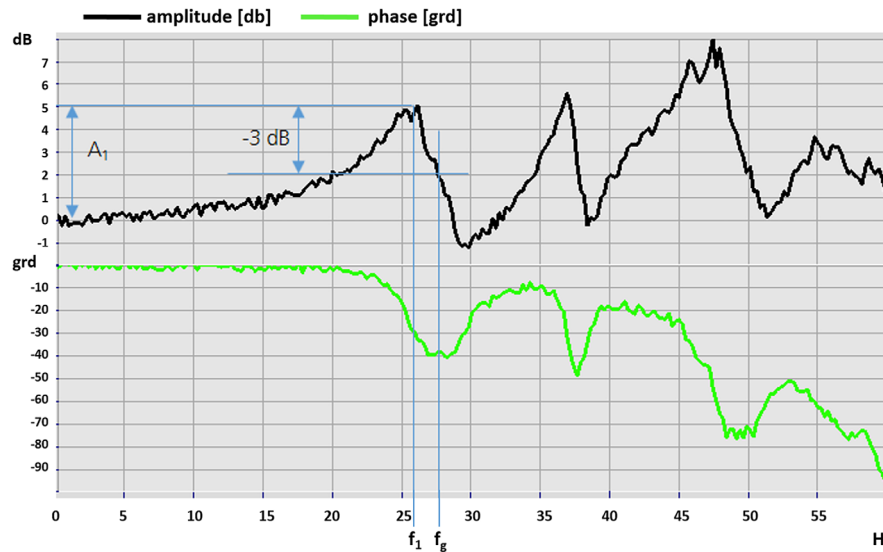
FIGURE 4 Equability axis test for X-axis

FIGURE 5   Bode diagram with determination of limit frequency f_g (*FQG*) in Hz

- **MPF**: Maximum position difference forward
- **APF**: Average position difference forward
- **MPB**: Maximum position difference backward
- **APB**: Average position difference backward

- **Transfer function test**: The actual and nominal position values of an axis-specific position control loop are brought into a functional relationship. For the nominal position value, a low constant feed rate is superimposed by a PRBS signal (Pseudorandom Binary Sequence, broadband noise, typically 0 … 100 Hz). Thereby, the frequency response of the amplitude ratio and the phase angle between the actual and the nominal position value are determined (in Figure 5 maximum at f_1 and −3 dB as cut-off frequency f_g).

  The following diagnostic parameters are formed here for each axis involved:

- **MAR**: Maximum value of amplitude ratio between actual and nominal position
- **FQG**: Cut-off frequency (named as f_g in the text above)
- **PSG**: Phase between actual an nominal position at frequency f_g

Please note: Using the determined limit frequency f_g enables an evaluation of the dynamics and the vibration tendency of the entire drive system (position control loop). If the k_v value of the position controller is known ($k_v = v/\Delta s$, with **v** – feed rate, Δs – deviation of position [nominal – actual]), the damping ratio **Dr** of the drive system can be determined as follows:

$$Dr = \pi f_g / k_v \tag{8}$$

Typical values for f_g range from 10 to 30 Hz and for k_v from 10 to 80 s^{-1}. To ensure low vibration tendency of the system, the damping ratio should be set to values between 0.8 and 1.0 using k_v:

