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Concept validation of a soft sensor network for wear detection in positive displacement pumps

PIF-condition monitoring II

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ABSTRACT

With increasing digitization, models are not only used during the design phase but throughout the life cycle of systems. Especially the use of models as soft sensors during operation offers opportunities in cost saving, easy data acquisition and therefore additional functionality of systems. Soft sensors are models of components that use easily accessible auxiliary quantities to estimate target quantities that are difficult to measure. Networks of soft sensors are the prerequisite for redundant data acquisition in a system and thus encourage the occurrence of data-induced conflicts, i.e., inconsistent values from different soft sensors, which may result from: (i) the breakdown or defect of a measuring sensor, (ii) model uncertainties of the soft sensors, (iii) change of component characteristics, e.g. due to wear. The resolution of these conflicts either leads to greater confidence in the model-based system quantities or allows the detection of changing components characteristics. Hence soft sensor networks can be used to detect wear in system components.

Wear in pumps and valves leads to a change in the flow rate and the inner leakage. Therefore, the detection of wear with soft sensors requires the detection of small changes in the system flow rates. In the full paper an analysis of the influence of small flow rate variations on redundant soft sensor outputs is carried out. For this, small flow rate variations are implemented on a test bench for positive displacement pumps. Furthermore, a systematic analysis of parameter and data uncertainties and their propagation in models for positive displacement pumps is carried out. The resulting flow rates and the measurement uncertainties from the models of the pump and the throttle valve of the test bench are compared and discussed with respect to data induced conflicts and the detection of wear.

1 INTRODUCTION

Positive displacement pumps are widely used in different technical applications. Especially eccentric screw pumps are prone to wear due to small gaps, their design material and their application with contaminated fluids. Particles may be trapped between rotor and the elastomeric stator. Therefore, the pump characteristics may change due to wear and, consequently, the service life of these pumps is low. Following this case, it is advised to use predictive maintenance with fault diagnosis, i.e. wear detection to ensure the operation and functionality. Wear in pumps leads to a change in the flow rate and the inner leakage. Therefore, the detection of wear requires the detection of small changes in the systems flow rates. The method for wear detection outlined in this paper is based on redundant estimation of the flow rate for a system consisting of a displacement pump prone to wear and a valve. The characteristic of the valve is assumed to stay constant.

The flow rate is estimated by soft-sensors based on easily accessible auxiliary quantities like pressure, temperature and rotating speed. This ensures the usability of the method for future pump applications due to inexpensive measurements.

2 LITERATURE OVERVIEW

Wear in fluid systems is due to solid contamination of the fluid. The contamination is due to the application or caused by, and leads to erosion and 3-body abrasion. The results on the fluid system are increased gap sizes. Due to the nature of fluid systems, particles are propagated through the system. [1]. Wear in fluid systems is drift-like and is therefore be classified as an incipient fault until the system fails in an abrupt fault [2].

During the life cycle of a fluid component several measures should be implemented to counteract wear. In the design phase the focus is on preventive measures. That includes proper implementation of particle filters but also designing the system to minimize wear e.g. with software support [3] [4] or design rules [1]. During operation of the fluid system, wear can be detected in the early stages with fluid condition monitoring, i.e. by counting particles [5]. For detecting later stages of wear a fault diagnosis system needs to be considered. Typically, the system then has already undergone some changes due to wear. In some pump applications with heavily contaminated fluids, e.g. for wastewater, this late detection is unavoidable.
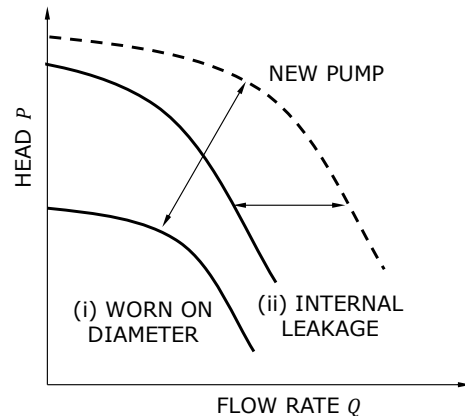

Figure 1: Comparison of (i) wear on impeller which reduces impeller diameter and (ii) wear on sealing surface pairs, which leads to internal leakage [6].

