Data driven condition monitoring based on a digital twin for a linear actuator realized as a closed hydraulic system

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ABSTRACT

Linear actuators, implemented as closed hydraulic systems, without external piping, are a state of the art drive concept, see (Gannon, 2017). Collecting data, used to train a condition monitoring (CM) for such drives, running 24/7, is cumbersome or even not possible. To gain training data, containing valid and invalid system states, we developed a simulation model, consisting of the most relevant physical effects. The simulated data are evaluated by a one-step feature approach and additionally with a two-step approach using two less complex fault state separation methods. In the end, the two-step method showed to be slightly better. The condition monitoring is not only used to recognize, but also to distinguish between accumulator and pump faults.

1. INTRODUCTION

Nowadays product cycles are changing fast, and so do motion and production cycles of actuators. On the one hand, malfunction of the system has to be avoided to keep up with the increased production frequencies which, on the other hand, cause more failures when an actor is driven at its limit. Precautionary service, like changing wear parts in fixed equal intervals, leads to additional costs and production time losses which again lead to additional costs. To minimize these expenses, it is important to identify system critical components which have to be serviced.

Usually it is not possible to obtain enough data just from measurements on the running machine to judge the reliability of single components or even the entire system. Furthermore, the training of a CM for such a system, using measurements at the real machine is time consuming and advised failures are not eligible or even impossible to provoke. Therefore a simulation model, just accurate enough to get the relevant effects but not too complex to take too much preterm computational power, was used to generate a set of test cases large enough to train the used classifiers. With the furthermore generated test cases, the accuracy of the CM was tested in absence of a prototype in a first step. The CM system complexity was intentionally kept low to be computable in real-time, on a conventional industry control system, to generate up-to-date system health information in a later step.

Condition monitoring for linear actuators has been addressed by the scientific community in previous publications. In (Hindman, Burton, & Schoenau, 2006), artificial neural networks are used to monitor the condition of a valve controlled linear actuator circuit. As inputs to the neural network, the time to achieve maximum change in rod-side pressure, the maximum change in rod-side pressure, and the maximum change in head-side pressure are used. A method for condition based monitoring for hydraulic actuators is also proposed in (Adams et al., 2016). The authors use different machine learning algorithms like k-nearest-neighbor, decision trees, and random forests to classify the condition of the actuators. The classifiers are used to distinguish between 6 states of the actuator, 1 baseline and 5 different fault states. In (Helwig & Schütze, 2016), features are extracted from raw sensor data of a fluid power system. After dimensionality reduction, the features are mapped to discriminant functions that allow the detection and quantification of fault conditions. A fault detection and diagnosis method for electrical linear actuators is proposed in (Ruiz-Carcel & Starr, 2018). It extracts features from electric current and position measurements. The features are selected to characterize the system dynamics during transient and steady-state operation and then combined to produce a condition indicator. In (Pedersen, Schlanbusch, Meyer, Caspers, & Shanbhag, 2021), acoustic emission (AE) sensors are used to identify the early stages of external leakage initiation in hydraulic cylinders. The impact of sensor location and rod speeds on the AE signal were investigated using both time- and frequency-based features. The root mean square feature was observed to be a potent condition indicator (CI) to understand the leakage initiation.

Since we develop a digital twin to train the condition monitoring model, approaches using signals like AEs or vibrations are not feasible, because they cannot be simulated precisely enough. There are some studies on the simulation of vibrations or AEs, for instance (Abramkina, Zhilenkova, & Borisenko, 2021; Filippov, Nikonov, Rubtsov, Dmitriev, & Tarasov, 2017; Sause & Horn, 2010), but only for very clearly defined cases. An easy-to-use generalization, as it would be necessary for a flexibly usable digital twin, is not known to us. However, some of the previously proposed approaches are similar to our approach in the way that they extract features from measured signals and apply a classifier in feature space. What differentiates our approach is that we extract features only from signals that can be well and precisely simulated and are affordable to measure on real systems. That enables using the digital twin of the system under investigation to generate training data for the model. Thus less test runs for data acquisition are required than in the previously proposed approaches, reducing required resources significantly. Moreover, the digital twin can be easily adapted or scaled if the system changes. In contrast, classical approaches require extensive collection of training data for every change of the system and for different fault cases. Therefore, the combination of a digital twin and a feature based CM system to one cyber-physical system is very advantageous.

