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Condition monitoring system for machine tool auxiliaries

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Abstract

Failures on machine tools not only occur on main components, but also on auxiliaries like cooling units or oil mist separators, which causes productivity losses similar to failures on main machine components. Due to their separation from the machine's control network, their health status is in most cases not monitored. In this study, a new approach for online condition monitoring of auxiliary units by the example of an oil mist separator connected to a 5-axis machine tool is presented. The data is analyzed via machine learning principles in order to deduct an adequate condition assessment, encompassing environmental influences.

Keywords: Condition monitoring; Manufacturing systems; Machine learning; Machine tools; Machine auxiliaries; Machine monitoring; Neural networks

1. Introduction

Machine tool breakdowns and unexpected need for maintenance negatively impact manufacturing systems performance. Approximately one fifth of machine tool downtimes are due to electrical and mechanical faults, not including tool breakage or CNC faults [1,6]. Failures not only occur on main machine components, but also on auxiliaries like cooling units, oil mist separators, chip conveyors and others. Failures on auxiliaries cause downtimes and productivity losses similar to failures on main machine components, such as drives, spindles or axes [1,3]. Auxiliaries are generally attached to machine tools in a modular fashion, and fulfill isolated tasks excluded from the machine's closed-loop control. Due to their separation from the machine's sensory network, their health status is in most cases neither monitored nor considered. This is due to their limited ability to be integrated into a machine tool's control system, and potentially also to lack of attention by machine tool users, as defects on auxiliaries are attributed a low severity, except for a few select cases. In this paper, a new approach for online monitoring of auxiliary units is presented. In order to account for the economical boundary conditions of machine tool equipment, and to ensure a uniform approach over

a large range of machine tool auxiliaries, a connectivity and monitoring platform was developed. As a result, a minimum of sensors is selected to monitor the health status of the unit. Using the connection to cloud computing, both the electronical as well as the mechanical hardware modifications could be reduced to a minimum. In addition, the auxiliary can be included in the data ecosystem of a machine tool in order to deliver the necessarily large and comprehensive data inflow containing useful information about their health status and potential performance issues.

By the example of an oil mist separator connected to a 5-axis machine tool, the monitoring system was deployed to a machine in fully operational mode for validation and data harvesting in a common shop floor setting. After a basic analysis of the physical phenomena and correlations, appropriate statistical models were derived, allowing to describe the behavior and health status of the oil mist separator. The particularity of this Condition Monitoring (CM) approach is that it acquires the necessary data while the machine is in operational mode, and includes any of the process and environmental influences in the model. Hence, no additional machine downtimes for test or diagnosis cycles is necessary, integrating the CM system seamlessly into any machine tool. Of the conceived system, all

parts such as hardware, data transmission and data analysis elements, can easily be applied to other types of auxiliary units.

The system specifically focuses on auxiliaries and utilities, which does not comprise the monitoring of tool health and wear, or the surveillance of built-in components such as axes and spindles.

2. State of the Art

The idea of Prognostics and Health Monitoring (PHM) systems in manufacturing is nothing new. However, recent forthcomings in Internet and Communication Technologies (ICT), in conjunction with advances in machine intelligence research have caused a spike of activities in this sector. The ubiquitous availability of affordable and rapidly deployable connectivity solutions, also referred to as the Industrial Internet of Things (IIoT), is an important driver of this development. Moreover, the strive for value creation from connected and smart devices, which is often time associated to the notion of Industrie 4.0 [7], opens up a large array of new possibilities. With a particular focus of intelligence transfer to machines, allowing them to mimic human traits in cognition and intelligence, the so-called biologicalization of machines and manufacturing systems will allow for new developments and accelerate industry-readiness for laboratory cases in the years to come [12].

2.1. Monitoring systems for machine tools and auxiliaries

In order to allow for the necessary cognitive capacities, monitoring systems need to be deployed to machines and machine-components alike. This can be a first challenging task in the deployment of PHM solutions, as proprietary communication schemes, heterogeneous data sources and incompatibility of proprietary protocols [4], and a subsequent lack of an open and neutral approach [2] result in an inherent loss of large amounts of data from machines [8].

