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Towards a Predictive Maintenance System of a Hydraulic Pump ⋆

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Abstract: In this contribution we present a model based approach towards predictive maintenance of the hydraulic pump of an injection-moulding machine for a system that remains in production. We present a methodology to iteratively gain a detailed understanding of a production facility. We describe our approach from problem evaluation, gathering of expert knowledge, data access, exploration of and knowledge mapping to the data, towards a first model. We discuss the advantages of the implementation of expert knowledge to define normal machine behaviour in terms of data-quality control and resource-friendly modelling. We present first results from a physical model of a subprocess and from a model based on vibration analysis and discuss their interplay and possible benefits from this different models.

Keywords: industrial analytics, predictive maintenance, hydraulic, hydraulic pump

1. INTRODUCTION

The rise of digitalization and industry 4.0 promises an optimization of industrial production based on data. Many players in industrial analytics promise to easily solve problems just by gathering and analysing data. While nowadays more and more data is acquired and more and more analytical tools become available, it appears that the benefits drawn from these treasures lack behind. In a recent industry survey, 68% of the survey respondents say that their company has a data analytics strategy, while only 30% have finalized data analytics projects (Lueth et al. (2017)). In addition, 60% think they are *good or excellent* in collecting data, while only 32% think they are *good or excellent* in generating insights from this data.

In this contribution, we focus on condition monitoring and predictive maintenance of an injection-moulding machine. Predictive maintenance has been promoted the leading application of industrial analytics. Similar to all other aspects of industrial analytics, there is great potential in these fields but, yet, it seems that there are too little successfull implementations. One reason for this discrepancy is the fact that the demands on industrial production leave little margin for implementation and tests of condition monitoring systems on *running* systems. Moreover, *relatively few people have experience in implementing the algorithms for these new problems* (Lueth et al. (2017) p. 24). Hence, companies often have to rely on external experts in data analytics who, however, have little to no experience in the industry. This becomes even more crucial if one installs a monitoring system on a running machine, as the condition of such systems is typically somewhat ill-defined between *as good as new* and *close to breakdown*. This makes the derivation of health indices and monitoring features more complicated than for a new system.

Big data and artificial intelligence (AI) are for sure a promising approach to predict a machine state and might be used without an in-depth understanding of the underlying processes. However, a good feature engineering to feed AI algorithms is essential for their successful implementation and might, depending on the system, need a process understanding. While the amount of gathered data is vastly increasing, many running systems are tailored for a specific task and data from different machines cannot be easily combined to build up a *big* anomaly or fault database which is crucial to classify different health states of a system with AI algorithms. Moreover, a general AI algorithm, like e.g. a neural network, that is implemented without considering the physics of the machines under investigation, is not utilizing the full potential burried within the data.

The main goal of this project, as defined by our partner *Procter & Gamble* (*P&G*), is to predict the breakdown of a critical component in an injection-moulding machine, i.e., a radial-piston pump that drives the hydraulics and that has led to several unplanned downtimes of the machine in the past. The machine produces small parts for tooth brushes with extremely critical quantity and, hence, each downtime may cause not only maintenance costs but also reduced sales on the market. Therefore, our partner has a high interest to turn unplanned downtimes and maintenance based on regular schemes into *predicted maintenance*. Since the quantity of the parts is so critical, the machine must run 24 hours on 7 days a week which causes additional difficulties in the implementation and test of ideas. These difficulties make a planned procedure mandatory, as every break in the production has to be well justified.

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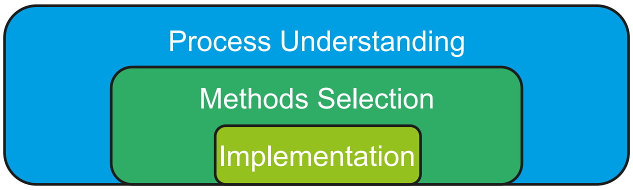

Fig. 1. Iterative-hierarchic design methodology

Based on an iterative-hierarchic methodology, we present our approach from problem evaluation, gathering of expert knowledge, data access, exploration of the data and knowledge mapping to the data, towards a first modelling. While this approach may appear tedious as compared to pure big-data driven approaches that are widely discussed in the literature (see e.g. Peng et al. (2010) for a review), we discuss the advantages of the implementation of expert knowledge to define a normal machine behaviour in terms of data-quality control and resource-friendly modelling. In this context, we present first results from a physical model of a subprocess and from a model based on vibration analysis.

