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Towards digitalization of hydraulic systems using soft sensor networks

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Today buzzwords like "smart machine" and "intelligent component" dominate the discussion about digitalization in the fluid power domain. However, the engineering fundamentals behind the words "smart" and "intelligent" often remain unclear. A common and target-oriented discussion needs transparent approaches including the applied technical system understanding. Therefore, this paper presents new concepts of soft sensor networks which allow the aggregation of information about fluid systems from heterogeneous sources. Soft sensors presented in this paper are physical models of system components that ensure transparency. Soft sensors and soft sensor networks are applied on exemplary hydraulic systems on three different levels: (i) the sensor level, (ii) the component level and (iii) the system level.

Keywords: soft sensor network, digitalization, condition monitoring, predictive maintenance
Target audience: mobile and stationary hydraulics, component manufacturers, system operators

1 Introduction

As the motto of the 11th IFK „Fluid Power Networks" states, the digitalization in the fluid power industry is becoming more and more important. New applications and functionalities are developed and may be a competitive advantage on the market. At the same time, hydraulic systems are characterized by their high power density, high reliability and good controllability for varying load requirements. Typically, such systems contain positive displacement pumps, hydraulic motors for energy conversion, accumulators for energy storage and valves to realize the control.

Despite of the high technical demands, hydraulic systems usually face a high cost pressure because of strong competition. Thus, implementing new digital features, such as integrated sensors, condition monitoring and predictive maintenance solutions are challenging. Integrating expensive hardware and sensors into hydraulic components can only be considered for high-end applications due to financial reasons. Furthermore, today's discussion about digitalization of the fluid power domain is dominated by buzzwords like "smart machine" or "intelligent component". However, the engineering fundamentals behind the word "smart" and "intelligent" often remain unclear and the conflict between cost pressure and the realization of new features is neglected. Given this background, soft sensors are a promising and cost effective solution.

Soft sensors are models of system components that allow the calculation of system variables. In control theory, soft sensors are usually called "observer". For their implementation, affordable computer hardware is necessary. The recent price drop of electronic hardware offers possibilities for a wide range of applications. The Raspberry Pi zero is a representative example. The fully equipped computer is half the size of a credit card and available for 5 $.

This paper presents new concepts of soft sensor networks combining multiple soft sensors to exchange and to gain information about technical systems derived from heterogeneous sources. All presented soft sensors are based on physical modelling and, thus, on clear fundamentals of engineering. The capability of soft sensors to contribute to the digitalization in hydraulic applications is demonstrated in this paper by focussing on three different levels: (i) the sensor level, (ii) the component level and (iii) the system level. Each application level is motivated by its own research question: (i) How can costs of hardware measurement equipment be reduced? (ii) How can components become self-aware and environmental-aware? (iii) How can additional information on system level be generated and used for predictive maintenance?

To address these research questions, in section 2 this paper gives a brief literature review on soft sensors and presents the further development based on hybrid soft sensors. Section 3 presents the soft sensor application on sensor level and discusses cost reduction as well as the calculation of immeasurable system variables by means of a pressure accumulator. Section 4 focuses on the soft sensor application on component level. Based on a simple fluid the implementation of a self-aware pump that recognizes its or the system's changing characteristic due to wear is discussed. Section 5 presents the soft sensor application on system level where each component is represented by a soft sensor. In this way, a redundant data acquisition based on different soft sensors is possible and allows data induced conflicts. Data induced conflicts are used as an indicator of changed system behaviour and provide an approach for predictive maintenance. Finally, section 6 gives a conclusion and an outlook on future research.

2 Soft sensors and soft sensor networks

Literature review

Soft sensor is the abbreviation of "software sensor" and represents a cyber physical system that measures a subset of system variables $X_{i,m}$ of a process and, on this basis, computes unknown system variables $X_{i,c}$ of this process. For this purpose, process models are needed to describe the relation $X_{i,c} = f(X_{i,m})$. These models can be subdivided into the following three main categories: (i) physical models, (ii) empirical models and (iii) data-driven models based on machine learning algorithms (e.g. artificial neural networks) /1/ /2/ /3/.

Initially, the process industry, with its challenging conditions like plant size, rough environment for measuring equipment and high costs concerning machine downtime, motivated the usage of soft sensors in the 1990s. Facing the high complexity of technical processes, an analytical description often is not possible. Hence, given the availability of historical plant data, most of the soft sensors in the process industry are based on data-driven models and artificial neural networks. Their main use is to back-up measuring devices, to replace hardware sensors, to estimate system variables for condition monitoring and controlling as well as to detect failure. In this context, Fortuna et. al. /4/ and Desai et. al. /5/ prove the use of soft sensors in distillation columns and batch bio-reactors, respectively. Furthermore, Kadlec et. al. /6/ give a detailed overview of further applications of soft sensors in the process industry.