For specific applications, monitoring encompassing a large variety of manufacturing equipment have been development. Exemplarily, Gontarz et al. presented an approach in 2015 allowing for a comprehensive resource consumption monitoring (including auxiliaries) in machine tools, with a particular focus on energy consumption monitoring [5]. Based on this system, Gittler et al. proposed an extension in 2018 aiming at the facilitation of monitoring via the concept of virtualized sensors. This fundamental approach for data acquisition, usable for all types of machine tools and shop floor machinery, first analyzes the general behavior of a component in order to combine one-time measurement effort and easily accessible signals into an overall monitoring of machine component activities [4].

Simultaneously, Barton et al. described a novel approach for components and sensors to be equipped with a self-description, allowing a rapid deployment of connectivity solutions and a live information access to shop floor equipment. The self-description dataset is interpreted by a Cyber Physical System (CPS) connector, and made available via an Open Platform Communication Unified Architecture (OPC UA) server to an OPC UA client of a superior system or platform [2].

Overall, an overall trend towards the deployment of affordable and easy to integrate connectivity and monitoring solutions can be observed – both in industry and research.

2.2. Data interpretation and information extraction

Similar to the issue with the transferability of data acquisition solutions from one machine to another, also the lack of adaptability of specific analysis solutions results in a low utilization of available information. Lee et al. criticize that the training of models currently happens rather in laboratory rather than applied industrial cases, resulting in a neglection of external influences and subsequently in a poor performance [8].

A majority of PHM systems focus on singular signals in order to determine the health condition of one or multiple specific parts, for instance bearings and gearboxes. A prominent example is the monitoring of motor currents, and the realization of subsequent Motor Current Signature Analysis (MCSA). For instance, Simon et al. described this approach in 2017 as the aggregation of electronic current features in order to determine a set of predefined disturbances [11].

For multi-variate analyses, more complex models need to be developed. With the recent acceleration in machine learning research, neural network frameworks are experiencing an extensive application also in manufacturing related cases. However, Lee & Kramer have proposed to use neural network to deduct models and recognize patterns in the behavior of machinery as early as 1993 [9]. They propose to use neural networks to monitor and detect machine degradations via a Pattern Discrimination Model (PDM) based on a Cerebellar Model Articulation Controller (CMAC). This allows to learn normal patterns under regular working conditions, and quantify the deviation from the pattern at subsequent measurements via a loss of model confidence. The confidence indication yields an index of how well a measurement fits to previously registered patterns, based on which a threshold allows to decide whether or not a fault is present. However, the loss of model confidence being an abstract measure, makes it difficult to interpret and certainly takes some experience to deliver reliable decisions. The authors defend this approach, as it is very difficult to accurately recreate bad or wrong behaviors for modeling purposes, wherefore the observation of a decay from normal behavior is considered an adequate procedure.

2.3. Disadvantages state of the art and research gap

In terms of data acquisition and monitoring solutions, recent approaches proposed by e.g. Barton et al. [2] appear promising, given that they focus on Open Communication Protocol Unified Architecture (OPC UA), are easy to deploy and allow to harvest not only information from a machine's NC control, but also the required meta-data from components and adjacent systems. In terms of cost and complexity, their deployment focuses on low-cost and readily available hardware platforms (e.g. Raspberry Pi, μ-controllers), with a low to intermediate deployment complexity level. However, the same does not hold true for data analysis approaches, which are case-specific,

complex and lack a transferability to other components or auxiliaries. Lee et al. also state that the reason for the low integration of PHM approaches lies in the low adaptability of learning algorithms for PHM purposes [8]. The generalized neural network approach of Lee & Kramer of 1993 is a rather abstract model delivering but an indicator of matching or non-matching level to previously registered patterns, which lacks a quantitative indication. Hence, future solutions should embrace recent advances in data acquisition and monitoring systems, while focusing on the development of universal and generalized learning models, which deliver quantitative results on the health or performance level of the investigated object.