The result of wear on the pump characteristics depends on the pump type, c.f. Figure 1. In centrifugal pumps the wear mainly reduces the diameter of the impeller, leading to a characteristics of a smaller pump of the same type. A different effect occurs, when wear widens the gap between sealing surface pairs. This leads to an internal leakage flow from high to low pressure zones which is proportional to the clearance and approximately constant over the pump flow range [6]. In pressure controlled systems, both types of wear change the systems flow rate.

There is a vast literature on fault diagnosis systems and predictive maintenance to recognize a changing flow rate. A survey of methods for fault diagnosis systems can be found in [2]. Fault diagnosis methods generally consist of a dynamic process model which is used to generate features. The chronological sequence of features and the difference of these features to features in normal operation lead to symptoms which are used for a diagnosis of faults. In this paper a new low cost approach for the detection of wear is presented. The symptoms are conflicting flow rate outputs of two soft sensors.

Soft sensors are not entirely distinguishable from the models used in fault diagnosis systems. Soft sensor is a compound of the words "software" and "sensor" and represents a system that uses easily accessible auxiliary quantities to estimate unknown target quantities. For this purpose, models that describe the relation between measured and unknown quantities are needed [7], [8], [9].

The origin of soft sensors lies in the process industry where, motivated by huge plant sizes, rough environmental conditions for measuring equipment and high costs of machine downtime, soft sensors relying on data driven models were developed. They are used mainly to back-up measuring devices, to replace hardware sensors, to estimate system variables for condition monitoring and controlling as well as detecting failure [10], [11], [12].

In fluid systems, soft sensors are mainly used to replace the volume flow measurement, since flow metering entails high costs and flow control being the most important control strategy in industrial applications [13]. Against this background Ahonen [14] and Leonow et. al. [15] present soft sensor approaches that are based on physical and empirical models of single centrifugal pump units representing the following pump characteristics: Q-H characteristic, Q-P characteristic or Q-I characteristic, where Q is the volume flow rate, H is the pressure head, P is the power consumption and I is the stator current of the electric drive of the pumps. Yong-feng et. al. [16] describe a method to estimate the volume flow rate of a gear pump, depending on the load pressure, rotational speed and varying viscosity of the hydraulic oil. Their experimental analysis shows, that their soft sensor can achieve an accuracy of ±2 % concerning the relative error. Beside the scientific publications, sof sensors have already entered the centrifugal pump industry where different pump manufacturers developed customized soft sensor solutions for their pumps [17], [18], [24].

A relatively new approach is the implementation of soft sensor networks. Networks of soft sensors are the prerequisite for redundant data acquisition in a system and thus encourage the occurrence of data-induced conflicts, i.e., inconsistent values from different soft sensors. The resolution of these conflicts either leads to greater confidence in the model-based system quantities or allows the detection of changing components characteristics. Hence soft sensor networks can be used to detect wear in system components [19], [20].

3   METHOD

With increasing digitization, standard solutions like OPC UA [21] allow for easy information transfer between components and therefore are the foundation for soft sensor networks. Combining the output of several soft sensors for fluid components in a soft sensor network leads to redundant calculations of the flow rate. This redundancy allows the occurrence of data-induced conflicts, i.e. inconsistent values from different soft sensors, which carry information.