The paper is structured as follows: Section 2 states the problem. In Section 3 the digital twin together with the acquired data is introduced, and in Section 4 the proposed data driven CM approach is explained. In Section 5, the experimental results are provided. Finally, Section 6 draws the conclusions of the work.

2. PROBLEM STATEMENT

The CM system is designed for a prototype of a closed circuit hydraulic linear actuator, see Fig. 1 and Fig. 2. The term 'closed circuit', in combination with hydraulics, states, that the fluid circuit does not consist of a tank or a reservoir connected to surrounding air. In the simplest case of such circuits, the fluid is directly shifted to and from between the pump and a suitable actuator. These systems are some times also called 'air tight' systems.

The system under study basically consists of an electric motor, a pump, a differential area cylinder, an accumulator and some valves, see Fig. 1. The use of a differential area cylinder requires some kind of fluid volume compensation to account for the different amount of displacement volume between the piston chamber A and the rod-side chamber B. This volume balancing is done by a by-pass, realized by two load-lowering valves and an accumulator, see the inner flow path in Fig. 1. Additionally, this by-pass accounts for fluid volume compensation due to temperature changes, e.g. the fluid volume increases with increasing temperature (Haas, 2013) p. 6.

Qualitatively, the movement of this hydraulic actuator can be divided into the cylinder's rod extension and retraction. For extension, fluid is pumped into A side, increasing the pressure. The check valve of the A sided load-lowering valve closes and the rod moves out of the cylinder. Concurrently, on the B side, the pump takes more fluid volume than the ring side of the cylinder displaces. This results in a B sided pressure drop, opening the check valve of the according load-lowering valve. The fluid difference is compensated by fluid from the accumulator. For piston retraction, fluid is pumped from cylinder chamber A to B. The difference in the displacement volumes of the cylinder increases the pressure on the A side. If this chamber pressure reaches a certain level, the corresponding load lowering valve opens to the center point which limits the maximum pressure. Beside this internal details, the hydraulic drive follows the rotation of the motor-pump unit.

From a practical perspective, there exist two common system failure origins. One is a accumulator, the other is a pump failure. Due to the fact that the accumulator under study is a gas loaded piston accumulator, it is more likely that there occurs a pressure reduction on the gas side than in case of a hydraulic bladder accumulator. This leads to a change of it's operating point which in turn causes a change of the dynamics of the entire system. The other relevant effect is pump wear. An increasing operation duration, or improper treatment of the pump lead to more friction and increased leakage losses. The tricky about this thing is, that both effects can occur at the same time, hence interacting with each other. For simple, hand crafted, failure detection algorithms it can happen, that both effects compensate each other and so virtually lead to a convenient system but in fact a system failure gets even more likely, see for instance (Haas & Pichler, 2022). However, this phenomenon did not occur significantly in the present test data. But it must be taken into account for further developments.