2. DESIGN METHODOLOGY

Recent research of our group has focused on telemaintenance (Aschenbrenner et al. (2015)) and teleoptimization (Fritscher et al. (2016)) of industrial machines. Together with our partners *KUKA Industries* and *P&G*, we aimed on possibilities to further increase the production efficiency of the *P&G* plant in Marktheidenfeld (Germany) that, with an *overall equipment efficiency* (OEE) of 83%, already runs close to the theoretical optimum. One lesson learned within these projects is the importance to consider the *context* in which the machine works. For example, the developed optimization tool provides an unique view on industrial processes by showing machine data and machine code synchronized to motion pictures of the process. This tool enabled experts to reduce the cycle times of an investigated process by ∼5% without additional wear (Fritscher et al. (2016)). To ensure the necessary attention on important contexts, we apply an iterative-hierarchical design methodology for the development of a predictive-maintenance system. As illustrated in Fig. 1, this methodology consists of three nested layers.

A comprehensive process understanding is the foundation of our method and represents the highest layer, which we call *process understanding*. There are many aspects that must be considered in this layer. Most important are inputs from different experts in the field, as well as technical manuals and drawings. The OEE of the plant or the production rate (PR) of the machine are also found in this layer. The goal of this layer is to develop strategies for the realisation of the project and to get into a position from which one is able to judge whether ideas are expedient.

In the next layer, called *methods selection*, current and target states are compared and available soft- and hardware tools are analysed and selected. For example, utilizing the generated process understanding, we can narrow the variety of tools for fault detection described by Isermann (2006) to those relevant for the process under investigation.

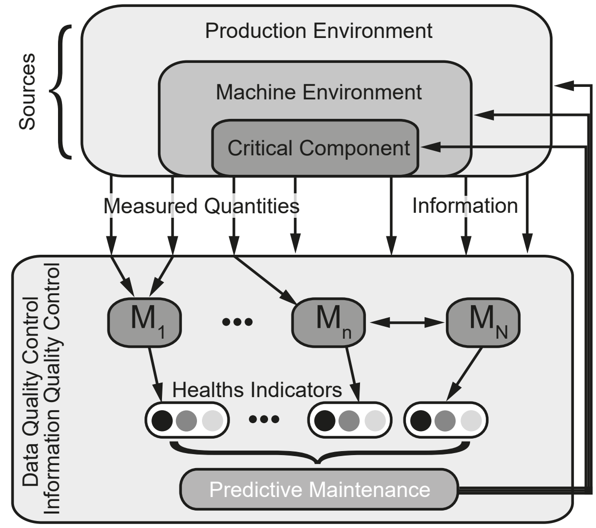

Fig. 2. Sketch of the predictive maintenance system.

The third is the *implementation* layer. It is related to all kind of *concrete* implementations of tools and analytical methods. As suggested by the nesting shown in Fig. 1, working within lower layers helps to improve and complete the picture of higher layers. In turn, it must be the goal of each implementation to contribute to this picture. Therefore, each implementation calls for another iteration through the methodology to revaluate previous runs.

3. PREDICTIVE MAINTENANCE SYSTEM

First outcome of this design methodology is the predictive maintenance system that we sketch in Fig. 2. The process itself consists again of three hierarchical layers. From each layer, we get information and data that are rated in terms of quality and usefulness before it is considered for recording. Examples for the *production environment* are the OEE of the plant or the environmental temperature. In the *machine environment* we find the PR of the machine, the machine signals, oil quality and weekly operation digrams. Lastly, for the *critical component* itself, we have maintenance reports or additional sensor data.

Some of this input streams will serve as and feed an automated quality control system of data and information. Within this control system, we embed all concrete implementations of analytical methods, their results in shape of health indicators and of course the prediction system itself, with its outputs to the production layers. This quality control system ensures a ressource-friendly operation of the predictive maintenance system in terms of data storage and computation time. For example, sensor data is not saved when the machine is out of operation and analytical algorithms are only triggered for specific states of the machine.