3. Solution Structure

3.1. Requirements and setup of the monitoring system

The setup fulfills the following boundary conditions and requirements: It disposes of multiple Inputs and Outputs (I/Os), which are either be of digital or analogue type, in order to measure variable, constant or constant variable component behaviors, as described by [4,5]. The hardware is based on affordable and available components, which is a low-cost common μ-controller enhanced with a Modbus controller and a Wi-Fi module for wireless connectivity. This generalized setup is able to accommodate data from other controller units, such as motor drives via TX/RX or Modbus, sensor and data acquisition units via direct I/O or via I²C, and other standard bus systems. The wireless communication system is used for the sake of simplicity for data transmission in order to omit wiring efforts and allow for data collection in inaccessible areas. It can also be used to deploy a fleet of similar Data Acquisition Systems (DAQ) on the same or multiple systems, and connect them wirelessly to a superior data collection or processing instance. The described setup is transferable to a variety of components without hardware modification. An overview of the fundamentals of the system is described in [4]. In order to prove its applicability, ease of use and the subsequent data analysis capabilities, the condition monitoring system was installed on a common OEM oil mist separator on a 5-axis machine tool.

3.2. Application to an exemplary use-case

Currently, oil mist separators are in most cases mounted behind or on top of machines, making them rather inaccessible. Furthermore, given their simple nature, monitoring of the filter condition is often times realized via a common bubble tube, allowing to estimate the pressure difference over a rough scale. In a large number of cases, these circumstances lead to a disregard of the condition indication of air filters, creating hazardous situations in which polluted air cannot be properly filtered, or even worse, potentially explosive oil mist is not properly evacuated from the machining room. Hence, it is an ideal use-case to show the applicability of an affordable condition monitoring system requiring little upfront effort and permitting in-service measurements and condition determination.
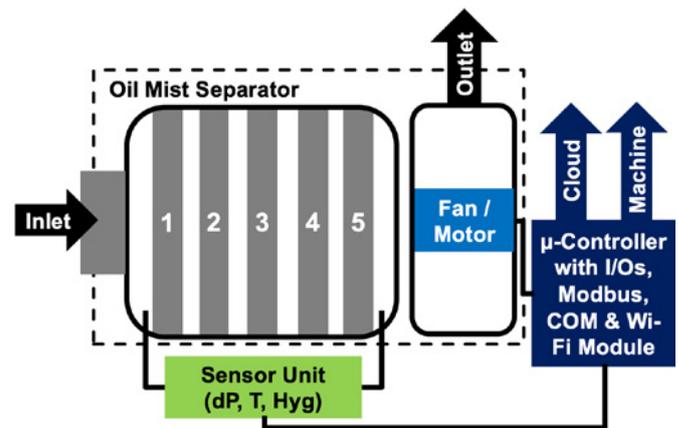

Fig. 1 - General setup (hardware and data acquisition) of the proposed system and its exemplary application to an oil mist separator.

For most monitoring purposes of active and controlled components, the basic measurement refers to the power intake of a component. It contains a high density of information about its current activity and state, given that it is enriched with additional data from surrounding components and systems.

For the exemplary application to the oil mist separator, a sensor unit was installed and wired to the DAQ system. As a very basic physical model, the relation between power intake, the volume flow and the pressure difference was considered (see equation 1).

$$P_M = \frac{Q * \Delta p}{\eta} \quad \text{with} \quad \Delta p = \Delta p(\rho, T) \qquad (1)$$

The pressure difference Δp is a function of air density ρ and temperature T, which need to be measured or observed. As a neural network can model proportional relations, conversion factors and proportional coefficients can be disregarded in this context. As the air density is mostly influenced by cutting oil and coolant particles, the humidity (Hyg) will serve as an observatory. For the remaining variables, the pressure difference (dP) over all filters and the temperature (T), as well as the power intake of the fan motor are measured and logged.

