SENSOR-BASED MODELING OF RADIAL FANS

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ABSTRACT

Predictive maintenance poses a new way to minimize costs and downtime of machinery. The combination of sensor data, intelligent algorithms and computing power allows this new approach to monitor the current health-state of machinery and detect possible failures early on or even in advance. Previous work in this field regarding radial fans focused on aspects such as vibration and noise, whereas this paper concentrates on the influence of multiple sensor data when modeling radial fans. In a case study multiple sensors are mounted on a radial fan and the importance of their signals on damage prediction is presented. The correlation between them is analyzed and the variable impact of sensor signals for approximating the rotational speed of a healthy and a damaged radial fan is identified.

Keywords: Condition Monitoring, Radial Fans, Predictive Maintenance

1. INTRODUCTION

Industry 4.0 and Internet of Things (IoT) are two trending topics in the field of computer science and production. With the increasing amounts of computational power, data transfer rates and cheap sensors, many use cases that were unthinkable ten years ago can nowadays be realized. One manifestation of these trends is a slow shift from preventive to predictive maintenance (Swanson 2001). This approach is especially promising for high-cost machinery or machinery with high safety regards, where an unforeseen failure resulting in downtime is disastrous. Radial fans are an integral part of a wide variety of industrial facilities and therefore one candidate application. They are mainly used as the core component of a ventilation system. Their application varies between simple air conditioning for buildings up to the ventilation of critical systems in chemical plants, where dangerous gases may build up over time with insufficient ventilation. Other examples are cement plants, wood processing plants and generally industry with dusty air. In contrast to axial fans, radial fans are designed to create higher pressure and perform more energy efficient, whereas axial fans are able to transport more volume and can be manufactured in a more compact way (Chung and Goetzler 2015).

Radial fans have a limited useful lifetime that can be prolonged with a detailed maintenance schedule. To delay the wearing of radial fans and lower the risk of premature, unforeseen failure, a maintenance interval is specified. Insight into the casing to inspect the impeller during operation is nearly, if not at all, impossible. Due to the nature of the high rotational speed of a radial fan, it has to be shut down before a service technician can begin the inspection. Additionally, as a safety measure, vibration sensors can be mounted on the bearings. As soon as the vibration exceeds a predefined threshold, the fan must be stopped and the cause of the increased vibration has to be detected, which further increases the downtime and respectively the costs, but prevents a possible failure. The downtime of radial fans without a backup results in a stoppage of the whole ventilation system. To complement the current preventive maintenance approach, additional methods to determine the overall health status of a radial fan should be elicited. The eventual goals of predictive maintenance are to approximate the remaining useful lifetime, detect the optimal time for maintenance and identify which parts have to be replaced next. The first step towards these goals and focus of this paper is to examine the influence of multiple sensor data on modeling radial fans.

This work is structured as follows. Section 2 contains a summary of the related work in the field of radial fans with a strong focus on the selected sensors. Section 3 describes the experimental setup, which has been chosen for the generation of data and the installed sensors and introduces the extensible sensor platform used to connect most of the sensors. In Section 4, the methodical approach is defined. Section 5 contains the results, followed by a brief conclusion in Section 6 and outlook in Section 7.

2. RELATED WORK

Renwick and Babson (1985) monitored the vibrations of a finish mill, cooler vent fan and gear reducer and they were able to detect specific problems of the machineries. They relied on their technical knowledge about the system and applied *Fast Fourier Transformations* (Bracewell 1986) on the vibration signals.

Garcia, Sanz-Bobi, and del Pico (2006) focused on a windturbine gearbox and designed a complete system named “Intelligent System for Predictive Maintenance” (SIMAP). They used a combination of artificial neural networks, fuzzy logic and an expert system with the possibility to generate a complete maintenance schedule and did not rely on a single model. They were able to give a prediction of the time remaining till failure, which is synonymous with the before mentioned remaining useful lifetime.

Jung, Zhang, and Winslett (2017) generated data with sensors mounted on vacuum pumps. They also tackled the prediction of the remaining useful lifetime with a more general framework based on vibration analysis.

Velarde-Suárez et al. (2006) focused on a predictive maintenance methodology, specifically for radial fans. In addition to vibration, they also used accoustic pressure signals and observed the deviation between a signal and a reference value for defined frequencies.