The derivation of health indicators is an important step to build up a shared anomaly and fault database among similar machines in the future, as it allows the introduction of company-wide measurement standards. Moreover, health indicators have an *immediatedly* interpretable added value in terms of anomaly detection.

In contrast, the prediction layer needs longer training time or even the occurance of a real breakdown to verify its functionality. However, with the already implemented methods and their individual health indicators we are well prepared to monitor and study future breakdowns which will enable us to activate the prediction layer.

3.1 Methods Selection

A principal understanding of the processes involved is derived by collecting and studying all kinds of available information from each layer in Fig. 2. Six different methods ($\mathbf{M_1}$ through $\mathbf{M_6}$) are considered for the implementation layer.

$\mathbf{M_1}$: *Empirical Signal Evaluation.* Together with our partner we decide to monitor a couple of signals as will be discussed in Sec. 4. The investigated injection-moulding machine *K-TEC 275* of manufacturer *Ferromatik* does not offer direct access to the necessary sensor data. While the system is a full feedback control system, yet, there is only basic monitoring of the machinery data implemented without the possibility to access it externally. This is indeed a very typical setup, as many machinery manufacturers do not offer access to the software system for example due to knowledge protection. To bypass this limitation, we install a *National Instruments SbRIO 9627* for data acquisition and a custom signal converter electronics to match all input signals to the capabilities of the *SBRIO*. This enables us to record, structure, synchronize and visualize the signals and to discuss with experts in the field. From the discussion health indicators in terms of classical limits are derived.

$\mathbf{M_2}$: *State Machine.* The gathered domain knowledge is implemented in a state machine of the pumping process and we utilize the nominal value of the pump to derive transition rules between the states as discussed in detail in Sec. 4 and 4.2. This contributes to the quality control system for data and information as shown in Fig. 2 and triggers specific algorithms like the physical model (Sec. 4.3) and the vibration model (Sec. 4.4) to avoid unnecessary computation.

$\mathbf{M_3}$: *Physical Model.* All hydraulic processes are powered by the hydraulic pump or by a pressure accumulator that in turn is reloaded frequently by the the pump. Pressures in the pump and in the accumulator are recorded and used in a physical signal model, as described in Sec. 4.3. This decison is based on the observation of the maintenance experts that the pump is not able to produce the given pressure. Therefore, deviations between model and signal indicate a degradation of the pump.

$\mathbf{M_4}$: *Operation Spreadsheets.* Another important input from the machine environment are weekly spreadsheets, where the real operation times of the machine are documented. Every break in the production is documented with a time resolution of seconds and with it also the effective production times. Such information is of course predestinated to be used in a state machine for the overall process. In the first prototype, the acquired data can be filtered once the information from the spreadsheets is available at the end of each week, which is of course in contradiction to a real-time system. However, we plan to implement a classification algorithm to detect states that produce useless data and avoid its storage and analysis in real time.

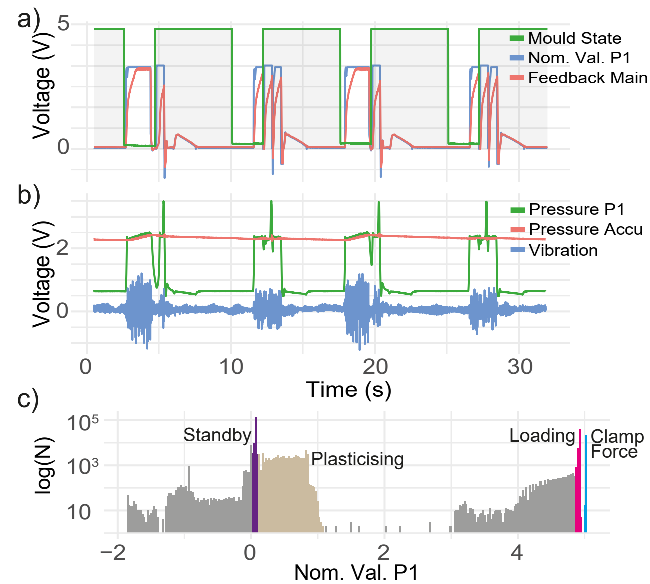

Fig. 3. Overview of a typical signal sequence.