Nowadays, soft sensors can be found in various fields of applications, e.g., manufacturing or chemical industry. A new field of application are fluid systems. Here, soft sensors are mainly used to replace the volume flow measurement, since flow metering entails high acquisition and installation costs. Concurrently, flow control is the most important control strategy in industrial applications /7/. Against this background Ahonen /8/ and Leonow et. al. /9/ 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. /10/ 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, soft sensors have already entered the centrifugal pump industry. The pump manufacturers Grundfos and KSB developed the Alpha 3 series /11/ and the PumpMeter /12/, respectively. Both soft sensors allow the model based determination of the volume flow rate in the current operating point of the pump.

New view on soft sensors

In contrast to the reviewed literature, a classification of soft sensors in distinct models needs to be overcome. Instead it is useful to combine different approaches developing hybrid soft sensors. Hybrid soft sensors are characterized by the combination of methods of problem condensation, e.g. dimensional analysis, cf. Pelz et. al /13/, domain specific knowledge (axiomatic and empiric models) and data-driven models. Figure 1 illustrates a generic hybrid soft sensor as a stack of filter disks representing the capability to combine, exchange and expand different approaches.

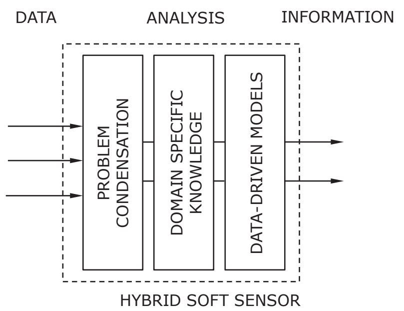

Figure 1: "Filter disks" of a hybrid soft sensor.

From this perspective, a soft sensor needs to be implemented as a digital twin of a respective component. In order to create synergies and to gain information, the exchange of information of the multiple soft sensors is necessary and useful. Consequently, this leads to soft sensor networks. Figure 2 shows the generic approach of a soft sensor network applied on the example of a hydraulic drive system. In the first step, electric signals are measured that are used by soft sensors to gain data based on their implemented models. In the second step, all data of the soft sensors needs to be merged. This allows a detailed analysis to gain information on system level and forms a basis for applications like predictive maintenance.

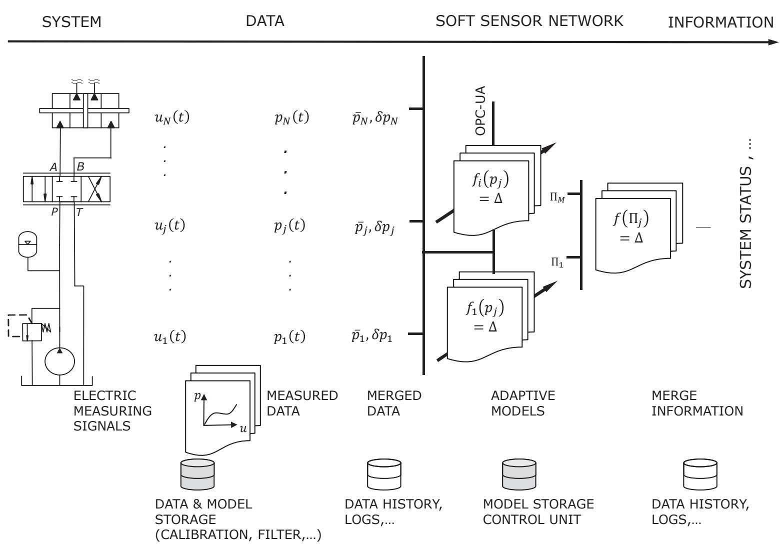

Figure 2: Generic approach to aggregate system information based on a soft sensor network.

3 Sensor level – cost reduction in hydraulic systems

As mentioned above, high cost pressure often prevents the use of expensive measurement equipment in hydraulic applications. From this perspective, the use of soft sensors provides a useful opportunity to realize the determination of desired system variables. Particularly in regard to hydraulic components, a large number of models already exists and is given by well-known literature /14/ /15/. On this basis, the application of soft sensors in the hydraulic domain suggests itself. In the following, the model of a pressure accumulator given by Pelz and Buttenbender /16/ serves as an illustrative example of a soft sensor application and its advantage usage.

The knowledge of the time-dependent energy content of a pressure accumulator during operation is often desired, but the metrological determination is costly and, thus, usually not considered. However, applications like the *Hybrid Air* of the PSA Group /17/ require the quantification of the energy content. As shown by Pelz and Buttenbender /16/, this is possible with axiomatic description of the time-dependent behaviour of a pressure accumulator by means of only three equations:

1. The equation of continuity that considers the temporal change of the density ϱ and the volume V, the mass flow rate at the inlet $\dot{m}$, i.e. the product of the density ϱ and the volume flow rate Q, and the mass flow rate due to permeability $\dot{m}_{perm}$

$$V\frac{\mathrm{d}\varrho}{\mathrm{d}t} + \varrho Q + \dot{m}_{perm} = 0. \tag{1}$$