The application and its wiring for the demonstration case of this study is shown in Fig. 1. The pressure difference was only measured across all filters, as this avoided hardware modifications and simultaneously raises robustness requirements for the learning algorithm, given that the data will be of higher aggregation level and therefore less precise. For the power intake, as well as the RPMs of the fan motor, a direct communication channel between the DAQ μ-controller and the motor controller unit was used. In this specific case, the motor controller was equipped with a basic communication module. However, the power intake and the RPMs can conveniently be measured with additional low-cost sensors in a similar fashion to the sensor unit at the filter set.

The black arrows (Fig. 1) depict flows of matter, which are oil mist at the inlet, and cleaned air at the outlet. The black connection lines show basic data transmission between sensors, sensor units, motor control and the μ-controller. The blue unit
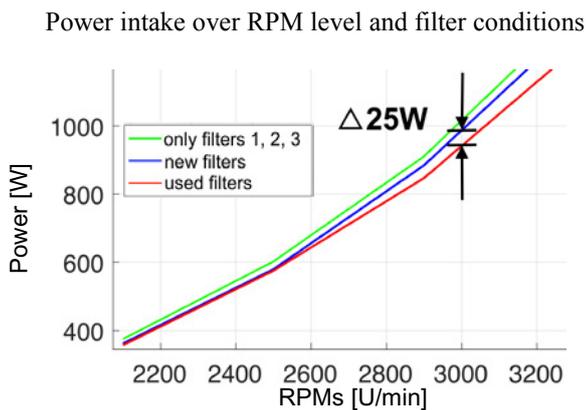
Power intake over RPM level and filter conditions

Fig. 2 - Power intake behaviour depending on the RPM operation level and the conditions of the filters (minimum filter configuration, new and used filters).

and the blue arrows depict the DAQ system including its communication modules, as well as the outbound data flow to the machine and the cloud database.

3.3. Data acquisition, transmission and analysis structure

The μ-controller acts as the central DAQ unit, which collects the raw values from the sensors, applies the necessary transformations, synchronizes the inbound measurements and adds a timestamp. Via the DAQ, the values were collected and sent to both a PC mounted on the machine, as well as pushed to a cloud database via the Wi-Fi module to allow for a more convenient processing. The DAQ also applied a preprocessing and data aggregation allowing to send only minimum payloads of data (1 set per minute) in order to reduce network traffic. The preprocessed data was stored in an SQL type database and subsequently analyzed, which can be conducted both in the computation unit of the machine, or on a centralized unit connected to the cloud.

4. Results

4.1. Measurement results and baseline analysis

The preliminary tests were carried out in order to define an order of magnitude for the power intake difference between a set of new filters and a set of used, ready to be replaced filters. The measurements were conducted in a laboratory setting in order to reduce disturbances to minimum. The oil mist filter was not connected to the machine tool for this test to omit variances in temperature and air density.

The data collected in this test bench approach does not allow to build any reliable model, but it is a necessary step in order to validate the viability and plausibility of future built models in a shop floor environment. The harvested data at different RPMs of the fan with different filter configurations (new, used, only a subset of filters installed) clearly shows that a distinction in the power intake can be made (see Fig. 2). In the higher RPM regions, the setup with filters requiring replacement (red line) clearly shows a lower power intake than the setup with new filters (blue line), where the absolute difference is of 25W. This result is the prerequisite for a Condition Based Maintenance

(CBM) approach, as it allows to quantify the decay of a target variable between a good and a bad setup, in contrast to the proposition of Lee & Kramer [9]. However, this observation cannot yet be transferred to an industry case, as the connection of the oil mist separator will have a significant impact on the behavior, and additionally introduce a set of disturbances. Fig. 3 depicts an excerpt of a raw data series that was measured with the oil mist separator connected to a machine tool under normal working conditions. The values have been normalized around their mean in order to show their fluctuations and how they may influence one another. One can see that changes in temperature (blue) and humidity (green) have a significant impact on the pressure difference (orange), and subsequently on the power intake of the fan motor (red).