$\mathbf{M_5}$: *Oil Quality Control.* Oil-quality control, which is a standard tool for monitoring of hydraulic systems, is rejected for implementation already at this level. On the one hand, the control intervals in external labs are too long to be used in a system that aims on real-time condition monitoring. On the other hand, the implementation of a real-time oil-quality monitoring has been ruled out for cost reasons. Moreover, according to the maintenance experts, the oil samples did not show any sign of contamination that could have indicated faulty behaviour of the pump in the past.

$\mathbf{M_6}$: *Vibration Model.* Instead, we decide to attach acceleration sensors directly to the critical component (pump 1) to monitor vibrations. Vibration analysis is a wide used standard in condition monitoring of pumps and in our case its use is also motivated by the occurance of unusual noise close to a breakdown of the pump. Powerful tools for vibration analysis exist in both, time and frequency domain (Isermann (2006)). Our implementation, as discussed in Sec. 4.4, is settled in the latter.

4. IMPLEMENTATIONS

In this section we give an exemplary presentation of three of the implemented methods ($\mathbf{M_2}$, $\mathbf{M_3}$ and $\mathbf{M_6}$).

4.1 Introduction to Recorded Signals

Since all of these methods utilize recorded sensor data, we give a discussion of the data beforehand which is mostly a result of the implementation of $\mathbf{M_1}$. In Fig. 3 we show a typical process sequence of some of the recorded signals that have already been synchronized.

Fig. 3 a) shows the nominal value (N_1) of pump 1 (blue line), the feedback of the main valve (red line), that controls the volume flow produced by the pump and the state of the mould (green line). The latter has two levels, where the high level means that the mould is closed for production of parts and can be used to preclassify in-production tasks of the pump. The shown data consits of a sequence of roughly 4 production cycles (∼30 s). Note that an equal length of cycles, as in the given example, cannot be presumed for all times in a feedback-controlled system.

The nominal value is utilized to classify different states of the pump (see Sec. 4.2). As we show in the histogramm of panel c), the four states of the pump, i.e., standby, plasticising, loading and clamp-force, are clearly distinguishable through the set nominal values. The nominal value and the feedback of the main stage show a high correlation of typically ∼ 0.90. In fact, the main stage is feedback controlled according to the nominal value. It determines the eccentricity of the pump, which in turn determines the stroke of the pistons, i.e., the extracted volume per revolution. Gradual changes in the correlation with time is a health indicator for the main stage (Fig. 2).

In Fig. 3 b) we show the pressure in the accumulator (red), the pressure in pump 1 (green) as well as the amplitudes of the vibration sensor. Noticeable at first sight are the pressure peaks in the pump, which only appear shortly after the mould is closed (Fig. 3 a). They are caused by the build-up of clamping force on the mould to withstand the injection pressure. The signal is clearly distinguishable from the accumulator loading which takes place whenever the pressure in the accumulator increases. Despite some offset, the signals of accumulator and pump are almost identical at loading times. The standby and the plasticising, as low-pressure processes, are also well distinguishable through shape and absolute values of the pressure gradient (Fig. 3 c). The vibration amplitudes appear to have a significant difference for different pump tasks (see Section 4.4 for details).

4.2 Statemachine as a Data Quality Control System

$\mathbf{M_2}$: As mentioned above, we consider a quality control system as an important factor for the implementation of a reliable and ressource-friendly predictive maintenance system. In that way, our approach is distinct from *big-data* methods where as much data as possible, even unstructured data should be stored and analysed. We are convinced that a thoroughfull filtering of the data utilizing available knowledge, as well as knowledge generated during runtime helps not only to reduce the amounts of disk space or computation times needed, but itself produces valuable output for the prediction of maintenance. For example, a health index based on the amount of data that has to be discarded as it does not fullfill quality requirements could be derived and may give indication for faulty behavior of the machine or avoid false predictions.