$$\pi f_g < k_v < \pi f_g / 0.8 \tag{9}$$

- **Bearing test**: The following additional hardware by ifm electronic GmbH was specified and tested for this case: VSE 100, including a capacitive acceleration sensor (VSA) radial mounted on the spindle. During the test, the spindle is run up to a defined rotational speed (usually 1000 rpm) without a tool or with a balanced test tool, load-free for
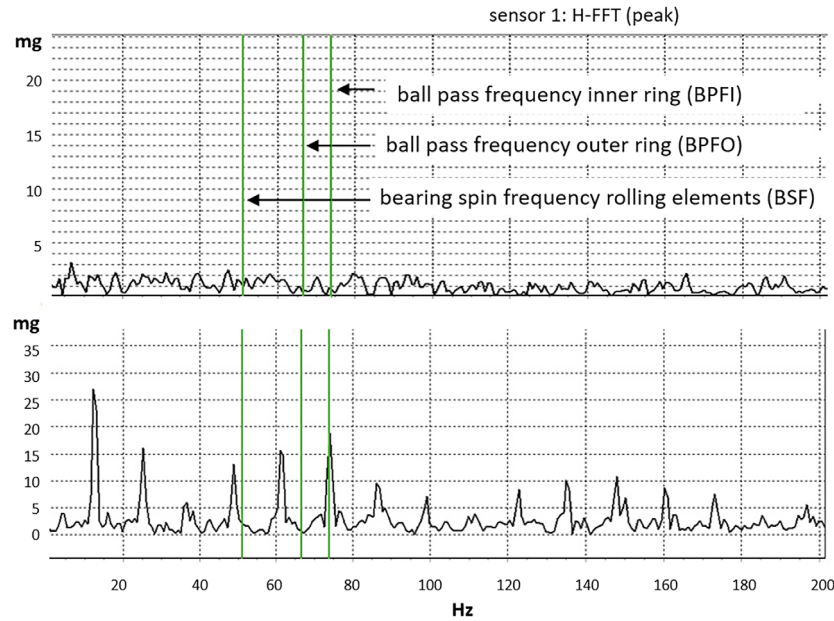
FIGURE 6 Comparison of the envelope spectra of an OK bearing (diagram on top) and of a not OK bearing with damage to the inner ring (diagram on bottom)

approx. 60 seconds. During this time, the oscillation amplitudes (acceleration) are measured at the ball pass frequencies specified by the bearing type and bearing rotational speed to detect a damage to the inner ring, outer ring, or the rolling elements. Figure 6, bottom, shows a clearly increased amplitude of the measured vibration acceleration (from 0.5 to 18.7 mg) on the line of the ball pass frequency of the inner ring (please note: the unit *mg* does not stand for milligrams, but for one thousandth of the acceleration due to gravity). The following diagnostic parameters are defined here:

- **AFI** : Acceleration amplitude at **BPFI**
- **AFO** : Acceleration amplitude at **BPFO**
- **AFS** : Acceleration amplitude at **BSF**

To calculate the diagnostic feature **D(t)**, all parameter values fulfilling condition (7) are first normalized to their possible value range ($P_0 \dots P_L$). Here, P_0 denotes a parameter value aimed at or idealized for the delivery condition and P_L denotes the value defined as the wear limit. Both values can be defined separately for each parameter-axis pairing used in the calculation of a diagnostic feature (see Table 1):

$$P_N(t) = (P(t) - P_0)/(P_L - P_0) \tag{10}$$

The result of (10) is then multiplied by a specified weighting factor (also specified separately for each parameter-axis pairing from Table 1 included in the calculation of a diagnostic feature).

$$P_W(t) = W P_N(t) \tag{11}$$

And finally, the diagnostic feature **D(t)** is the sum of all $P_W(t)$ to be included in the calculation according to Table 1:

$$D(t) = \sum P_W(t) \tag{12}$$

Since, by convention, the sum of all weighting factors used to calculate a diagnostic feature must always add up to 10, the following applies:

$$0 \leq D(t) \leq 10 \tag{13}$$

TABLE 1 Array of diagnostic parameters and machine axis

Axis		X				Y				B				Spindle			
$P(t)$	Dm	P_0	P_L	D	W	P_0	P_L	D	W	P_0	P_L	D	W	P_0	P_L	D	W
CW	µm	5	30	1	1												
CCW	µm	5	30	1	1	10	40	1	2								
RE1	µm	10	40	1	8												
RE2	µm	10	40			10	40	1	6								
MCF	A	1,5	3,5	2	3			2	5	1,0	2,0	1	5				
ACF	A	1,0	2,0	3	2,5			3	5	0,5	1,5	2	5	1,0	1,5	1	10
MCB	A	2,0	4,5	2	3			2	5	1,0	2,0	1	5				
ACB	A	1,5	3,5	3	2,5			3	5	0,5	1,5	2	5				
MPF	µm	10	40	2	2												
APF	µm	5	20	3	2,5												
MPB	µm	10	40	2	2												
APB	µm	5	20	3	2,5												
MAR	-	1	0,8	4	1	1	0,7	4	1								
FQG	Hz	40	20	4	8	50	35	4	8								
PSG	grd	−10	−40	4	1	−10	−40	4	1								
AFI	mg													1	10	2	4
AFO	mg													1	10	2	4
AFS	mg													1	10	2	2

This makes the classification of the value range into 10 intervals of equal size described in Section 3 very simple:

$$0 \le D(t) < 1 \rightarrow K_0$$
$$1 \le D(t) < 2 \rightarrow K_1$$
$$2 \le D(t) < 3 \rightarrow K_2$$
$$\dots$$
$$9 \le D(t) \le 10 \rightarrow K_9 \tag{14}$$

The tests presented above result in a matrix of the diagnostic parameters described above (rows) and the axes involved (columns). A milling machine with three linear axes (X, Y) a rotary axis (B) and a spindle was used as an example. Please note: The X-axis is equipped with an additional direct position measuring system.