Rusiński et al. (2014) tried to find if the current operation of a radial fan creates resonance, which means the configuration of the fan needs to be adapted to prevent faster degradation of the fan.

Datong et al. (2009) followed another approach. They measured the efficiency and noise emmitted from different radial fans and compared them to sucessfully find suitable modifications of the fan to reduce the emitted noise and increase the efficiency. This indicates the correlation between efficiency and noise. Their experiments required a hemi-anechoic chamber to reduce noise and create comparble results. Khelladi et al. (2008) gave theoretical background on how to calculate the emitted noise of radial fans. Abid et al. (2012) focused solely on tonal noise emitted by an axial fan and created a model to identify healthy and damaged axial fans.

Summarizing, one common approach is to monitor vibration, which is applicable for different rotational machinery. Vibration signals provide additional information, as some authors applied fast fourier transformations to check the harmonic frequencies. The second most common way to predict the health of machinery is to analyze the noise emitted during operation. All these previously mentioned papers either focus on few signals to predict the health of machinery or proposed a holistic framework for predictive maintenance such as SIMAP. However, none of the reviewed related literature examined the influence of different kinds of sensor data and their combination to model the state of radial fans. The goal of this paper is to analyze the impact of different sensor signals for health prediction of radial fans.

3. EXPERIMENTAL SETUP

In our experiments we investigate the behavior of a radial fan driven by a two-pole electric motor with a power of 37 kW (see Figure 1). The motor speed is adjustably by an electric frequency converter up to a rotational speed of 2960 rpm and pressure loss of the system can be modified by a control flap, which results in a large flexibility of operating states that can be investigated. An impeller with a weight of 38 kg, 12 impeller blades and a diameter of 625 mm is used as reference. Another set of impellers is modified in a specific way to simulate long term abrasive stress on a short time scale. The engine shaft is connected to the engine by a coupling (see Figure 2). This setup is common for many industrial applications and therefore is chosen for the experimental campaigns.

Figure 1: New Radial Fan.

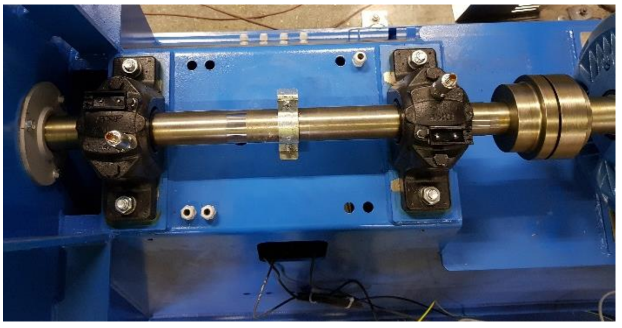

Figure 2: Engine Shaft, Spherical Roller Bearings, Coupling and Vibration Sensors without Protective Cover.

3.1. Sensor Types

The first step to model the health state of radial fans is to identify appropriate sensors for the modeling later on, where some restrictions need to be addressed. Considering the possibly predominating high gas flow rates, high pressures, heat or abrasive media inside the case of radial fans, the range of compatible/possible sensors, which can be mounted inside the case, is limited. Another restriction is sensor cost. Ultimately, every sensor has to be sold to the customer, which means that the least expensive sensors should be used to achieve the

required accuracy and to draw conclusions about the current health state of the fan. Furthermore, such sensors should be durable, maintenance-free and non-calibratable. Every intrusive measurement system has an impact on the process itself, therefore we focus on non-intrusive methods.
The backbone of every prediction model, agnostic of the methodical approach, are the chosen sensors and the quality of the signals. Most failures are forecasted by subtle physical manifestations in the system. Some possibilities are an increase in temperature (friction) and accelerated wear of mechanical components (vibrancy).

3.1.1. Vibrations and Temperature

In industry applications, monitoring vibrations of the bearings and temperature is state of the art. This allows determining a vast variety of machinery fails. In most cases, amplitudes, frequencies and envelopes of vibration signals are processed to pinpoint the exact cause of failure, e.g. imbalances, cracks, bearing damage or lack of lubricant.

3.1.2. Noise

As mentioned in Section 2, the emitted noise might indicate the current health state. Although some of the literature focuses on the emitted noise in an experimental setup, in real world scenarios this idea poses difficulties. Often the environment is polluted by noise emitted by other machinery or will not allow any additional external acoustic sensor due to space restrictions. In contrast to Datong et al. (2009), who experimented in a hemi-anechoic chamber, fans installed in production plants most likely are not deployed in such a controlled environment and the noise emitted by radial fans is disturbed by other sources of inference. Because of this, we do not use microphones in our experimental setup.

