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VALIDATION OF A SOFT SENSOR NETWORK FOR CONDITION MONITORING IN HYDRAULIC SYSTEMS

Jakob Hartig, Christian Schänzle, Peter F. Pelz*

Institut für Fluidsystemtechnik, Technische Universität Darmstadt, Otto-Berndt-Straße 2, 64287 Darmstadt
* Corresponding author: Tel.: +49 6151 1627100; E-mail address: peter.pelz@fst.tu-darmstadt.de

ABSTRACT

With increasing digitization, models are more important than ever. Especially their use as soft sensors during operation offers opportunities in cost saving, easy data acquisition and therefore additional functionality of systems. In soft sensor networks there is redundant data acquisition and consequently the occurrence of inconsistent values from different soft sensors is encouraged. The resolution of these data-induced conflicts allows for the detection of changing components characteristics. Hence soft sensor networks can be used to detect wear in system components.

In this paper this approach is validated on a test rig. It is found, that the soft sensor network is capable to determine wear and its extent in eccentric screw pumps and valves via data induced conflicts with relatively simple models.

Keywords: soft sensor, condition monitoring, wear, hydraulic system

1. INTRODUCTION

Increasing automation and digitization provide sensor data in a unified architecture and thus encourage the usage of soft sensors. Soft sensors are models of components that use easily accessible auxiliary quantities to estimate target quantities that are difficult to measure. [1]

Soft sensors are not isolated, however. The development of communication standards like OPC-UA allow for easy information transfer between soft sensors for different components. [2] An interconnected soft sensor network is formed. In soft sensor networks there is redundant data acquisition and consequently the occurrence of data-induced conflicts is encouraged.

Different methods have been developed to deal with conflicting data sources. On the one hand, conflicts can be seen as part of the systems normal behavior. Then data from multiple sources can be used to reduce uncertainty and to improve the overall level of data quality. Simple methods for data reconciliation of conflicting sensor data are voting systems. [3] More elaborate fusion methods are the Bayes method [4, 5], Dempster-Shafer method [6, 7], and heuristic methods [8, 9]. In the process industry for the estimation of process states data reconciliation methods are implemented. The goal is to fuse the conflicting data, i.e. reconcile the state of the system with the conservation laws of mass and energy. With a quadratic minimization method, the measured system states are changed until the values satisfy the conservation laws. [10] On the other hand conflicts between data sources can be seen as part of erroneous system behavior. Thus different methods use conflicting data for fault detection and fault isolation [10, 11]. 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. 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 [12].

In this paper a soft sensor network approach for condition monitoring [13–15] is validated where data-induced conflicts are used to derive additional information about the hydraulic system.

2. CONDITION MONITORING BASED ON A SOFT SENSOR NETWORK

In this paper a simple soft sensor network for a hydraulic system is considered (c.f. **Figure 1**). The hydraulic system consists of a pump and a valve where the valve represents any hydraulic resistance. This case example considers the perspective of a pump manufacturer whose pump is used in an unknown fluid system. Regarding the pump, the complete environment, e.g. valves, filters or similar, can be described as one generalized resistance. The pump and the resistance are each represented by a soft sensor which is subject to uncertainty and lack of knowledge e.g. component characteristic changes due to wear. Measured quantities in the system are the pump speed as well as temperature and pressure differences over the components.

The purpose of the soft sensor network is to generate redundant data of the volume flow from two different sources, firstly the soft sensor of the pump and, secondly, the soft sensor of the resistance, i.e. valve. In this way, the soft sensor network enables the occurrence of data-induced conflicts which are inconsistent values calculated by two different sources. The aim is to generate additional information about the system based on the data-induced conflicts.

Data-induced conflicts may result from, firstly, the breakdown or defect of a measuring sensor, secondly, model uncertainties of the soft sensors and, thirdly, change of component characteristics, e.g. due to wear. [15] The resolution of these data-induced conflicts either leads to greater confidence in the model-based system quantities or allows for the detection of changing components characteristics.