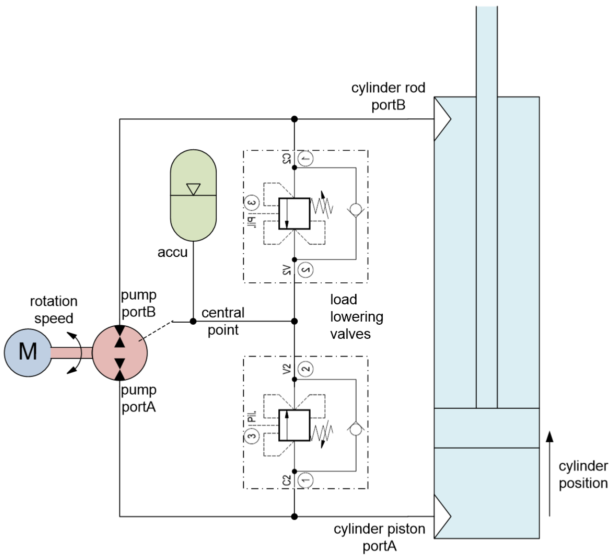
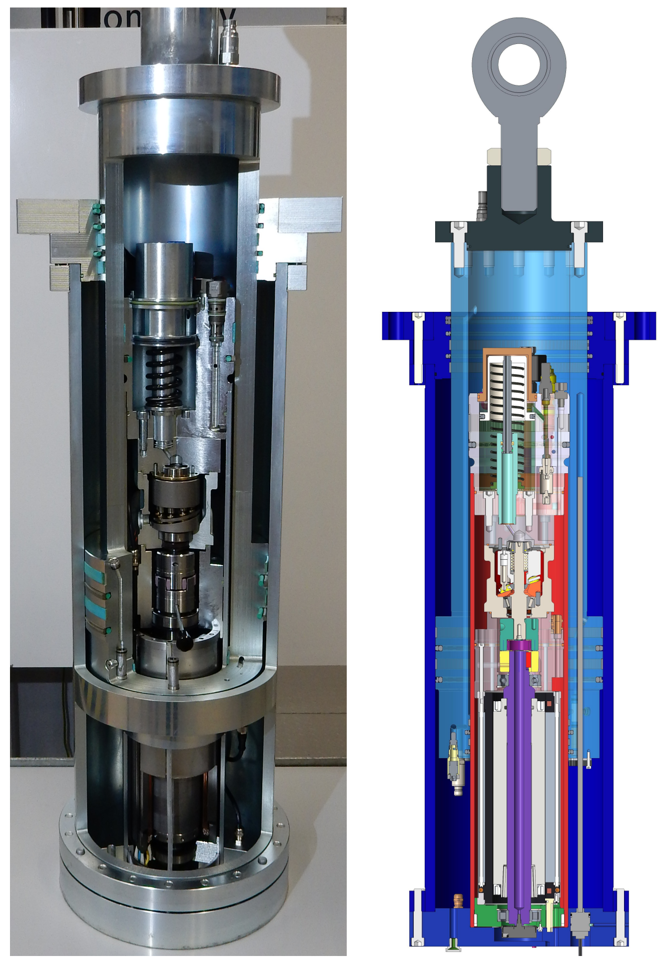


Figure 1. Closed hydraulic system with two load lowering valves to balance the pressure.

In this work we propose an approach which is capable of detecting all possible failure states, caused by the previously discussed system component effects. The example system 'PiK', on which the approach is evaluated/tested, is a self-contained servo hydraulic axis of Bosch Rexroth (Fig. 2) (Guender & Schwacke, PatentNr: DE102014215080A, 2014).
Special consideration was given on easy applicability of the approach by using only system states respectively conditions, which could be measured out of the box or with a minimum of effort. The additional benefit of fault detection should mainly be a matter of software to be integrated at most sold axis at the end not of additional hardware. With the gained operating experience of several axis, the quality would raise on the other hand side.

3. DIGITAL TWIN

A simulation model of the entire system, further called 'digital twin' (DT), was built in order to acquire training data for the condition monitoring algorithm. More information about DT's can be found in (Boschert & Rosen, 2016), (Wikipedia, 2022) and (Haas & Pichler, 2022). Further it is planned to update the simulation model and extend this data set by prototypal and life time measurement data in order to sharpen the failure recognition.
The hydraulic circuit was modeled using Matlab® with Simulink® (Mathworks, 2019) and in turn 'hydroLib3' (Manhartsgruber & Haas, 2016), which is a package for hydraulic component simulation. Elements of this library are implemented as blocks, which can be arranged using 'physical ports'. The entire simulation model is depicted in Fig. 3. The DT consists of the pump connected to the



(a) prototype (b) CAD

Figure 2. Cross sections of Bosch Rexroth 'PiK'.