3.1.3. Moisture

The degree of moisture can influence mass- and energy balances of the system and therefore such sensors are part of the measurement campaign.

3.1.4. System Efficiency and Power Consumption

As a first characteristic to determine the health of a fan, the system efficiency is considered in such way that energy consumption is correlated with gas flow rate and temperature rise of the gas after passing the fan. To calculate the efficiency we determine gas flow rates by measuring gas temperatures and differential pressures at a Venturi-tube, as well as electrical power consumption.

3.1.5. Abrasion and Caking

The detection of these parameters is accomplished by optical examination during standstill, as it is common in industry. Different methods to quantify the damages and to determine the remaining useful lifetime are currently under investigation.

3.2. Sensor Setup

The measurement of process parameters is accomplished twofold.

3.2.1. Self-build Setup

We use a self-developed data acquisition and data processing system (see Figure 3) that contains a certain set of sensors. Two temperature sensors (MAX31855K) measure gas temperatures at inlet and outlet of the fan, two gyroscopes (BMX055) determine accelerations and rotations at the bearings in all 3 dimensions, a hygrometer (HDC1000) measures the surrounding moisture, an ampere meter (WAGO 857-550) the electrical power consumption and a rotation speed control counter (GS100102) the revolution. Sensors are connected to sensor hubs that send data to a computer for further procession. Sensors are attached to specific positions by using special 3D-printed mounts.

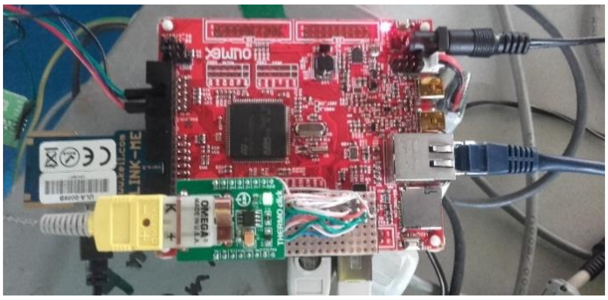

Figure 3: The Prototype Platform (built on STM32F407 from STMicroelectronics).

3.2.2. Commercial Sensors

As a reference, additional commercial senors are applied to measure gas temperatures (JUMO PT100), bearing temperatures (JUMO 902050/40), pressures (KSE DMU2), revolutions (IFM DI602A) and vibrations (IFM VTV122) of the system. Data acquisition is completed by a commercial datalogger (Graphtec GL820 and HBM QuantumX MX840B, respectively) and data is post processed afterwards.
The data acquisition rates of both systems can be adjusted to find an optimum between accuracy and data traffic. Currently we experiment with sampling rates between 50 Hz and 300 Hz.

3.3. Custom Sensor Platform

The number and type of sensors needed to predict maintenance intervals depends on the particular application. Therefore, the sensor platform has been designed to be modularly expandable using the same hardware and firmware.

3.3.1. Hardware System Concept Sensor Platform

Figure 4 shows the system concept of the sensor platform. In the picture on the left (shown in blue) is the gateway to collect data, which allows a connection to the internet. This gateway can also store the data locally in a

CSV file. Through the system bus (shown in green), the gateway communicates with the sensor nodes, which are the heart of the sensor platform. The data communication is based on TCP / IP and uses 100 Mbit/s Ethernet. At least one sensor node is necessary for the measurement, significantly more sensor nodes can be connected to the gateway. The limiting feature is the data rate of 100 Mbit/s, which cannot be exceeded. The net payload data rate is significantly lower (about 50 Mbit / s), since the packet sizes differs depending on the sensor type from 50 to a few 100 bytes and the overhead of TCP / IP (40 bytes per packet) must be taken into account.
In our example, we used the STM32-E407 development board from Olimex for the sensor platform, which provides both Ethernet and the necessary connections for the sensors. Via I2C, SPI, UART and analog and digital inputs, the sensor data are read in. The sensor platform contains a real-time clock that precisely documents the time of the measurement on a millisecond basis.