The overall (non-normalized) fluctuations of the power intake have an absolute difference of 40W. Comparing this value of 40W of in-use fluctuations with the results of Fig. 2 (25W), it becomes evident that the environmental influences on the power intake outweigh by far the influences due to filter deterioration. Hence, a regression fitting (even over very long periods of time) does not yield any resilient results. A purely physical model does not justify the effort, as it would need to be constructed according to each setup (machine air passage, diameter of waste air pipe, length of waste air pipe, number of bends, characterization of the flow type, etc.). However, these observations imply two constraints for the development of a machine learning model: (1) The environmental influences need to be integrated in the model learning, and (2) the model accuracy needs to be far more precise than +/- 10W in order to allow for a determination of the actual condition.

4.2. Data preprocessing and dependency exploration

As a prerequisite for the model teaching, (1) the approximate interdependency of variables, as well as (2) an appropriate level of entropy needs to be confirmed. For (1), a scatter plot of the measurement variables of the power consumption, combined with the relative humidity and the temperature reveals the correlations (see Fig. 4). For (2), it is sufficient to consider the ranges of all variables, which
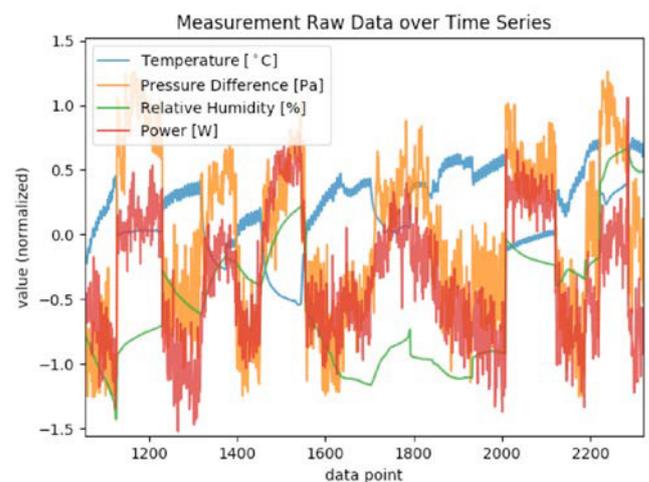

Fig. 3 – Excerpt of the measured raw data time series (normalized for visualization purposes), showing the cross-interference of the variables.
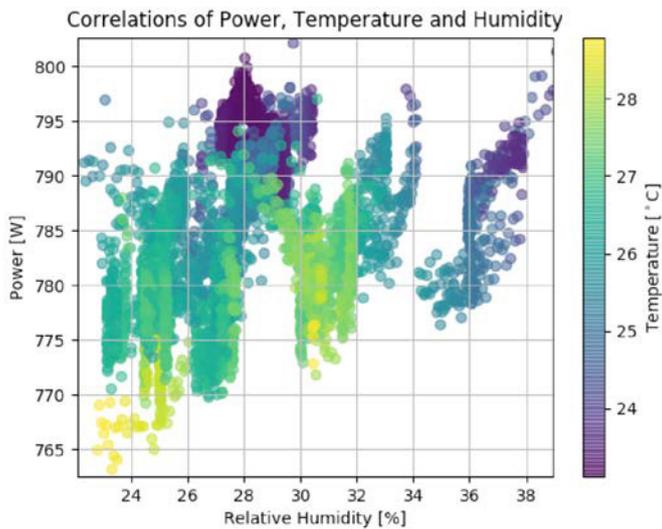
Fig. 4 – Scatter plot demonstrating the interdependency and variable entropy of temperature, humidity and power intake of the oil mist separator.

demonstrate an overall large spectrum in all three dimensions. The power consumption of the air filter depends on both relative humidity, as well as the temperature. The relative humidity (on the x-axis) itself does not allow for a precise relation directly to the power consumption (y-axis), yet the enrichment of the information with the temperature (color-axis) allows for a more precise approximation of the required power intake. Since the pressure difference and the power intake exhibit a similar behavior (see Fig. 3), the pressure difference will naturally be fed to the model. However, it needs to be confirmed whether it is sufficient to approximate the overall power intake with an accuracy of far less than +/- 10W. Additionally, the decay of the power intake due to filter deterioration is not yet regarded in this plot either.