As a first step towards a real-time quality control system we have implemented a statemachine for the subprocess of the critical component. The results of the exploratory analysis, described above is used to create a state machine for the tasks of the pump. Fig. 4 shows the corresponding state diagram. Our analysis has shown that state transitions always show a switching of the nominal value *via* values close to zero or even negative ones. For simplicity we have summarized such intermediate states within the

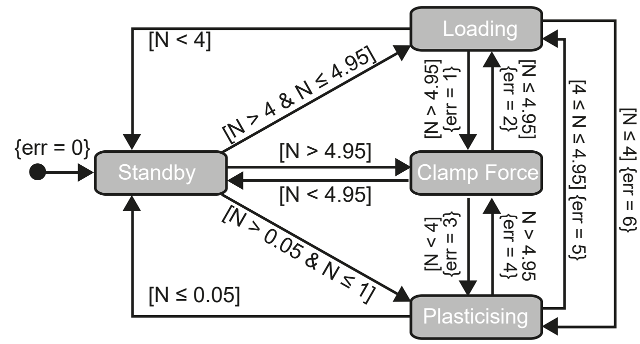

Fig. 4. State machine to classify the tasks of the pump.

standby state. As can be seen, our state machine allows direct transitions between the three active states (*loading, clamp force, plasticising*). Such anomal transistions may occur, e.g., due to value fluctuations, missing datapoints, ill-defined transition rules, or previously unseen cases and, therefore, contribute to another health index. For example, direct transitions between accumulator loading and build-up of clamp force may occur if the loading takes more and more time due to a degradation of the pump. Subsequently, the loading is interrupted by a new production while the final pressure in the accumulator is not reached.

The state machine is used to classify the current pump states during runtime and call state-dependent algorithms to analyse the data and for example compare with previous results to detect gradual changes or sudden anomalies. Moreover, it is utilized for monitoring the quality of the data itself in terms of completeness, fluctuations or time jitter. In addition, we analyse the amount of valid transitions between the states in relation to the number of production cycles. The normal machine behaviour consists of one clamp-force and one plasticising event, while we observe between one and three loading events per production cycle. A deviation from this ratios might indicate faulty behaviour and they, therefore, represent the health indicator of $\mathbf{M_2}$.

4.3 Physical Pressuresignal Model

$\mathbf{M_3}$: We choose the accumulator loadings for the implementation of a first model, as it can be easily described by the ideal gas law. The accumulator consists of a gas bubble, filled with N_2, that is separated from the oil volume by a membrane. The pump produces an oil flow into the accumulator that leads to a compression of the gas, which in turn leads to a pressure increase.

The algorithm sets its initial pressure offset to the current value of the accumulator. For each timestep, the current oil flow produced by the pump is calculated from the actual setting of the main stage. The feedback of the main stage is proportional to the eccentricity of the pump and, therefore, proportional to the piston stroke. For the maximum feedback, the pump should deliver its nominal stroke per turn which is 100 ccm. Currently, we simplify the process by assuming an even distribution of the total stroke over one turn and neglect that the pump consists of nine pistons.

At time step n the pressure p_n in the accumulator at constant temperature and constant substance is given by:

$$p_n = p_0 \left(\frac{V_{N_2}}{V_n} \right)^{\kappa}, \quad (1)$$

with the adiabatic exponent κ, the base pressure of N_2 p_0, the initial volume of N_2 in the accumulator V_{N_2} and the current volume $V_n = V_0 - V_{\mathrm{oil_n}}$. V_0 is the total volume available in the accumulator and $V_{\mathrm{oil_n}}$ the current volume of oil in the accumulator.

The oil volume flow per second q_n is calculated as $q_n = f_M \cdot M_1 \cdot q_{max}$, with the motor frequency f_M, the nominal stroke of the pump q_{max} and the relative position of the main stage M_1, as given by its feedback. At each time step, we calculate the new oil volume in the accumulator $V_{oil_n} = V_{oil_{n-1}} \cdot q_n \cdot \Delta t$ and the pressure in the accumulator according to

$$p_n = p_{n-1} + p_0 \left(\left(\frac{V_{N_2}}{V_{N_2} - V_{oil_n}} \right)^{\kappa} - \left(\frac{V_{N_2}}{V_{N_2} - V_{oil_{n-1}}} \right)^{\kappa} \right). \quad (2)$$

In Fig. 5 a) we show a direct comparison between the measured pressure in the accumulator (grey circles) and the model result (turquoise line) for a short example. The paramters where set according to the input from the experts or as found in technical descriptions of the system. The adiabadic parameter κ was set to 1.25 which resulted in the best approximation to the real data. As a matter of fact, the process is neither fully isothermal ($\kappa = 1$) nor fully adiabatic $\kappa = 1.4$. But as stated in the introduction, the condition of the pump is not well defined which generates a uncertainty in the determination of κ.