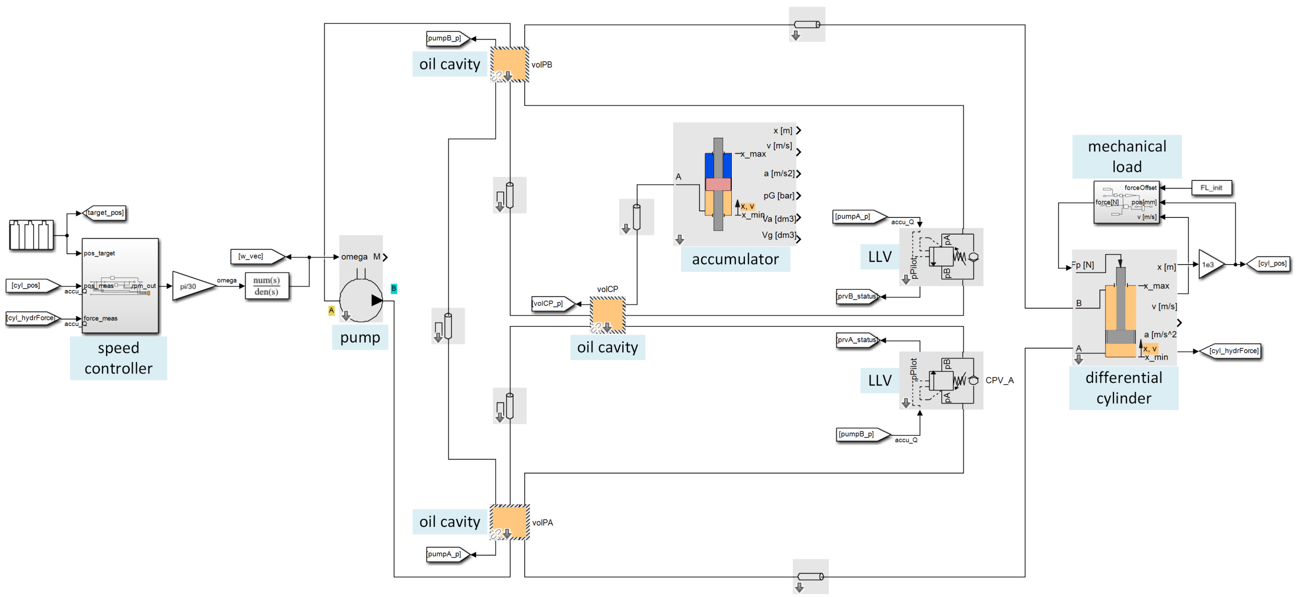


Figure 3. Matlab Simulink setup of simplified hydraulic circuit.

differential cylinder with pipes. Pipe losses are modeled using Hagen-Poiseuille friction. The fluid needed for compensating the different flow rates due to the different cylinder areas is provided by load-lowering valves connected to the piston-type accumulator, which is modeled as a gas filled equal area cylinder. The load-lowering valves are modeled as pressure controlled variable orifices. The accumulator is connected to the valves at the 'central point' (CP) which is also one of the points where the actual pressure value can be detected. Furthermore, the pressure at the pump ports A and B is known. Three other signals are recorded for the analysis: The rotational speed of the motor which matches the rotational speed of the pump and the target and actual cylinder position, which is in the end the state the user claims.

These data are subsequently analyzed to extract meaningful features for distinguishing the fault states and training a supervised classifier. We define two isolated failures, namely a pump leakage and an accumulator failure. Since the two failures can also occur at the same time, we have 4 failure states in the training data that are for simplicity reasons numbered from 0 to 3:

- state 0: no failure
- state 1: pump leakage
- state 2: accumulator failure
- state 3: pump leakage and accumulator failure

With the digital twin, any of the process variables can be simulated and therefore be acquired for the training data set. However, since the trained classifier should be also applied in real world, we restricted the measured signals to those that are also available at the real system. Hence, the following 6 signals $x_1, \ldots, x_6$ are available for failure detection:

- x_1: pressure pump port A
- x_2: pressure pump port B
- x_3: pressure of central point next to the accumulator
- x_4: target rotational speed omega of the pump required from the position controller
- x_5: actual cylinder position
- x_6: target cylinder position