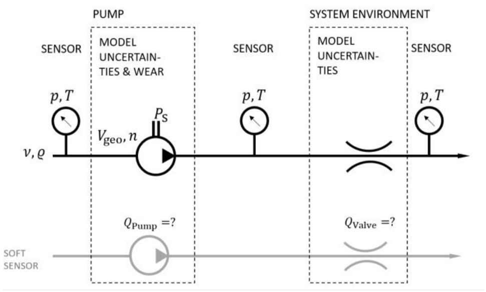

Figure 1: Soft sensor network for wear detection in hydraulic systems.

In the following data-induced conflicts caused by changing component characteristics are considered to detect wear in system components. To validate this approach three research questions need to be answered:

1. What is the error and uncertainty for the two soft sensors? Error is the deviation of the computed flow rate from the true value and uncertainty describes an interval around the computed value which contains estimates that can be reasonably attributed to the true value.
2. Can wear be determined via data-induced conflicts?
3. Is it possible to isolate the worn component?

In the following these three questions are discussed based on an experimental investigation.

3. METHOD

3.1. Test rig for simulated wear

Wear in pumps, valves and other components leads to a change in the flow characteristics. Therefore, at a given pressure, the detection of wear with soft sensors requires the detection of small changes in the flow rates. This is the motivation for an experimental analysis of the flow rate variations on redundant soft sensor outputs and their use for wear detection. [16]

Hence a test bench was set up on which a leakage of the components can be adjusted representing wear. For this reason, bypasses for the positive displacement pump and the valve were in integrated into the test bench (c.f. **Figure 2**).

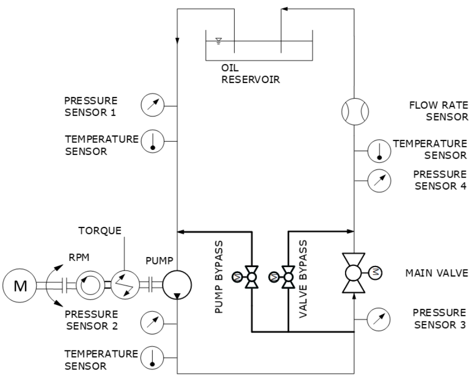

Figure 2: Test rig for simulating wear in a hydraulic system.

The pump used in the test rig is a progressive cavity pump and the valve is represented by a ball valve. The eccentric screw drive pump with a geometric volume of $V = 0.0723\,\mathrm{l}$ is driven by an asynchronous motor with $18\,\mathrm{kW}$. The resistance of the system is mainly determined by the main ball valve. The bypass flows are controlled with electric ball valves. All measured points are 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 is of the type Shell Tellus 10. The temperature of the oil during experiments was held at $30° \pm 1°\,\mathrm{C}$. The temperature was measured before and after the pump and the results were averaged for calculating oil density and viscosity. The soft sensor network was tested for the rotational speeds 200 rpm, 300 rpm and 400 rpm of the pump.

3.2. Soft sensors

Since the volume flow is a conservation quantity it needs to be identical in the considered pump and valve. Hence the purpose of both soft sensors, the pump and the valve, is to generate redundant data of the volume flow rate.

For the valve the well-known and simple K_{v} model is used. The flow rate is determined by

$$Q_{\mathrm{valve}} = K_{\mathrm{v}}(\alpha)\sqrt{\frac{\Delta p_{\mathrm{valve}}}{\Delta p_0}\frac{\varrho_0}{\varrho}}, \tag{1}$$

where $\Delta p_0 = 1\,\mathrm{bar}$ and $\varrho_0 = 1000\,\mathrm{kg/m^3}$ and the pressure difference over the valve $\Delta p_{\mathrm{valve}} = p_2 - p_4$ and ϱ is the fluid density.