One impact of our model, worth mentioning, is the fact that we decided to monitor signals from both pumps. Our first model attempt delivered very poor results that we could only compensate by significantly increasing the speed of the pump. It turned out, that the two pumps in the system may load the accumulator simultaneously, which was not known by the experts of our partner. Therefore, we extended also the state machine in Fig. 4 for the second pump which is not shown for simplicity. In contrast to pump 1, pump 2 has only the tasks plasticising and accumulator loading.

Fig. 5 b) shows the distributions of the relative error of the model for a short example log that contains ∼500 production cycles and ∼600 accumulator loadings for the three cases of pump 1 loading, pump two loading and both pumps loading simultaneously. As can be seen the model is quite accurate with ∼99% of the relative errors below 2.5% The total mean squared error amounts to ∼2.3 bar, while typically the pressure values are in the range between 180 bar and 195 bar. For cases where both pumps load the accumulator simultaneously, the relative error between model and real pressure signal appears normally distributed about Zero as one would expect for random deviations. In contrast, if pump 1 or pump 2 load the accumulator alone, there seems to be a systematic error which calls for further investigation, since it might already give hint for a degradation of the pump. We would like to emphasize, that AI approaches, like an artificial neural network would simply fit the parameters to achieve best results and, hence, overlooks such deviations.

As stated above, a wear of the pump leads to the symptom that it is not able to produce enough pressure in the system. In an early stage, such a degradation might get simply compensated through longer loading times by the feedback control of the machine and is hence not detectable by the machine operator. The model, however, assumes a certain volume flow per second and the error distribution will change even if the final pressure is reached by just pumping for a longer time. Therefore, the error distribution is yet another health indicator (Fig. 2).

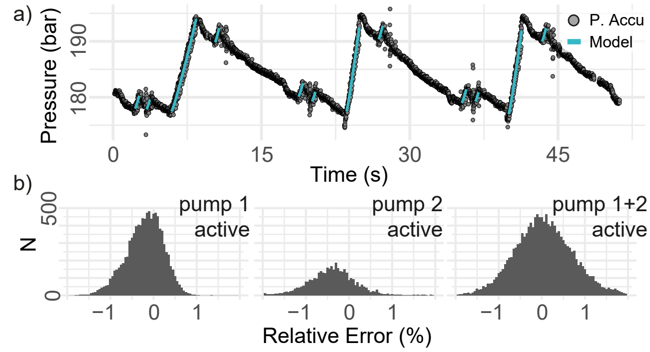

Fig. 5. Exemplary results from the pressure signal model.

4.4 Vibration model

M$_6$: Some investigations on vibrations are based on fault detection and classification, e.g. Do and Chong (2011). While this approach appears very accurate, it requires a testbench where the hydraulic-system is modelled prior to real-life application, which is in contradiction to our approach. Hence, we create a fingerprint of the running system where the vibrations are analysed with a focus on unusual perturbations, as described by Karadeniz (2013). We consider usual as the most prevalent frequencies in our training set as well as frequencies that must occur, like the frequency of revolution and its higher harmonics. From a statistical analysis we derive a health indicator for anomaly detection, as suggested by Beebe (2004).

Utilizing the state machine described in Sec. 4.2 we label the data according to the states and calculate correlation coefficients in the frequency domain within one state at different times and between different states. For the *intra-state* correlation coefficient, we get typically values higher than 0.90, while the *inter-state* correlation coefficients are significantly lower (≤0.55). This is also in line with the time-domain picture of Fig. 3 b), where we observe different intensity levels for different states. Hence, to use the vibration signal for anomaly detection, we have to distinguish between the states and not analyse the evolution of the overall spectrum.