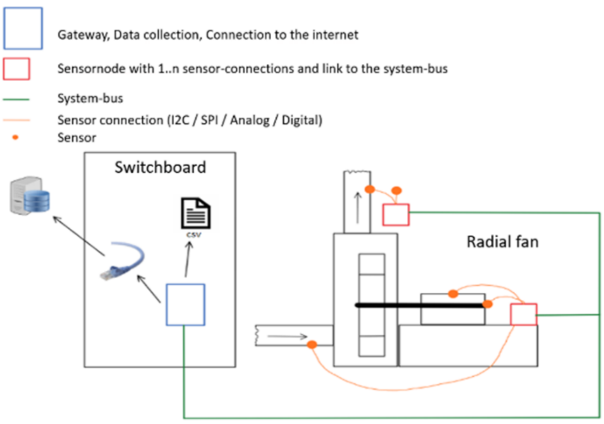

Figure 4: System Concept Sensor Platform, taken and adapted from Grasböck and Schmidt (2017).

3.3.2. Firmware Architecture Sensornode

The firmware is designed to read the sensors on a millisecond base or a multiple of milliseconds. Then data is transmitted to the gateway via Ethernet / TCP-IP.
Each sensor uses one task to process its data. For the transmission of the sensor data to the gateway, a separate task is used. Thus, new sensors can be added simply by adding tasks without changing the software of existing sensor tasks.
The operating system is FreeRTOS, which is an open source embedded real time system. STM's board support package has been enhanced for our application so that the different sensors are easy to be read. The CMSIS library of ARM was used unchanged, for the HAL (hardware abstraction layer) the software was adapted.

4. METHODICAL APPROACH

As mentioned in Section 3, every sensor mounted on a fan increases its costs and sensors cannot be placed on the impeller itself. The first step towards modeling the health state of a radial fan is to gather as much data from as many sensors as possible. Because the radial fan is placed in an experimental setup, we can measure the efficiency accurately and generate a characteristic curve of this specific, brand-new fan. Afterwards we will model the efficiency with the sensors, available in real world scenarios. This test run will be repeated several times. Between each test run, highly abrasive air will be used to wear off the impeller. After each cycle a technician will sight check the impeller for a subjective impression of the state of wearing and caking. As soon as the predefined vibration-threshold is reached and safety-issues may occur, the impeller will be changed and the experiment starts again with the first iteration. The highly abrasive air poses a possible health-hazard, therefore an additional filter system will be attached, preventing the highly abrasive air from contaminating the surrounding area. The construction of this filter system has not been finished yet. As an interim stage, several pre-damaged impellers, which show common deterioration patterns in different stages are prepared and will be used to sample sensor data. With all this data available, several machine learning algorithms for modeling the current state of the radial fan are applicable.
To select suitable sensors, several considerations are necessary. If the signal of a specific sensor has an influence on the prediction of the health state of a radial fan, a deviation of this signal between the same operational conditions of a healthy and faulty/worn fan should be noticeable. Another indication for the impact of sensor data is a changing correlation between different signals.
The data used for the scope of this paper was generated by the following configuration of the experimental setup. Two different impellers, one brand new and one pre-damaged (see Figure 5), were mounted to generate two different datasets, one with good running conditions and one with a known damage. The rotational speed was incremented stepwise from 0 rpm to 2960 rpm in 370 rpm-steps, each with a recording period of 15 minutes to gather data from different running conditions, resulting in a total observation period of 4 hours.

Figure 5: Manually Pre-Damaged Impeller.

5. RESULTS

In this section, the results of the analysis of the experimental runs are presented. The relation between the different sensor types and the rotational speed is the modeling goal, because it is the only manually adjustable and monitored parameter of the experimental setup at the given moment. The efficiency, which will be used for the advanced modeling goals and prediction of the remaining useful lifetime, will be available once the experimental setup is complemented by the filter system mentioned in the previous section.

5.1. Preliminary Experiments

The preliminary experimental setup used before the pre-damaged impeller was available, generated data from two vibration and one rotational speed sensor, using a new impeller. A first analysis shows a reoccurring pattern of vibration signals during an increase and decrease of the rotational speed (see Figure 6). If each signal is compared with itself during ascents (see Figure 6, Subsection 1 and 3), the signal is correlated with a Spearman's Rank of 0.798 (Vibration Sensor 1) and 0.874 (Vibration Sensor 2) and a Pearson's R of 0.748 and 0.888. During the descents (see Figure 6, Subsection 2 and 4), the signals correlate with a Spearman's Rank of 0.879 and 0.912 and a Pearson's R of 0.897 and 0.936. These correlations confirm the importance of previous works that monitored vibration signals and underline their usefulness for health state modeling of radial fans. Especially a change in a reoccurring pattern under similar running conditions may be an additional, more subtle indication of a damage.