4.3. Fitting via machine learning and decay identification

Similar to Lee & Kramer [9], the model is only trained on normal and good behavioral states of the oil mist filter. The idea is to develop and train a model solely on a small set of data harvest after the machine is newly introduced to service, or after new filters have been installed. The input values (temperature, humidity, pressure difference) harvested later on during the use phase are then fed to the model, and subsequently compared to the target variable (power intake) which should result in a difference between predictions and actual values. The model reconstruction error represents the decay of the filter conditions, and gives an indication on how far the difference between the predicted behavior and the actual condition is. This value is then compared to the findings of Fig. 2, in order to give a quantitative indication of the current condition.

As a first step, a machine learning model in the form of a conventional backpropagation artificial neural network is constructed. For the determination of parameters, a brute force approach over the number of layers, number of nodes, optimizers, learning rates, dropout rates and momentums was applied. The model was trained only over a minor part of data

points, in this case on data points representing 8 hours of the oil mist filter in use after fresh filters had been installed. The results of the fitted model (as a prediction on the trained values) over the actual values are shown in Fig. 5.

The fitting of the model shows appropriate results, given that the actual values oscillate no more than +/- 4W around the prediction, on average even less than +/- 2W. This value is largely sufficient in terms of accuracy, as previously defined in the baseline analysis. However, since the training of the model is only carried out on a small dataset, and since environmental conditions of an oil mist filter do not change in intervals of seconds, the quantity of data and its entropy have natural boundaries. Yet, the model accuracy clearly demonstrates the applicability of a machine learning model integrating machine and environmental influences on machine tool auxiliaries. In order to determine whether the model trained in a normal state can reliably identify decay in the condition of an auxiliary, the prediction model therefore needs to be applied to subsequent data of the oil mist filter in use, to obtain the model reconstruction error.

Fig. 6 shows the application of the trained model to subsequent two weeks of the filter being in use in a regular shop floor setting, connected to a 5-axis machine tool performing routine milling tasks. The raw values of the model reconstruction error exhibit a strong oscillation (light blue line). However, the indication of a filter decay does not have to be determined at every instant, wherefore the application of Simple Moving Average (SMA) helps to show a more intuitive and clearly identifiable trend line over time (dark blue line). During the time of the filter in service, the model reconstruction error first oscillates around 0 (red line) with an error of approximately +/- 3W in the SMA, which may be due to a lack in model accuracy, missing input variables or noise. Yet, a trend already becomes visible in this region. After around 2400 data points, the decay of the filter becomes more evident, as the model reconstruction error approaches a reduction of power intake of almost 10W.

From the baseline analysis, a difference of 25W represent the power intake variation between a fresh filter, and a filter
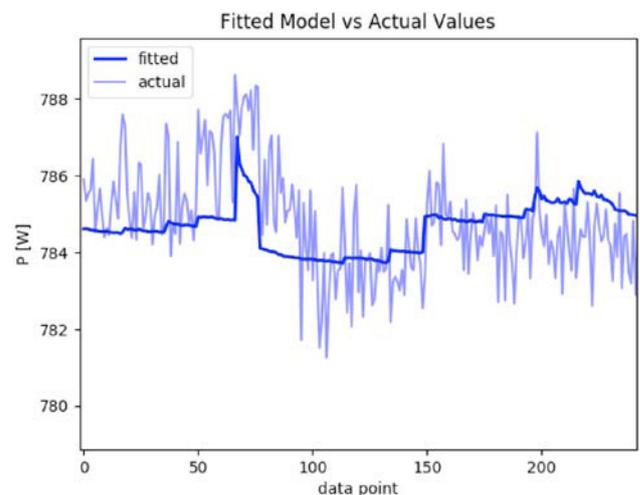