The fluid system under consideration consists of a positive displacement pump, i.e. a eccentric screw pump, and a valve as hydraulic resistance (c.f. Figure 2). Both components are modelled and their flow rates are calculated from pressure, temperature and rotational speed measurements (c.f. section 3.1). The occurrence of data induced conflicts between these models allows for the detection of changing component characteristics. Hence, soft sensor networks can be used to detect wear in system components. The case investigated in this paper is the wear of the pump with constant system resistance. Due to greater gaps and missing press fit, hydraulic resistance like valves or heat exchangers are less prone to wear.
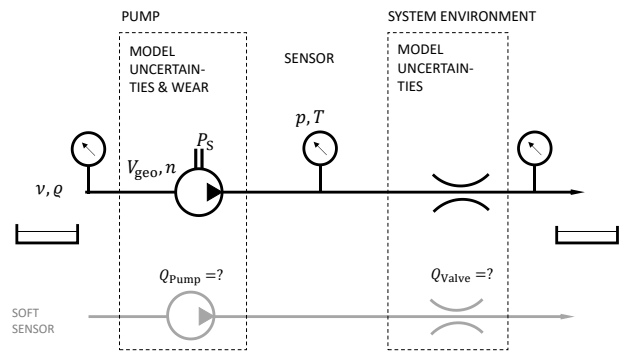

Figure 2: Soft-sensor network for wear detection in positive displacement pumps. The flow rate output of two soft-sensors is compared.

In a pressure controlled fluid system, wear in pumps has an effect on the flow rates (c.f. Figure 1). Consequently, for the efficient validation of the wear detection method, wear can be simulated by bypass flows [22]. Therefore, for the validation of the method, a test-bench for simulating wear in the pump with a bypass flow was built (c.f. section 3.3). The validation is carried out in a two step process: (i) First the bypass is closed and the models are calibrated for constant resistance at different rotational speeds of the pump. This represents the components behavior without wear. (ii) Secondly, wear is simulated by opening the bypass at different degrees of opening for constant rotational speeds of the pump and constant resistance.

3.1   MODELS AND UNCERTAINTIES

For the flow calculations a type independent model for positive displacement pumps is used [23]. The flow Q is determined by the geometric volume V_{geo} and the rotational speed n minus the gap losses Q_{L}.

$$Q_{\text{pump}} = nV_{\text{geo}} - Q_{\text{L}} \qquad (1)$$

The gap losses are modelled by

$$Q_{\text{L}+} := \frac{Q_{\text{L}}}{\nu \, V_{\text{geo}}^{1/3}} = L_{\Delta p+} \, \Delta p_+^{\,m}, \qquad (2)$$

where

$$\Delta p_+ = \frac{\Delta p \, V_{\text{geo}}^{2/3}}{\nu^2 \varrho}. \qquad (3)$$

Measured quantities are the rotational speed n and pressure difference Δp. The fluid density ϱ and kinematic viscosity ν are derived from a calibration curve via temperature measurements. The parameters $L_{\Delta p+}$ and m are fitted in a calibration process, i.e. linear least squares, with no bypass flows.

Considering the valve, the well known K_{v}-Model is used

$$K_{\text{v}} = Q_{\text{valve}} \sqrt{\frac{\Delta p \, \varrho_0}{\Delta p_0 \, \varrho}} \qquad (4)$$

where $\Delta p_0 := 1 \, \text{bar}$ and $\varrho_0 := 1000 \, \text{kg/m}^3$. The density is the measured fluid density ϱ in the pump.

The fitted parameters and the corresponding parameter uncertainties can be found in Table 1. Fitting was done with a robust nonlinear least squares method.

Table 1: Model parameters and uncertainties (in unit and as percentage) for pump and valve model.

Parameter	Unit	Value	Uncert.	Uncert. in %
V_{geo}	l	0.0723	-	-
$L_{\Delta p+}$	-	$3.68 \cdot 10^{-19}$	$7.88 \cdot 10^{-18}$	2141
m	-	1.99	0.95	48
K_{v}	$\dfrac{\text{l}}{\text{min}}$	13.56	0.12	0.88

3.2 DATA INDUCED CONFLICT

By comparing data of different sensors that measure the same quantity, conflicts may emerge. This can be promoted by targeted redundancy. The data induced conflicts carry information since there must be a cause for the conflict. The data induced conflict can be attributed to: (i) sensor break down, (ii) soft-sensor uncertainty or (iii) component

characteristics change. The classification can be made by looking at the time history of the sensor data and the uncertainty quantification of the soft-sensor.