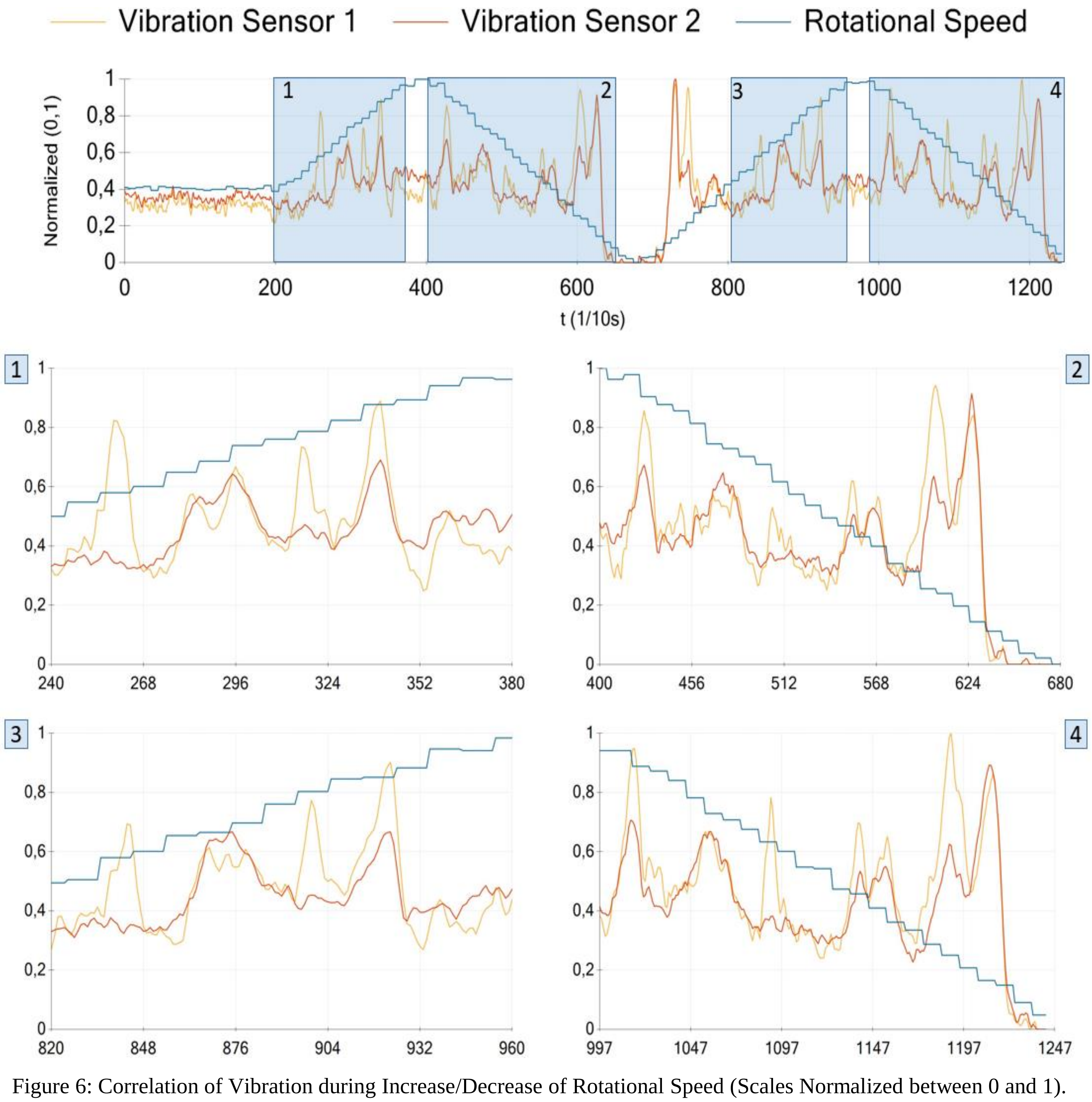

Figure 6: Correlation of Vibration during Increase/Decrease of Rotational Speed (Scales Normalized between 0 and 1).