Fig. 5 - Results of the machine learning model plotted against the actual measured values.
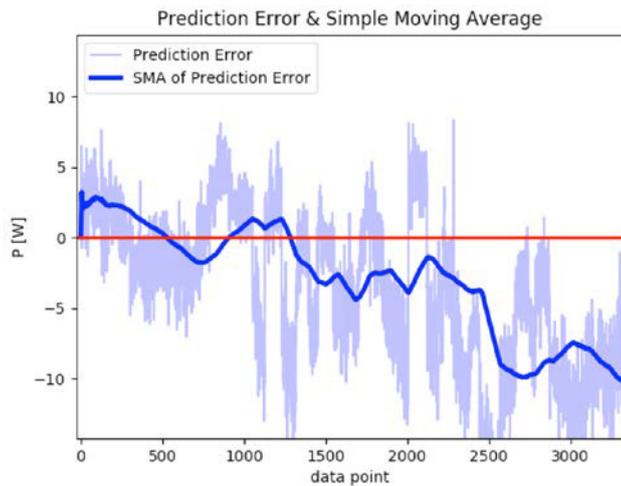
Fig. 6 – Evolvement of the prediction error over consecutive measurements, actual values and Simple Moving Average.

that needs replacement (as demonstrated in Fig. 2). The model suggests a difference of 10W, which is, according to the manufacturer of the oil mist separator, an appropriate value for the decay over the horizon that the data was harvested. As a conclusion, a deterioration of the filter condition was detected and appropriately quantified by the system, proving its applicability and viability in an industrial shop floor setting use-case. In combination with the thresholds identified in Fig. 2, the condition monitoring system presented in this approach can be used to generate alarms for CBM purposes in a manufacturing environment. Since there are no precise values on when a filter should effectively be replaced, an effective assessment of the model prediction error as a condition indication cannot be performed. Moreover, at this point it cannot yet be confirmed that the model prediction error can be used for a Remaining Useful Lifetime (RUL) estimation, e.g. based on an extrapolation of the decay trend line (Fig. 6).

5. Outlook

Even though the viability and reliable identification of decay of the condition of an auxiliary has been demonstrated, different aspects demand refinement or improvement. In order to reduce the oscillations of both the raw data and the model, a preliminary clustering could be applied. This can reduce noise due to disregarded disturbances or measurement errors. Additionally, it can help to exclude large external disturbances (e.g. operator opening the door of the machining room, thereby momentarily altering the system characteristic), and to separate stationary from non-stationary process behaviors.

In terms of application of the demonstrated approach to other auxiliaries, preliminary tests on other machinery and also machine components show promising results. Since an oil mist separator exhibits a rather constant behavior with only little variation, the approach needs to be tested more extensively on variable auxiliaries and consumers in general, especially in terms of required training data set size and variable entropy during model training data acquisition. Overall, the transfer to integral machine components also appears promising.

In addition to that, a more sophisticated approach to the hyper parameter optimization should be used. The described brute force approach is computationally expensive, even though the training data set was comparably small – hence, it lacks transferability to use-cases where data is generated in higher frequency ($>10^1$ Hz) regions, or where it is generally necessary in larger quantities. Hyper parameter optimization allows to weigh model exploration versus exploitation, i.e. it permits to both enlarge the potential solution space and to reduce the insecurity in the known solution space.

The proposed system cannot only be used for mere condition monitoring, but also for more sophisticated CBM or potentially even Predictive Maintenance (PM) cases, by fitting the model reconstruction error and interpolating its function. Therefore, the integration into more complex and encompassing PHM application frameworks, such as described by Sarazin et al. in 2019 [10] is worth further investigation.

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