For the calibration of K_{v} as a function of valve opening α a third degree polynomial was used. The parameter identification was done with a robust nonlinear least squares method. The results for the fit for different rotational speeds for the pump can be found in **Figure 3.**

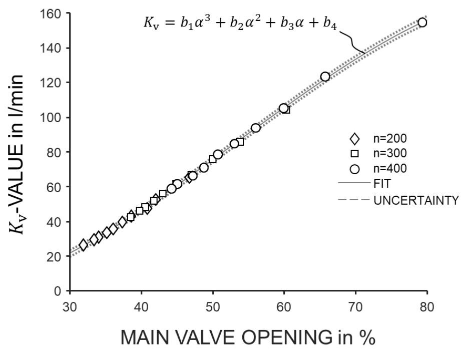

Figure 3: Calibration curve for the valve model.

The soft sensor of the pump is based on a type independent efficiency model for positive displacement pumps [17]. The flow is determined by the geometric volume V and the rotational speed n less the gap losses Q_{L}.

$$Q = nV - Q_{\mathrm{L}} = nV - Q_{\mathrm{L+}}\nu V^{\frac{1}{3}} \tag{2}$$

The gap losses are modelled by

$$Q_{\mathrm{L+}} = L_{\Delta p+} \cdot \Delta p_{+}{}^{m}, \tag{3}$$

where $L_{\Delta p+}$ and m are model parameters that need to be calibrated. Δp_{+} is the dimensionless pressure difference given by

$$\Delta p_{+} = \frac{\Delta p\, V^{2/3}}{\nu^2 \varrho}. \tag{4}$$

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 results for the fit for the pump model can be found in **Figure 4.**

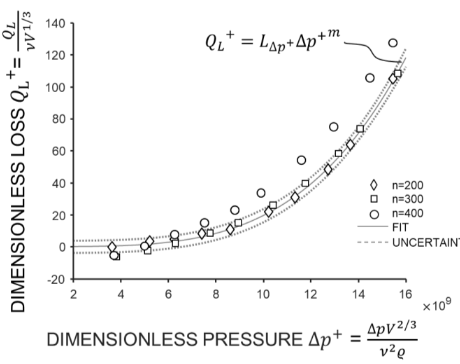

Figure 4: Calibration curve for the pump model.

3.3. Propagation of Uncertainty

Soft sensors should be considered as sensors. Uncertainties should therefore be included in their calculated values. In the following two sources of uncertainty in soft sensors are considered: the systematic and stochastic uncertainty from the measurements e.g. pressure measurement as well as the systematic uncertainty from the calibration procedure (c.f. **Figure 5**).

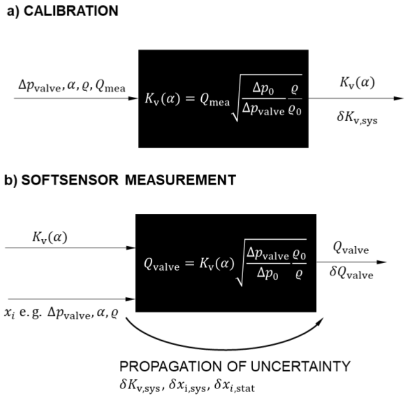

Figure 5: a) Calibration and b) soft sensor measurement with propagation of uncertainty.

The uncertainty from the calibration and from the measurement is propagated through the model to yield the soft sensor uncertainty. Stochastic and systematic uncertainty is propagated independently.

4. RESULTS

In the following the results for closed bypass valves (i.e. no wear), wear in one component and simultaneous wear in both components are discussed.

4.1. Function of the soft sensors

To check whether the soft sensors reflect the volume flow in the hydraulic system, soft sensor outputs and flow rate measurements for closed bypass valves are compared. It is found that the relative deviation from the true value (relative error) for the valve soft sensor is < 2 % and < 0.5 % for the pump soft sensor. 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. The relative uncertainty for the valve soft sensor is < 5 % and < 1 % for the pump soft sensor.