A sensor breakdown is usually identified by sudden changes or interrupts. In case (i) the system needs maintenance. Case (ii) cannot be avoided since uncertainty is inevitable. This case can be identified by knowing the uncertainties of the soft-sensors. If the uncertainties of two soft-sensors overlap, the conflict is due to sensor uncertainty. Case (iii) is the most valuable case for this paper since system change can be identified. It occurs, when the cases (i) and (ii) can be excluded. [19]

3.3 TEST SETUP

The schematics for the test bench for the simulation of pump wear can be seen in Figure 3. The eccentric screw drive pump under consideration has a geometric volume of $V_{\text{geo}} = 0.0723 \, \text{l}$ and is driven by an asynchronous motor with $18 \, \text{kW}$. The resistance of the system is mainly determined by the main ball valve. The bypass flow is controlled with an electric ball valve. All measured points were approached from lower degrees of opening to avoid mechanical play in the valves.

A torque meter with built-in speed sensor measures the rotational speed of the pump. The volume flow rate Q_{main} after the valve is measured with a screw type flow meter. Pressures are measured with piezo resistive sensors and temperatures are measured with Pt100 resistance thermometers.

The oil was Shell Tellus 10. The temperature of the oil during experiments was held at $30° \pm 1° \, \text{C}$. The temperature was measured with a temperature sensor before and after the pump and the results were averaged for the determination of oil density and viscosity.

4 RESULTS

The soft sensor network was tested for the rotational speeds 100 rpm to 600 rpm for the pump in steps of 100 rpm. In Figure 4 the computed and measured flow rates are shown for 200 rpm and 500 rpm as a function of the volumetric inefficiency ε_{vol}, defined as

$$\varepsilon_{\text{vol}} := 1 - \eta_{\text{vol}} = \frac{Q_{\text{mea}}}{n \, V_{\text{geo}}}. \qquad (5)$$

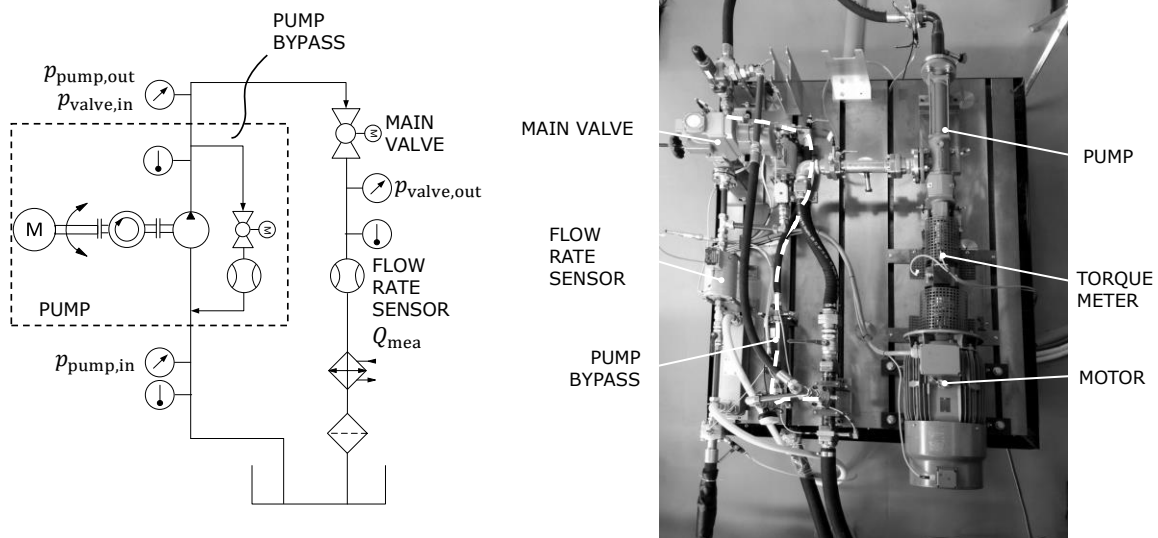The volumetric inefficiency indicates the wear condition in the pump.