5.2. Pressure Signals

The pressure signals at the inlet, aperture and the differential pressure (measured, not calculated) show a strong correlation with each other and the rotational speed (see Table 1). Both impeller have similar characteristics, the correlations do not change significantly. An error cannot be detected by examining the correlation alone.

Table 1: Pearson's R^2 of the Healthy Impeller (top line) and the Damaged Impeller (bottom line) for the Pressure Difference, Rotational Speed, Pressure at Aperture and Pressure at Inlet.

	Press (Diff)	Rotational Speed	Press (Aper)	Press (Inlet)
Press (Diff)	1.000 1.000	0.951 0.956	0.993 0.999	0.995 0.999
Rotational Speed	0.9505 0.9564	1.000 1.000	0.951 0.949	0.953 0.951
Press (Aper)	0.993 0.999	0.951 0.949	1.000 1.000	0.999 1.000
Press (Inlet)	0.995 0.999	0.953 0.951	0.999 1.000	1.000 1.000

As the high correlation indicates, a function to approximate an arbitrary pressure signal by a different one can be found. An example is as follows, calculated with Genetic Programming solving a Symbolic Regression Problem (Affenzeller et al. 2009) using the HeuristicLab Framework (Wagner et al. 2012).

$$P_{Inlet} = c_0 \cdot P_{Aperture} + \frac{c_1 \cdot P_{Aperture} + c_2}{c_3 \cdot P_{Aperture} + c_4} + c_5$$

$$\begin{aligned} c_0 &= 1.1664 \\ c_1 &= 1.1387 \\ c_2 &= -94.699 \\ c_3 &= 0.0066872 \\ c_4 &= -61.742 \\ c_5 &= 3.2566 \end{aligned} \tag{1}$$

Equation 1 approximates the pressure at the inlet with the pressure of the aperture and five constants, achieving an R^2 of 0.99992 and a mean absolute error of 4.14. This illustrates the interchangeability between these two pressure signals. Due to the high correlation, any of these three pressure signals can be approximated by the others. This is illustrated by Equation 1. Equation 2 shows the relation between the rotational speed and the pressure signals, whereas the pressure at the inlet was not necessary, which seems plausible, considering the strong correlation.

$$RotationalSpeed = c_0 \cdot P_{Difference} + \frac{1}{c_2 \cdot P_{Aperture} + c_3} + \frac{c_4 \cdot P_{Aperture}}{c_5 \cdot P_{Aperture} + c_6} + c_7$$

$$\begin{aligned} c_0 &= 1.4035 \\ c_2 &= -4.4875E-05 \\ c_3 &= -0.0019993 \\ c_4 &= -425.69 \\ c_5 &= -0.22457 \\ c_6 &= -319.32 \\ c_7 &= 520.95 \end{aligned} \tag{2}$$

5.3. Temperature Signals

We monitored the temperature at the inlet and the outlet of the radial fan and the ambient temperature. The basic idea is that a damaged impeller may create more friction and therefore a raise in temperature occurs. Figure 7 shows the three monitored temperature signals and the rotational speed during the test run, normalized between zero and one.

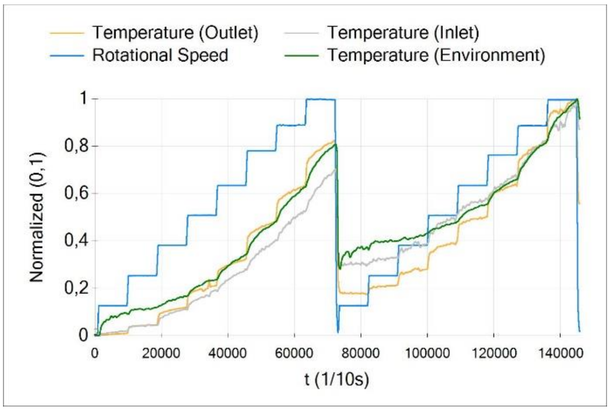

Figure 7: Temperature Signals and Rotational Speed of the Test Run, Normalized between 0 and 1.

Further on, the Pearson's R^2 and Spearman's Rank of the different sensor data were calculated, as shown in Table 2 for the healthy impeller and Table 3 for the damaged impeller. They indicate a strong correlation of these four signals.

Table 2: Pearson's R^2 (top line) and Spearman's Rank (bottom line) for the Temperatures and Rotational Speed of the Healthy Impeller.