4.2. Wear in one component

To check how the soft sensors react to wear and whether a data-induced conflict can be determined the bypass is opened during measurement. For pump wear the volume flow is plotted above the opening degree of the pump bypass represented in **Figure 6**. The speed and pressure difference were kept constant at all operating points by controlling the main valve opening (pressure controlled system).

The measurement point with a nearly closed bypass resembles the results from section 4.1. The two soft sensors calculate the actual volume flow within their uncertainties

With increasing wear (i.e. with increasing opening degree of the pump bypass), the actual volume flow decreases. Since the valve is not exposed to wear, the valve soft sensor shows the actual flow rate. Only the pump soft sensor deviates from the actually volume flow with increasing wear. This is because the volume flow of the pump soft sensor is determined by the speed and the pressure difference. Since these two variables are kept constant, a constant volume flow is calculated despite wear. The actual volume flow is not constant due to a backflow through the bypass.

The valve soft sensor, in turn, calculates the reduced volume flow, since the valve soft sensor takes the pressure difference and the valve opening degree of the main ball valve into account.

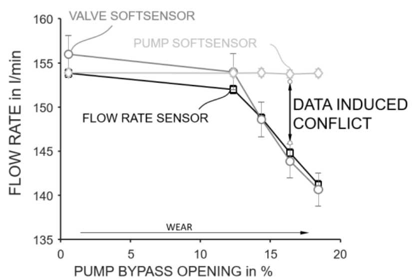

Figure 6: Soft sensor outputs for wear in pump.

The soft sensor network shows data induced conflicts between the calculated flow rates of the two soft sensors. Where the errors of the two soft sensor outputs do not overlap (c.f. **Figure 5**) a data induced conflict of type (iii) occurs.

The data induced conflict is the result of pump characteristics changes. In the results, the size of the data induced conflict increases with increasing bypass flow, i.e. the simulated wear. The same was found for wear in the valve.

Hence the proposed soft sensor network can be used to detect wear in the pump. However, due to the uncertainty of the two soft sensors, a difference of 6 % between the two soft sensor outputs indicates wear. Thus, wear in early stages cannot be identified.

4.3. Combined wear in pump and valve

In fluid systems wear is caused by particles and is consequently propagated through the system. This leads to combined wear. [18] To investigate this the flow rates for pump and valve bypasses are varied simultaneously.

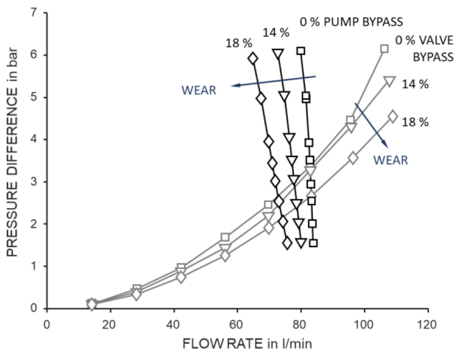

Figure 7: Characteristic curves for pump and valve with varying opening degree for bypass.

In **Figure 7**, the pressure is plotted above the volume flow at different bypass openings for valve and pump. For each bypass flow the pump- and valve characteristics are shown as lines. As soon as the pump wears out, its characteristic curve shifts to lower flow rates. With the same pressure difference at the pump, less volume can be pumped due to internal leakage. When the valve is worn, the characteristic curve shifts to lower pressures so that at the same pressure difference, more volume flow can flow through the valve due to the enlarged valve cross-section. The characteristics intersect at the respective operating point.

To investigate combined wear further, different bypass openings are set for the pump. In this series of measurements, the speed and pressure difference and the opening of the valve bypass remains constant at 16 % (c.f. **Figure 8** left). The volume flow trend of flow meter and valve soft sensor is the same. The absolute values have a relatively constant difference which corresponds to the constant bypass opening degree of 16 %. At 0 % bypass opening degree, the pump soft sensor initially outputs the actual volume flow. Only with increasing wear a larger deviation occurs.