Please note: Column D contains the sequence number of the calculated diagnostic features for each axis separately.

As an example, diagnostic feature 1 for the X-axis $D1\_X$ is calculated as follows:

Step 1: Normalization

$$CW\_X_N = (CW\_X(t) - CW\_X_0)/(CW\_X_L - CW\_X_0)$$
$$CCW\_X_N = (CCW\_X(t) - CCW\_X_0)/(CCW\_X_L - CCW\_X_0)$$
$$RE1\_X_N = (RE1\_X(t) - RE1\_X_0)/(RE1\_X_L - RE1\_X_0) \tag{15}$$

Step 2: Weighting

$$CW\_X_W = W\_CW\_X * CW\_X_N$$
$$CCW\_X_W = W\_CCW\_X * CCW\_X_N$$
$$RE1\_X_W = W\_RE1\_X * RE1\_X_N \tag{16}$$

Step 3: Addition

$$D1\_X = CW\_X_{W+} \, CCW\_X_{W+} \, RE1\_X_W \tag{17}$$

Reaching one or more limit values provides information about which component or assembly must be maintained or replaced. By default, the following events E are generated and stored for each diagnostic feature by the following predefined logical links (shown here with the example of $D1\_X$)

$$\text{IF } (D1\_X > 1) \text{ THEN } E1\_X\_1$$
$$\text{IF } (D1\_X > 2) \text{ THEN } E1\_X\_2$$
$$\text{IF } (D1\_X > 3) \text{ THEN } E1\_X\_3$$
$$\dots$$
$$\text{IF } (D1\_X > 10) \text{ THEN } E1\_X\_10 \tag{18}$$

5 | IMPLEMENTATION

5.1 | Infrastructure

Both the diagnostic features $D(t)$ stored weekly by the condition monitoring system using process-independent tests, and the load parameters recorded during the process (energy consumption, cumulated machining times) as well as the event values E are stored in the Linked Data Platform "Linked Factory"[25] developed by Fraunhofer IWU.

The "Linked Factory" can be seen as a cloud solution highly optimized for storing data in the context of production engineering. In any case, all the tool applications available (condition monitoring, forecast, front-end) solely access the Linked Factory directly via the so called REST[26] (Representational State Transfer) interface and receive responses in JSON or XML format.[27]

The infrastructure also is able connect the events E (see Section 4) with virtual representations of real components and with metadata from external systems, for example, ERP (Enterprise Resource Planning) applications, which are necessary for a service activity. For this purpose, four information views were defined that can be delivered to a mobile device. The data assigned to the information views are often heterogeneous and are located in different systems. Linked data technologies[28] are used to link this information semantically (Semantic Web)[29,30] and to query it via SPARQL requests. Information such as 3D geometries, material data, maintenance history, or service documents can thus be obtained from external systems. Depending on the application, the data platform serves as a proxy server for the original data sources or delivers data that has already been persisted internally.