	Temp (Outlet)	Rotational Speed	Temp (Inlet)	Temp (Env)
Temp (Outlet)	1.000 1.000	0.913 0.976	0.988 0.997	0.982 0.996
Rotational Speed	0.913 0.976	1.000 1.000	0.868 0.967	0.855 0.967
Temp (Inlet)	0.988 0.997	0.868 0.967	1.000 1.000	0.996 0.999
Temp (Env)	0.982 0.996	0.855 0.967	0.996 0.999	1.000 1.000

Table 3: Pearson's R^2 (top line) and Spearman's Rank (bottom line) for the Temperatures and Rotational Speed of the Damaged Impeller.

	Temp (Outlet)	Rotational Speed	Temp (Inlet)	Temp (Env)
Temp (Outlet)	1.000 1.000	0.900 0.962	0.977 0.994	0.948 0.988
Rotational Speed	0.900 0.962	1.000 1.000	0.827 0.936	0.748 0.931
Temp (Inlet)	0.977 0.994	0.827 0.936	1.000 1.000	0.973 0.995
Temp (Env)	0.948 0.988	0.748 0.931	0.973 0.995	1.000 1.000

5.4. Signal Smoothing

A necessary preprocessing step to utilize the signals from the gyroscopes, acceleration and vibration sensors was to smooth the signal. As shown in Figure 8 and Figure 9, a moving average filter was applied. The smoothed signal indicates the changes in rotational speed. All gyroscope and acceleration signals show similar margins of noise, which suggests the presence of electromagnetic interference or another source of disturbance influencing the sensor signals.

All gyroscope and acceleration sensors provide data in x, y and z dimension. Each sensor is identified by an ID as multiple sensors of the same type could be attached on a fan. As an example: *Acceleration 3 – Y* means the signal of acceleration sensor with ID 3 in y direction. This ID does not imply that at least three acceleration sensors are mounted on the radial fan.

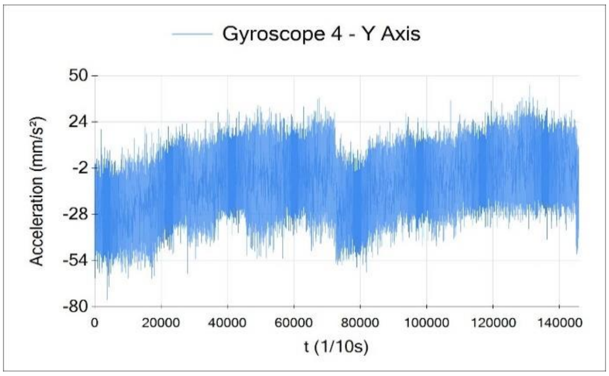

Figure 8: Gyroscope Signal (raw).

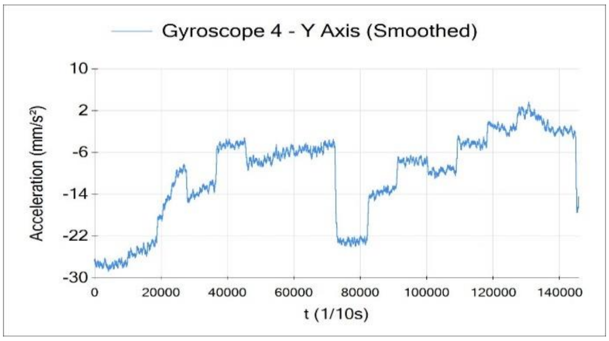

Figure 9: Gyroscope Signal smoothed by a Moving Average Filter (sliding window size 401, type central).

5.5. Combination of Gyroscope, Acceleration and Vibration Signals

We applied a linear regression (Draper, Smith, and Pownell 1966) and a random forest modeling approach (Breiman 2001), calculating the variable impacts for the healthy and damaged impeller by approximating the rotational speed. The top five influencing variables, calculated by using a linear regression model and a random forest model are presented in Table 4 and Table 5 (healthy impeller), and Table 6 and Table 7 (damaged impeller). For the calculation of the variable impacts, each sensor data was shuffled individually and the resulting worsening of the models are quantitatively described by the variable impact. The linear regression solution for the healthy impeller achieved a Pearson's R^2 of 0.989 and a mean absolute error of 71.68, the random forest solution a Person's R^2 of 0.999 and a mean absolute error of 0.22. For the damaged impeller the linear regression solution attained a Pearson's R^2 of 0.995 and a mean absolute error of 46.62, the random forest solution a Pearson's R^2 of 0.999 and a mean absolute error of 0.18.