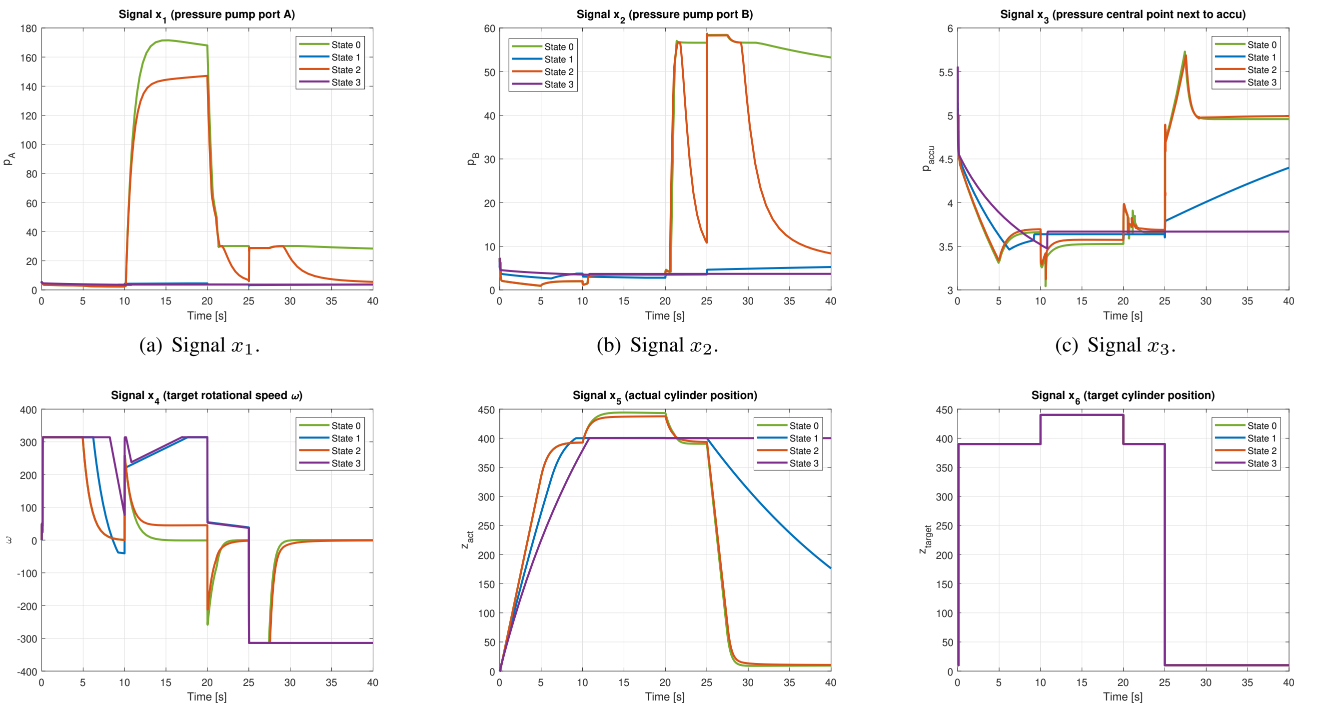
The six measured signals of the system under study for one exemplary case of each failure state are depicted in Fig. 4. Overall, 493 observations were measured, 108 of state 0, 75 of state 1, 180 of state 2, and 130 of state 3. The observations within each state have different severity of failure, so that most cases are covered by the training data.

The acquired data are used to extract features and subsequently learn a classifier in the feature space that is capable to distinguish the 4 failure states.

4. DATA-DRIVEN CM APPROACH

In this section, the way from a pure visual analysis to a data-driven classification model is outlined. Moreover, the finally selected feature for the model is presented.

Based on a purely visual analysis of the signals in Fig. 4, it should be rather simple to detect a pump leakage. The failure state leakage (state 1 and state 3) differs significantly from the no-leakage case (state 0 and state 2), for instance in signal x_1 between 10 s and 20 s. But also in many more parts of the signals, the failure pump leakage can be easily distinguished from the the no-leakage case, even when all measured observations are considered However, the detection of accumulator



(a) Signal x_1.

(b) Signal x_2.

(c) Signal x_3.

(d) Signal x_4.

(e) Signal x_5.

(f) Signal x_6.

Figure 4. Exemplary plots for each state and each measured signal.

failure (state 2 and state 3) is not trivial. Even for the four exemplary cases shown in Fig. 4, it is very difficult to distinguish it clearly from the case of no accumulator failure (state 0 and state 1). When considering all measured observations it turned out to be even impossible to identify the accumulator failure just by visual analysis of the signals. Hence, we tried to identify features to distinguish the states from each other in a data-driven approach.