Figure 7 shows the interaction between machine, condition monitoring, forecast (lifetime prediction), information views of the front-end (visualization), and the "Linked Factory".
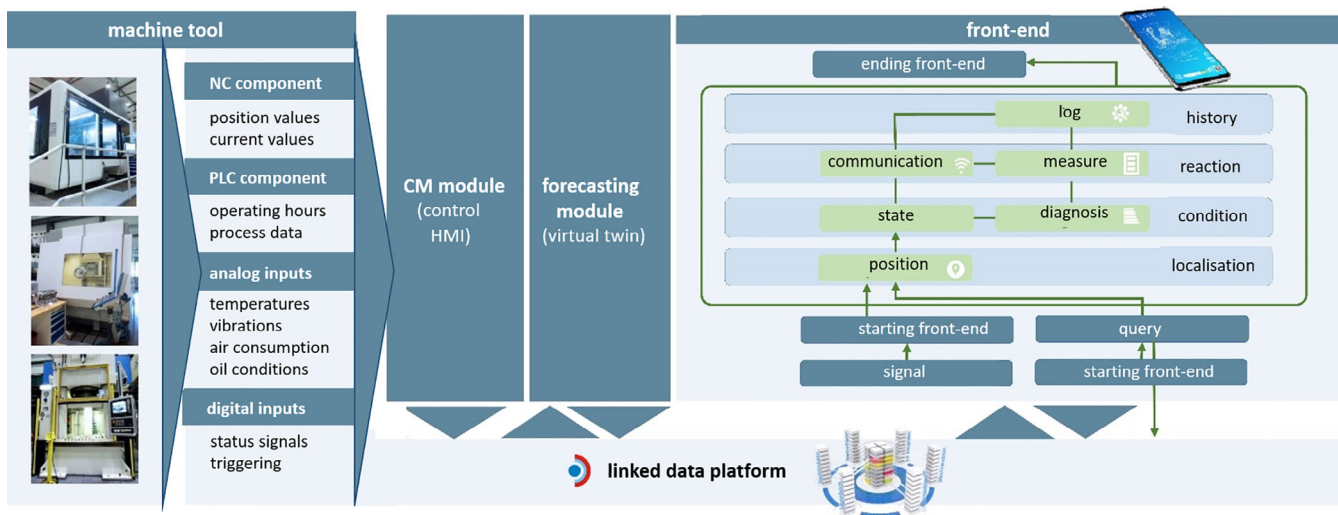

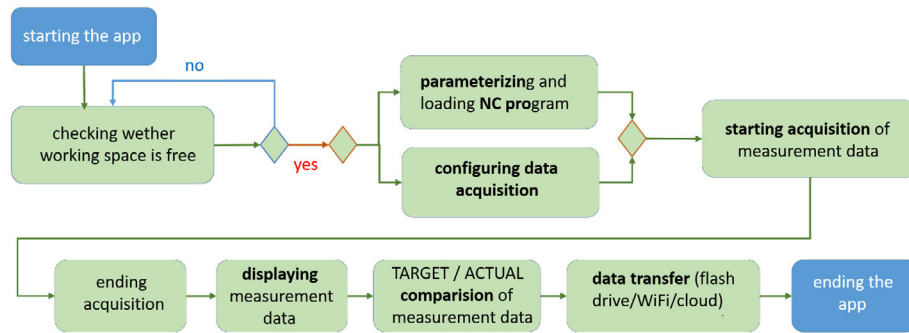**FIGURE 7** Data and information structure

FIGURE 8 Flowchart of the monitoring tests

5.2 | Condition monitoring (shop floor)

Every test described in Section 4 is performed according to the procedure shown in Figure 8:

The test app is implemented on the HMI (Human Machine Interface) PC of the respective machine control system. All tests described in Section 4 are automatically executed one after the other at the request of the operator. The time for performing the tests (weekly, always on the same day of the week at the same time) should be firmly scheduled into the production planning. After the test series is started, the control of the machine is automatically parameterized accordingly and an NC program is started that realizes the axis movements required by the test (2-axis-drive of a circle, 1-axis linear drive, switching on the PRBS signal, ramp up the spindle speed). Parallel to the running of the NC program, the required data (axis positions, axis currents, vibration amplitudes) are recorded in every IPO cycle of the numeric control (raw data). After completion of the recording, the corresponding diagnostic feature (see Table 1) are calculated and transferred to the cloud (Linked Factory).

5.3 | Forecasting tool

As already mentioned, all data structures described below are stored in the Fraunhofer Linked Factory. The task modules described in Structograms 1 and 2 access the dataset via the REST interface mentioned above. Please note that only the data structures and task modules necessary for a basic understanding of the processing have been listed here.

Structure 1. Master data

MASTER
```
Axis  Diag.feature  Limit
```

Axis- and diagnostic feature-specific classes (see Structure 4) are required for classifying the diagnosis values (see Figure 7). The class size is a compromise between the desired accuracy (smallest classes possible) and the statistical certainty (as many entries per class in table REST as possible).