For each state of the pump (Fig. 4) we investigate occuring amplitudes in the frequency domain as examplified in Fig. 6 a) for the state *loading*, and derive a vibrational fingerprint. For this purpose, we first transfer the signal sequence into the frequency domain by applying a fast fourier transform (FFT). Then we define a threshold for amplitudes and apply a peak detection algorithm. This is done iteratively until a substantial set of samples is generated. Then we apply a clustering of the frequencies to account for the finite and varying resolution of the FFT and determine for each cluster the distribution in frequency and intensity space. In addition, we define the

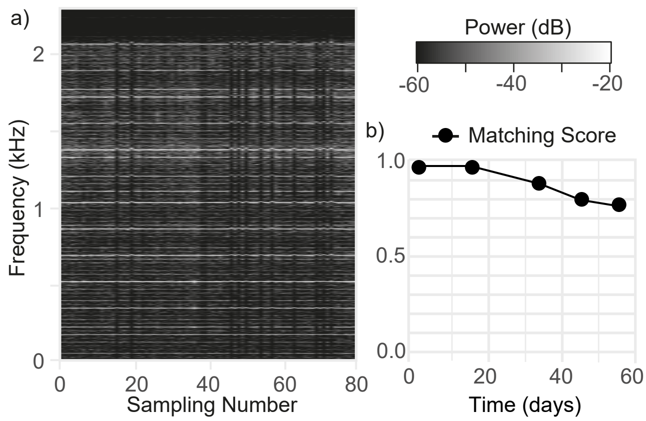

Fig. 6. a) Frequency *fingerprint* for accumulator loading. b) Evolution of matching score with time.

probability that a cluster appears by counting its entries and devide through the number of samples taken. Finally, the vibrational fingerprint of a state is given by all clusters that have a probability of more than 80%. As mentioned in Sec. 1, it is unclear in which condition the pump is at the moment. Therefore, there is some uncertainty in determining the number of samples to be condensed in the fingerprint of a normal machine behaviour. Currently, the fingerprint used is build from 100 accumulator loadings.

At runtime, the statemachine described in Sec. 4.2 triggers the analysis of vibrations (V) according to the state of the pump. Recorded vibrations are transfered again to the frequency domain and the same threshold and peak detection used for the fingerprint (P) is applied. Formally, the matching-score Ψ is calculated as the proportion of frequencies that appear in both, V and P:

$$\Psi(V) = \frac{|V \cap P|}{|P| + |V \setminus P|} \tag{3}$$

We define the numerator of Eq. 3 as a sum over the matching-coefficients C_m. To determine individual matching-coefficient we compare the intensities (I_f) for each frequency in the new vibration spectrum to all frequencies in the fingerprint. We define confidence intervalls according to the inter-quartile range (IQR) of the intensity distribution of the fingerprint frequencies. C_m is given by:

$$C_m = \begin{cases} 1 & \texttt{if Q1} \le I_f \le \texttt{Q3} \\ 0.75 & \texttt{if Q1 - 1.5} \cdot \texttt{IQR <} I_f \texttt{ < Q1} \\ 0.75 & \texttt{if Q3 <} I_f \texttt{ < Q3 + 1.5} \cdot \texttt{IQR} \\ 0 & \texttt{other cases.} \end{cases} \tag{4}$$

Where $Q1$ and $Q3$ are the first and third quartiles, respectively.

In Fig. 6 b) we show the evolution of the matching score with time for the state *loading*, where the individual points in the graph represent an average over the scores from ∼100 loading cycles. Obviously, the matching score is decreasing with time. In principal, this may indicate a degradation of the pump. However, due to the mentioned problem to accurately define the necessary size of the time window for the fingerprint, the observed decrease may also be due to a too short window, which leads to a non-stable behaviour of the described algorithm. However, this can be easily fixed once we are more confident about the appropriate size and, hence, the matching score represents a valuable health indicator of the system.

5. CONCLUSION

In this contribution we have presented an iterative-hierarchical methodology for the implementation of a predictive-maintenance system in an industrial machine that remains *in production*. We have shown the successfull implementation of the system on an injection-moulding machine of our partner $P\&G$. Moreover, we have discussed the implementation of a state machine as a quality-control system and the implementations of two signal models. The derived health indicators are already able to detect anomalies in the sensor data. In addition, we have acquired a substantial high-quality base of structured and synchronized data over a time span of currently 7 months (0.6 TByte) that is already filtered in terms of quality and usefullness.

6. FUTURE WORK

The final step is, of course, to prove the prediction capability of our system. However, the work presented in this contribution has prepared the *trap* and we now have to wait for the system to fall into it. Once a breakdown of the system occurs, we can analyse the evolution of our health indicators towards the breakdown and evaluate their prediction horizon. Moreover, we are able to increase the chances to observe such a breakdown by rolling out the developed predictive maintenance system to similar machines.

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