Figure 3: Circuit diagram and test bench for simulating wear in pumps and valves via bypass flow.

For both rotational speeds, the computed flow rate of the soft sensor for the pump Q_{pump} does not change. This is due to the pump soft sensors lack of knowledge, that the pump is worn, i.e. is bypassed. When opening the bypass, the flow rate for the valve soft sensor Q_{valve} decreases. The valves soft sensor observes the drop in the flow rate due to the pump delivering less fluid. Therefore, the pressure difference over the valve is lower than before and by equation (4) a lower flow rate is determined.

Besides the obvious difference in flow rate between different rotational speeds, the uncertainty of the soft sensors varies between speeds. For the case of 500 rpm, the error bars for both soft sensors barely can be seen behind the markers. For 200 rpms the errors for the valves soft sensor are larger, indicating a larger relative error. However, in both cases the uncertainties of the valves soft sensor include the measured flow rate Q_{mea}. Hence, the soft sensor for the valve predicts the measured flow rate.

4.1   UNCERTAINTY ANALYSIS

The true flow rate Q_{mea} is measured for validation purposes, thus the deviation of the computed flow rate Q_{valve} from the true value, i.e. relative error e_{rel}

$$e_{\text{rel}} = \frac{Q_{\text{valve}} - Q_{\text{mea}}}{Q_{\text{mea}}}$$

can be given. The valve soft sensor predicts the flow rate with a relative error of 2% for 200 rpm and with an relative error of less than 1% for 500 rpm.

However, in an application the true flow rate is not known and therefore the relative error is not relevant. To assess whether the soft sensors are useful for determining the true flow rate and detecting wear, the uncertainty of the soft sensors has to be determined.

As is well known, the uncertainty describes an interval around the computed value Q_{valve} or Q_{pump} which contains estimates that can be reasonably attributed to the true value. The uncertainties for the flow rate outputs of the soft-sensors Q_{valve} and Q_{pump} are determined via uncertainty propagation. Uncertainties of fitted parameters are considered as systematic errors in the error propagation.

The resulting uncertainty for the valve soft sensor is about 8% for 200 rpms and 1.7% for 500 rpms and a volumetric inefficiency of 20%. Consequently, the soft sensor for the valve can detect smaller relative fluctuations for higher flow rates.

Comparing the parameters and uncertainties of Table 1 with the uncertainties in Figure 4 leads to the question why, despite the large parameter uncertainties, the pumps soft-sensor has a lower total uncertainty. This is mainly due to the loss term $Q_{\text{L}} \approx 0$, since gapless eccentric screw pumps are modeled. Thus only the uncertainty of the valve soft sensor is of interest here.

The contributions to the uncertainty of the valves soft sensor can be found in Table 2. The total uncertainty is mostly due to the systematic uncertainty, since fluctuations decrease due to long

measurement times. The order of magnitude of the systematic error of the valve soft-sensor is nearly constant between different pump speeds. This can mainly be contributed to an increase of the uncertainty for K_v with increasing rotational speed and a decrease of error for the pump sensors. This inverse relation is due to the use of equation (4) both for parametrization and the calculation of the flow rate.

With regard to cost efficiency, the uncertainty of the soft sensor can be easily reduced by using a lower systematic error for the pressure sensor after the valve, i.e. hydraulic resistance. Other options are a variable parameter K_v for the valve during calibration and a refinement of the valve model.

4.2   VALIDATION

As the results indicate, the soft sensor network shows data induced conflicts between Q_{valve} and Q_{pump}. Where the errors of the two soft sensor outputs do not overlap (c.f. Figure 4) a data induced conflict of type (iii) occurs.