Structure 2. Axis-specific class limits

CLASS
```
Axis  Diag.feature  Class  From  To
```

Structure 3. Diagnosis values

VALUE
```
Machine  Axis  Diag.feature  Timestamp  Diagnostic value  Work load
```

Data contained in Structure 3 are continuously updated using the bearing tests described in Section 5.2 (see Figure 7, Task **Data Transfer).**

The following Structure 4 is required for the registration of exceeding the warning value or the limit value and also for the documentation of performed maintenance. Maintenance actions are manually registered by the maintenance staff via a corresponding registration mask/routine. The two timestamps upon reaching the warning or limit value are added after activating the module LIMIT (see Structogram 1**).**

Structure 4. Historical data of axis

HISTORY
```
Machine  Axis  Diag.feature  TimeStamp Limit  Timestamp Maintenance
```

Whenever a limit value is exceeded by the actual diagnostic value, the corresponding entries in the following structure REST are generated from the structures MASTER, VALUE, HISTORY, CLASS by means of the task LIMIT (see Structogram 1) as data basis for further statistical evaluation:

Structure 5. Specific remaining lifetime

REST
```
Machine  Axis  Diag.feature  Class  Rest work load
```

After every activation of the task LIMIT, the task STATISTICS (see Structogram 2) is activated. Based on the data available in table REST (see Structure 5), safe wear margins (= recommended maintenance period) that are diagnostic feature and class-specific are calculated and stored in table SAFE. If the assembly is exchanged within the recommended maintenance period, there is only a 10% risk for the corresponding limit values to be reached, that is, the machine remains capable for production with a safety margin of 90%.

Structogram 1. Procedure of the task LIMIT

Task LIMIT
Activation: Diagnostic value exceeds corresponding limit value
Parameters: timestamp call, machine, axis, diag. feature, work load call
```
Add entry in HISTORY➔machine, axis, diag.feature, timestamp limit = timestamp call
Select in HISTORY for machine, axis, diag.feature➔timestamp last maintenance
In CLASS, select all entries for axis, diag.feature➔class, from, to
In VALUE, select all entries for machine, axis, diag.feature with (timestamp > last
timestamp mainten.) and (from < diag.value < to)
For every selected entry in VALUE, an entry is made in REST    ➔    machine, axis,
diag.feature,
rest work load = work load call – work load
Activation of module STATISTICS (axis, diag.feature)
```

The calculation of the safe work load prognosis is carried out within the task STATISTICS in a self-optimizing way, that is, after each new data set in the REST table recorded by the LIMIT module, the safe workload value becomes more reliable.

Structogram 2. Procedure of the task STATISTICS

Task STATISTICS
Activation: after every activation of module LIMIT
Parameter: axis, diagn. feature
```
In REST, select for each class separate all entries with axis, diagn. Feature
Calculate mean value and standard deviation of all selected entries
Using all available entries, calculate
Safe work load = mean value – 1.282 standard deviation
```

Notice: Since the underlying tests can only be performed at certain time intervals (weekly) in practice, the remaining lifetime (wear stock) can also only be recalculated at these intervals.

5.4 | Front-end

The visual support was designed in the form of a front-end that uses web technologies such as WebGL[31] and the WebXR[31] to utilize virtual and augmented reality (VR and AR) technologies[32] in a browser-based manner on mobile devices such as smartphones, tablets, and data glasses. In this context, AR enables overlaying and augmenting the real environment, for example, machines with virtual objects and information. Current smartphones and tablets were selected as the target hardware, since they offer flexible use in the production environment and are often part of the standard equipment of a machine operator or maintenance technician. The handling of this hardware and its mostly intuitive operation is very familiar to each user group. The focus in the realization of the front-end was placed on the infrastructure of information provision and the user-specific visualization in various information views. The use of data glasses was not taken into account for use in the production environment.

Current AR applications in industrial production are predominantly in the area of service support, where the real environment is supplemented by digital instructions for the maintenance and repair of technical equipment.[33] By combining information from condition monitoring and statements derived from it on the predicted remaining service life of components, the additional aim is to provide visual and functional support for the user even before damage occurs. If the purpose of AR in this use case is to create benefit for the user, the visual and communicative support must be highly informative, unambiguous, quick to grasp, and ergonomic. In order to realize these requirements, the four information views LOCALISATION, CONDITION, REACTION, and HISTORY were defined and targeted data assignments were made.