For that purpose, we did not only compare the signals amplitudes at certain time stamps, but we extracted also a big number of features from the raw signals. To do so, a sliding window is moving over all signals, and in each sliding window of each signal many features are extracted. The features include typical statistical features like mean, standard deviation and kurtosis as well well as more advanced features in time-, frequency-, and time-frequency-domain proposed in literature before. Moreover, the whole feature extraction procedure was done with different sliding window lengths between $0.5\,\mathrm{s}$ and $2.5\,\mathrm{s}$. As stepsize, half of the window length was chosen. This extensive feature extraction step delivered overall 109800 features for each of the 493 observations. For further details about the feature extraction procedure see (Pichler, Ooijevaar, Hesch, Kastl, & Hammer, 2020).

Due to the curse of dimensionality and computing and storage capacity, it is of course impossible to continue with this enormous number of features. Therefore, we have selected only the features that are necessary to distinguish between the different states. For this purpose we used feature selection algorithms (Guyon & Elisseeff, 2003). More precisely, we applied forward feature selection with Dy-Brodley measure (Dy & Brodley, 2004) or Mahalanobis distance (McLachlan, 1999) as selection criterion. However, both criteria resulted in the same feature sets. Of course, we cannot present here all features computed in the feature extraction step, it would go beyond the scope of this paper. Therefore, we present below only the features that were selected by the feature selection algorithm as significant for distinguishing the state.

Furthermore, we tested two different supervised scenarios for feature selection and classification, (i) a four-state scenario, where each of the four states is classified at the same time, and (ii) a two-times-two-state scenario, where first no-leakage and leakage and no-accu-failure and accu-failure are distinguished from each other and subsequently combined to the four-state case, i.e.

- no-leakage and no-accu-failure $\rightarrow$ state 0
- leakage and no-accu-failure $\rightarrow$ state 1
- no-leakage and accu-failure $\rightarrow$ state 2
- leakage and accu-failure $\rightarrow$ state 3

Since scenario (ii) performed much better in our tests, we present only the selected features for that scenario. In both cases (no-leakage vs. leakage as well as no-accu-failure vs.

accu-failure), a two-dimensional feature space was selected by the feature selection method.

The first feature for leakage classification, denoted by $f_{l,1}$, is the so-called short-time average zero-crossing rate of signal x_4 at time stamp 19.5 s in a window of 1.5 s length. The short-time average zero-crossing rate of a discretely sampled signal $y_1, \dots, y_n$ is defined as

$$f_{l,1} = \frac{f_s}{2n} \sum_{i=1}^{n-1} |\operatorname{sgn} y_i - \operatorname{sgn} y_{i+1}|, \tag{1}$$

where f_s denotes the sampling frequency and n the number of samples. The second feature for leakage classification, denoted by $f_{l,2}$, is the median value of signal x_4 at time stamp 18.0 s in a window of 2.0 s length. Again, for a discretely sampled signal as above that means

$$f_{l,2} = \operatorname{Mdn}(y_1, \dots, y_n) \tag{2}$$

where Mdn denotes the median function.

For accumulator-failure classification, the first selected feature, denoted by $f_{a,1}$, is the average magnitude difference of signal x_1 at time stamp 0.25 s in a window of 0.5 s length. The average magnitude difference is defined as

$$f_{a,1} = \frac{1}{n-2} \sum_{i=1}^{n-1} |y_i - y_{i+1}|. \tag{3}$$

The second feature, $f_{a,2}$, is the range of signal x_1 at time stamp 0 s in a window of 0.5 s length, where the range is simply defined as

$$f_{a,2} = \max y_i - \min y_i. \tag{4}$$

In these two feature spaces ($f_{l,1} \times f_{l,2}$ for pump leakage, $f_{a,2} \times f_{a,2}$ for accumulator failure), a supervised classifier is trained. Since the states of no-leakage (states 0 and 2) vs. leakage (states 1 and 3) are quite easy to distinguish from each other, we use a simple logistic regression classifier (Webb, 2002) for that case. The states no-accumulator-failure (states 0 and 1) vs. accumulator-failure (states 2 and 3) are more difficult to be distinguished. Hence, we use more advanced classifiers based on kernel density estimation or Gaussian mixture models. It is able to handle even strong non-linearities in feature space. For more details about the classifier see for instance (de Ridder et al., 2017).