Table 2: Contributions to uncertainty of valve soft-sensor, including contributions of different inputs to the uncertainty in flow rate output.

	contribution to uncertainty in l/min	
	200 rpm	500 rpm
total uncert.	0.84	0.55
system. uncert.	0.84	0.55
stat. uncert.	0.00	0.01
K_v	0.10	0.25
$p_{v,in}$	0.22	0.09
$p_{v,out}$	-0.52	-0.22
ϱ	0.00	0.00

The data induced conflict is the result of pump characteristics changes. In the results, the size of the data induced conflict increases with increasing volumetric inefficiency, caused by the bypass flow, i.e. the simulated wear.

Hence, the soft sensor network under consideration can be used to detect wear in the pump. However, to find wear in an early stage, the approach is limited to operating ranges where the uncertainty of the valve model is low, i.e. high rotating speeds of the pump.
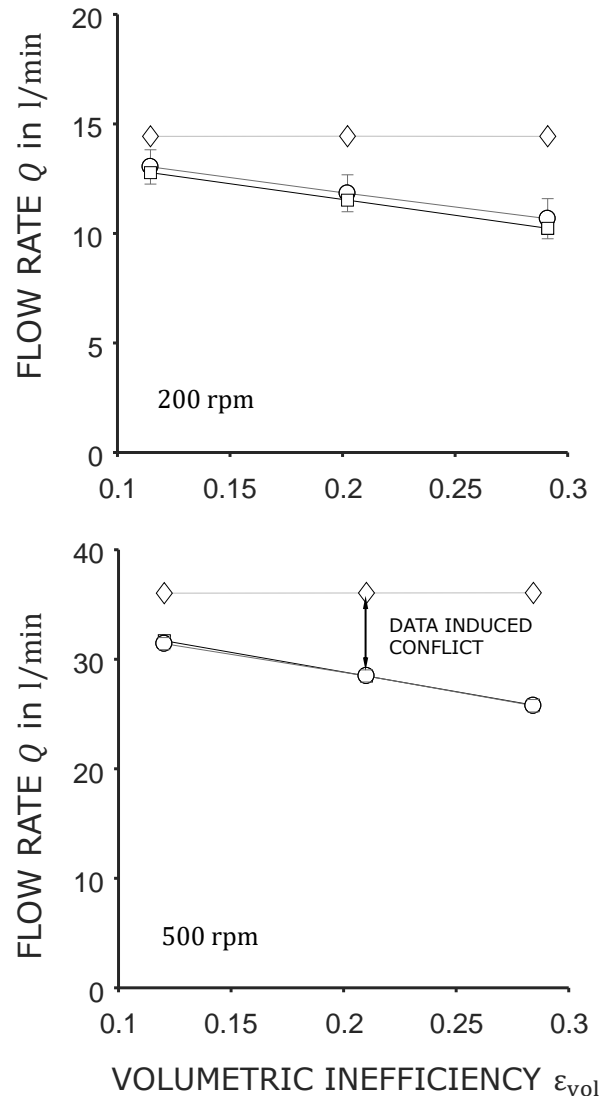

Figure 4: Comparison of soft-sensor outputs with measured flow rate for two different rotation speeds for the pump. Some uncertainty-bars vanish behind markers.

5   CONCLUSIONS

The soft sensor for the valve is capable of determining the measured flow rate with high accuracy. The relative error lies within errors known from the literature [16]. The uncertainty of the soft sensor limits the flow rate prediction to the uncertainty band and the uncertainty is mainly influenced by the fitted parameter for the valve model and the pressure sensors. To decrease the uncertainty, the pressure sensor after the hydraulic resistance should be changed for a sensor with higher accuracy.

The soft sensor network is capable to determine wear and its extent in eccentric screw pumps via data induced conflicts with a relatively simple model for the systems resistance. The determination of the uncertainty is important to classify unavoidable data-induced conflicts in redundant data acquisition. The approach is more powerful at high rotating speeds due to the uncertainty having less influence at higher flow rates.

In future investigations wear of the system resistance, i.e. valve should be taken into consideration. To link wear and the simulated wear the bypass approach and worn components should be compared.

6 ACKNOWLEDGEMENTS

7 REFERENCES AND BIBLIOGRAPHY

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