Table 4: Overview of the Top Five Variable Impacts calculated from a Linear Regression Model using a Healthy Impeller.

Sensor Type	Impact
Acceleration 3-Y	0.519
Gyroscope 4-X	0.273
Acceleration 1-Y	0.069
Acceleration 9-Z	0.036
Gyroscope 8-Y	0.029

Table 5: Overview of the Top Five Variable Impacts calculated from a Random Forest Model using a Healthy Impeller.

Sensor Type	Impact
Acceleration 9-Z	0.147
Gyroscope 4-X	0.044
Acceleration 7-Z	0.024
Acceleration 9-Y	0.020
Gyroscope 4-Y	0.014

Table 6: Overview of the Top Five Variable Impacts calculated from a Linear Regression Model using a Damaged Impeller.

Sensor Type	Impact
Vibration 21	0.721
Acceleration 9-Z	0.374
Gyroscope 4-Y	0.086
Vibration 22	0.081
Acceleration 9-Y	0.040

Table 7: Overview of the Top Five Variable Impacts calculated from a Random Forest Model using a Damaged Impeller.

Sensor Type	Impact
Vibration 21	0.155
Vibration 22	0.031
Acceleration 9-Z	0.025
Gyroscope 4-Y	0.023
Acceleration 1-Y	0.012

These results show a clear divergence of variable impact between a healthy and a damaged impeller. Vibration had a major influence on modeling a damaged state, but was negligible for a healthy impeller. The signal from the acceleration 9 sensor in z-dimension had a relevant impact on all four models, but was more important for the healthy impeller. The gyroscope 4 signal in x dimension only had a noteworthy impact on modeling healthy fans.

6. SUMMARY AND DISCUSSION

The pressure signals alone can give a good approximation of the rotational speed, but the intentional and prevalent error of the current experimental setup could not be indicated by the pressure signals alone. A possible leak in the tube may have an influence on the relation between the pressure signals. Therefore, it is advised to keep all three pressure signals and discourage the usage of one pressure signal as a substitute alone, which is possible as shown in Section 5.2.
The data from the temperature sensors also correlate with the rotational speed, but the correlation alone could be misleading. As the experimental setup defines two runs, each with eight increments of the rotational speed, the power consumption of the radial fan increases, more work is done and more heat is dispersed. Therefore, both the rotational speed and the temperature will be monotonically increasing. The second run was executed after the first run later the same day. The offset temperature was still elevated from either the first run or the weather conditions. More experimental runs with different changes in rotational speed are necessary to rule out a spurious correlation.
As for the gyroscope, acceleration and vibration sensor data, a preceding smoothing was necessary, eliminating most of the noise. Another approach may be a reduction of the sampling rates. A complementary spectrogram should be created to further investigate the signal before reducing the sampling rates, preventing a possible loss of information.
The calculated linear regression solutions and random forest solutions suggest a disparity of variable impacts between a healthy and a damaged impeller. The vibration signal had very little impact on the experimental run with the healthy impeller, in opposition to the run with the damaged one. The data from the acceleration sensor 9 in z-dimension had a noticeable impact on each model. This may be useful for the approximation of the rotational speed, but is a weak indication of a damage, whereas the data from gyroscope 4 in x-dimension only had an impact on the modeling of the fan with the healthy impeller. A desired outcome from the variable impact calculation for error modeling would be a great disparity between a healthy and damaged impeller. If a signal has a high or low impact on both impeller it is probably negligible for error modeling.
Further on, not only the absolute value of a signal should be investigated, also a change of a reoccurring pattern could be interesting (see Section 5.1), although this approach requires more research and insight than a simple threshold-analysis.

7. OUTLOOK/FURTHER STEPS

As soon as the experimental setup is completed (insofar as the filter system is integrated), the same methodology currently used to approximate the rotational speed, will be applied on the efficiency of healthy and gradually damaged impellers, mounted on a radial fan. The characteristics curve and a spectrogram will be created. With this data available, the influence of the sensors on health modeling will be explored by applying the concept of variable interaction networks (Winkler et al. 2012).
A possible direction for future work may be guided by the work of Saxena et al. (2008) and related publications to predict the remaining useful lifetime.

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