Extracting the selected features from the training data and annotating the data into No-leakage vs. Leakage respectively No-accumulator-failure vs. Accumulator failure classification problems, the according feature spaces of the training data are shown in Fig. 5 and Fig. 6. Also in the feature spaces it is obvious that leakage detection is an easier task than accumulator failure detection, since the classes are linearly separable.

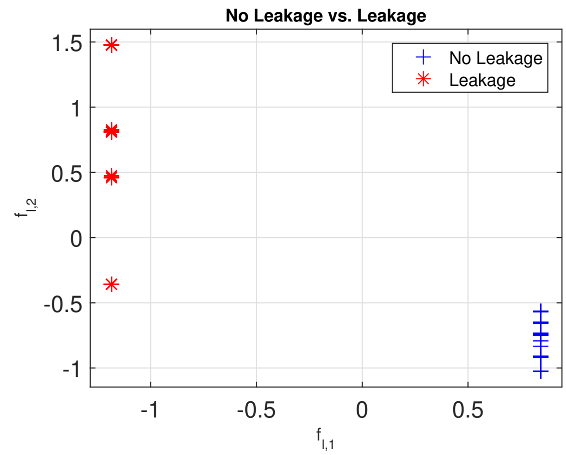


Figure 5. Training data for pump leakage detection in feature space.

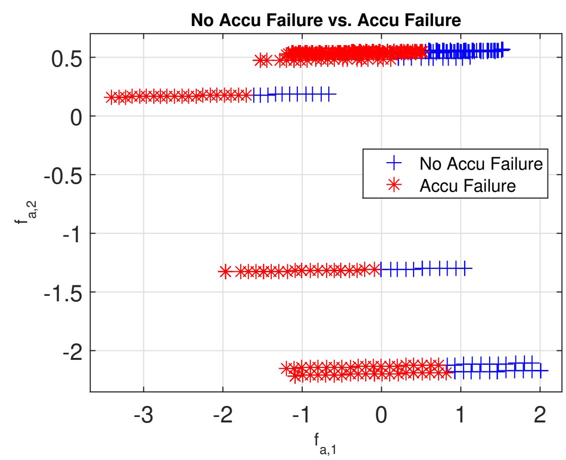


Figure 6. Training data for accumulator failure detection in feature space.

5. EXPERIMENTAL RESULTS

In this section, the data for validation of the proposed approach are briefly described. Furthermore, scatter plots, confusion matrices and accuracy values of the validation scenario are provided.

5.1. Validation Data

For validating the proposed approach, 98 test measurements with randomly distributed parameters were generated. Assigning the true states to these randomly distributed measurements, the distribution of the states of the validation measurement is as follows:

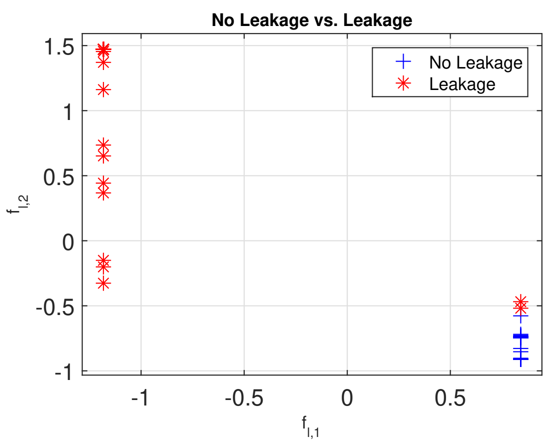


Figure 7. Validation data for pump leakage detection in feature space.

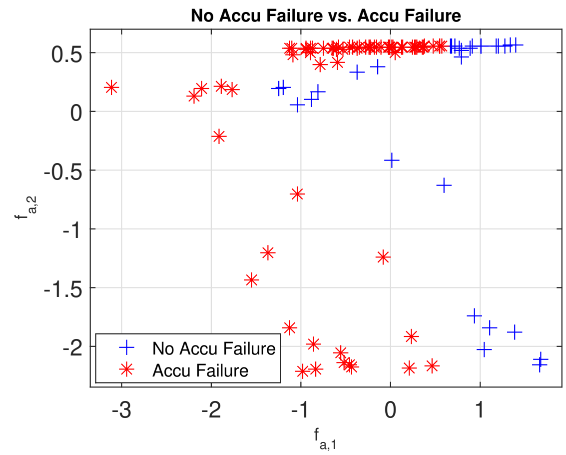


Figure 8. Validation data for accumulator failure detection in feature space.