The main task of LOCALISATION is the "view into the machine". For this purpose, a CAD-based, geometrically simplified, and real-time 3D model of the entire evaluated machine is used. The machine visualization is divided into primary objects (monochrome, monitored by condition monitoring) and secondary objects (semitransparent, not monitored). The initial visualization includes all objects, with sensor positions represented by three-dimensional markers. Communication between data platform and AR front-end is bidirectional. If an event occurs in the Linked Factory, the user is prompted for a status query. In this, the affected primary object is marked and the user is forwarded to the information layer CONDITION via touch interaction with the geometric representation.

In the CONDITION view, the type of fault (if determined) and the component state are assigned to the event values provided. The condition types are Normal (no event), Critical (event), Fault, and Undetermined. The event case is specified in more detail by the static calculation approach (wear model, lifetime prediction). The remaining life (wear stock) of the component is visually integrated into the AR view with a timeline (optionally calendar overview). The interactive event and fault signaling is used to forward to the REACTION information view.

Depending on the signaling, the focus of REACTION is on offering a quick on-site response. Functions such as immediate stock inquiry of an affected component and the provision of direct communication and information channels are prioritized to enable the user to act quickly via the AR front-end. Direct service response is supported with virtually overlaid assembly and inspection instructions as well as the optional use of video, image, and text information.

The HISTORY information view provides information about error conditions that have already occurred and the actions taken to correct them. Thus, the complete logbook of all error states identified so far and the associated actions can be viewed at any time.

The preparation of the data for these four developed views and the assignment of information relevant only for the respective view enables a target and user-oriented application of the overall solution on the machine.

The prototypical implementation of the front-end follows the information views already described. The LOCATION information view is provided in the 3D view and AR view variants. The 3D visualization of the machine model was realized with A-Frame[19] to ensure the support of the machine model in the 3D and AR view and to test the interaction between model objects and associated metadata. The integration of two model views allows retrieval and location mapping of event and forecast information both dependent and independent of the users' location. Users with less knowledge of the particular machine setup can use the AR view to see event values of affected components in direct relation to the real machine. This functionality can be extended in further stages for the training of operators and service personnel. Figure 9 shows a first prototypical implementation on a tablet pc with an AR interface.

The purpose of the visualization is to provide time-saving and active support for people in production. User-friendliness, functional data infrastructure, and easy transferability to different types of machines and sensor data

FIGURE 9 Prototype of the AR view with component highlighting on a tablet pc

evaluation were decisive development criteria. Following the initial technical testing, it will be necessary to carry out extensive user tests on the user experience (UX)[34] in order to validate and further optimize the practical usability.

6 | CONCLUSION

A proof that the algorithm for calculating a safe remaining component or assembly lifetime works in practice cannot be provided at this stage of the work. For this, the number of documented machine failures or related maintenance actions is not high enough, yet. The assumption that the remaining axis work load (from reaching a certain wear class until the wear limit is reached, seen over several similar machines) is subject to a normal distribution, has also not been proven, yet. For this purpose, a chi-squared test is to be carried out after an appropriate number of cases has been identified.

Regardless of these facts, the monitoring tests described in Section 4 can be used independently to a large extent. For this purpose, the trend of one or more diagnostic features over time or energy can be visualized on the machine. This visualization can be used to very roughly approximate the time at which the wear limit is reached. It is also possible to display the trends of a specific diagnostic feature on a specific axis as a function of the workload of the axis across multiple machines in a common diagram.

In order to conclude from the recorded sensor data, which drive component is affected, fixed links resulting from empirical knowledge are currently used. In the future, machine learning methods will play a decisive role in this process and will complement existing expert know-ledge.

In addition, the decoupling between the front-end and the actual data sources implemented in the described condition monitoring system makes it possible to flexibly adapt the overall system to further application scenarios: the interfaces of the Linked Factory can be extended in order to specify additional data sources. Here there is no need to modify the clients on which the assistance application runs. Moreover, the front-end can also be further developed independently of the back-end. Since the clients rely exclusively on web technologies, the assistance application can easily be realized on other devices, provided that they have a web browser supporting WebXR as an interface for 3D frameworks.

PEER REVIEW

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DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

CONFLICT OF INTEREST

The authors declare no potential conflict of interest.

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