For valve wear, conversely, the opening degree of the pump bypass remains constant at 16 % and the opening degree of the valve bypass varies from 0 to 18 %. (c.f. **Figure 8** right). The pump soft sensor outputs a constant deviation from the actual volume flow, since the pump bypass opening degree is constant at 16 %. The volume flow of the valve soft sensor deviates from the actual volume flow after initial overlapping with increasing wear.

It still remains to be clarified whether the defective component can be determined using the two soft sensors. For this purpose, we consider the same graphs of combined wear and tear, which corresponds most closely to the real, unknown system state.

Comparing both soft sensor outputs in **Figure 8** we find that the characteristics of the two wear patterns are very similar and regardless of the wear condition in the system, the volume flow from the valve soft sensor is always smaller than that of the pump soft sensor. Hence, without further information we are not able to determine which component is defective.

5. CONCLUSION

It is found, that the soft sensors, despite being relatively simple can predict the systems flow rate with a relative error lower than 2 % and an uncertainty lower than 5 %. Consequently, the soft sensor network consisting of the soft sensors for the pump and the valve can reliably detect differences of 6 % in flow rate between two soft sensor outputs. Thus, the network is capable to determine wear and its extent in eccentric screw pumps via data induced conflicts. To isolate the

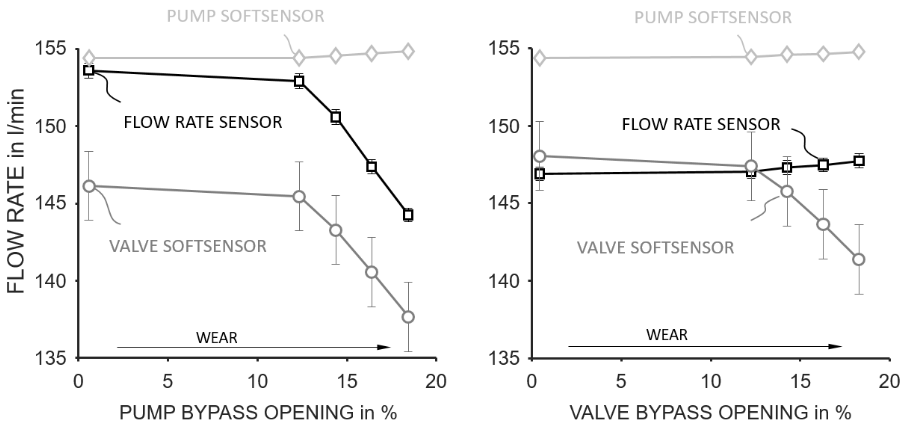

Figure 8: Results for combined wear with varying wear in pump (left) and varying wear in valve (right).

worn component additional information (e.g. temperature) is necessary.

Furthermore, the application of the proposed method shows, that the determination of the uncertainty of soft sensors is inevitable to reliably classify unavoidable data-induced conflicts in redundant data acquisition.

In future studies the concept should be tested with more complex systems. In addition to that, the transient behavior of the soft sensor network should be investigated.

ACKNOWLEDGEMENTS

This research has been funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation)–Projektnummer 57157498 – SFB 805

NOMENCLATURE

α	valve opening in %
K_v	valve parameter
$L_{\Delta p+}$	pump parameter
m	pump parameter
n	rotational speed
Δp	pressure difference
Δp_+	dimensionless pressure
$\Delta p_{\mathrm{valve}}$	valve pressure difference
Δp_0	atmospheric pressure
p_2	pressure sensor 2
p_4	pressure sensor 4
Q	volume flow rate
Q_{main}	main volume flow rate
ϱ	fluid density
ϱ_0	density of water
V	geometric volume
ν	kinematic viscosity

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