Table 1. Confusion matrix for pump leakage detection.

		Estimated state	
		No leak	Leak
True state	No leak	50	0
	Leak	0	48

Table 2. Confusion matrix for accumulator failure detection.

		Estimated state	
		Accu OK	Accu fail.
True state	Accu OK	30	0
	Accu fail.	4	64

- 11 measurements of state 0
- 19 measurements of state 1
- 39 measurements of state 2
- 29 measurements of state 3

By comparing this ground truth to the estimated states of the classifier, an assessment of the detection accuracy of the proposed method is possible.

5.2. Results

In a first step, we evaluate separate classifiers for no-leakage (states 0 and 2) vs. leakage (states 1 and 3) classification and no-accumulator-failure (states 0 and 1) vs. accumulator-failure (states 2 and 3) classification. In a second step, the results of those two classifiers are combined to a final classification of the failure state as described already in Section 4.

In the case of leakage detection, we have $11 + 39 = 50$ measurements without leakage and $19 + 29 = 48$ measurements with leakage. A logistic regression classifier is trained in the feature space $f_{l,1} \times f_{l,2}$ using the training data described in Section 2. The features space of the validation data is shown in Fig. 7, and the confusion matrix in Table 1. The accuracy of the leakage classification is therefore 100 %.

For accumulator failure detection, the number of measurements is $11 + 19 = 30$ without accumulator failure and $39 + 29 = 68$ with accumulator failure. This time, a mixture of Gaussians classifier is trained in the feature space $f_{a,1} \times f_{a,2}$ using the training data described in Section 2. Again, the features space of the validation data is shown in Fig. 8, and the confusion matrix in Table 2. The accuracy of accumulator failure classification is therefore 95.92 %.

The results of the two single classifiers are subsequently combined to the four fault states, the resulting confusion matrix is shown in Table 3. This confusion matrix results in a classification accuracy of 95.92 %. Since the leakage detection has perfect accuracy of 100 %, the overall accuracy is of course the same accuracy as the accuracy of accumulator failure detection.

The results show that the digital twin allows discrimination of the four failure states with high accuracy. However, it increases accuracy to split the classification task into two simpler tasks as done here: we first distinguish between no-leakage and leakage respectively no-accumulator failure and accumulator failure and combine then the results to a final failure state estimation. If we combine all features in a four-

Table 3. Confusion matrix of failure state classification.

		Estimated state			
		0	1	2	3
True state	0	11	0	0	0
	1	0	19	0	0
	2	3	0	36	0
	3	0	1	0	28

Table 4. Confusion matrix of failure state classification in the four-dimensional feature space.

		Estimated state			
		0	1	2	3
True state	0	11	0	0	0
	1	0	19	0	0
	2	2	0	37	0
	3	0	2	2	25

dimensional feature space ($f_{l,1} \times f_{l,2} \times f_{a,1} \times f_{a,2}$), the accuracy decreases to 93.88 % with the confusion matrix as shown in Table 4. We tried different types of classifiers in that four-dimensional feature space, the one that worked best was the kernel density estimation based classifier that was also used for accumulator failure classification. The reason for the decreased accuracy is probably the usage of a too complex classifier together with a relatively small data set for the rather simple problem of leakage detection. Also the curse of dimensionality might affect the result, since the two two-dimensional feature spaces are populated more densely the four-dimensional feature space.

6. CONCLUSIONS

An approach was found to identify system errors and separate the possible system faults in the 4 classes with a high accuracy of 95.92 % using a split method with 2 steps. Separating the 4 fault possibilities in one step was more time-consuming and additionally more uncertain. We are therefore confident to get a computable solution in a next step which can be implemented on a commercial industry controller system and be tested at a real actuator.

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BIOGRAPHIES

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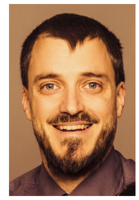

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