2. The equation of energy that considers, firstly, temporal change of the volume specific inner energy, i.e. the product of the density ϱ, the isochoric heat capacity c_V and the gas temperature T, secondly, the enthalpy flow due to mass flows at the inlet and due to permeability, multiplied with the isobaric heat capacity c_p and gas temperature T, and thirdly, the heat flow due temperature difference between gas temperature T and ambient temperature T_U with the accumulator surface A and the heat transfer coefficient k

$$V\frac{\mathrm{d}\varrho c_V T}{\mathrm{d}t} + \left(\varrho Q + \dot{m}_{perm}\right)c_p T + kA(T - T_U) = 0. \tag{2}$$

3. The thermal equation of state of an ideal gas considering the pressure p as a function of the density ϱ, the gas constant R and the temperature T

$$p = \varrho R T. \tag{3}$$

With known initial conditions $p(0) = p_0$, $T(0) = T_0$ and the integrated volume flow Q that gives the time-dependent volume V

$$V = V_0 + \int_0^t Q\mathrm{d}t\,, \tag{4}$$

the solution of the non-linear equation system (1) to (3) is possible and all remaining unknowns, i.e. the pressure p, the temperature T and the density ϱ, can be calculated. Pelz et. al. /16/ proof a good correlation between the numerical solution and the solution of the linearized description. Given the transmission function, the description of the time-dependent behaviour of a pressure accumulator including the energy content only needs the measured volume flow rate at the inlet. At this point, calculated values of the volume flow rate (see section 5) may also serve as input and can replace the rather costly measurement of the volume flow rate. As the example shows, the implementation of soft sensors on the sensor level can reduce the expenses for measuring equipment.

4 Component level – self-aware and environmental-aware components

During operation, components of a fluid system will change their characteristics due to wear. However, the operator must ensure that the fluid system still fulfils its function permanently or needs to identify the worn out component in the case of a malfunction. On the other side, it is in the interest of each component manufacturer to be aware if his component or another system component, i.e. the system environment, caused a malfunction of the system. From both points of views, a self-aware and environmental-aware component that detects its changing characteristic and describes it quantitatively is of high interest. Consequently, this leads to the research question *how can components become self-aware and environmental-aware*?

Soft sensors are able to provide a solution, which is demonstrated on an exemplary generic fluid system, shown in Figure 3. This case example considers the perspective of a pump manufacturer whose pump is used in an unknown fluid system. From this point of view, only parameters of the pump, e.g. size, control, power supply and the working fluid are known. Regarding the pump, the complete environment, e.g. valves, filters or similar, can be described as one generalized resistance. Furthermore, the pressure and temperature are measured at the outlet of the pump. The function of the fluid system is to realize a specified volume flow rate.

In the case of wear, three scenarios are possible: Firstly, the pump characteristic changes, secondly, the system environment characteristic changes or, thirdly, both characteristics change. In either case, the function, i.e. the volume flow rate, will change and must be controlled, e.g. via the pumps rotating speed. At this point, the manufacturer needs a soft sensor of his pump and a soft sensor of the system environment monitoring the pump's conditions. In the following subsections, both soft sensors and their fusion to a self-aware and environmental-aware pump are presented and discussed.

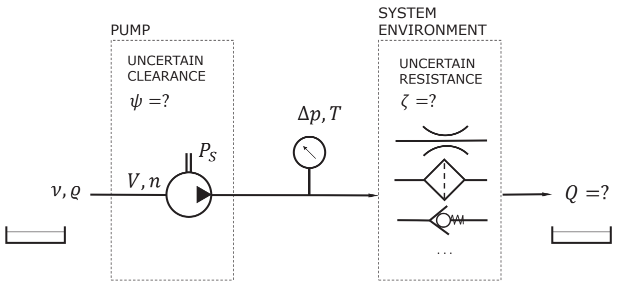

Figure 3: Schematic view of a generic fluid system.

4.1 Soft sensors of the pump and the system environment

The function of the exemplary fluid system shown in Figure 3 is to realize a specified volume flow rate. The volume flow rate is a conservation variable that is equal for the pump and the environmental system. Hence, it is the starting point of both soft sensors.

Considering the pump, the volume flow rate Q is the difference between the theoretical volume flow Q_{th} and the internal leakage Q_{l}. The theoretical volume flow Q_{th} is the product of the geometric volume V and the rotation speed n that lead to the description of the volume flow rate

$$Q = nV - Q_l. \tag{5}$$

The internal leakage $Q_l = Q_l(\Delta p, \nu, \varrho, V, \psi,)$ is derived by Pelz et. al. /13/ to be a function of the pressure Δp, the working fluid properties, i.e. kinematic viscosity ν and density ϱ, and the geometric parameters of the machine, i.e. the geometric volume V and the relative gap ψ. Taking dimensional analysis into account, Pelz et al. /13/ develop a semi-analytical model of the volumetric efficiency η_{vol}

$$\eta_{vol} = 1 - \frac{1}{Re}\; Q_l^+(\psi, \Delta p^+), \tag{6}$$

with the Reynolds number Re and the specific internal leakage Q_L^+. The specific internal leakage Q_L^+ is a function of the specific pressure Δp^+ and relative gap ψ. The mentioned dimensional numbers are defined as

$$\eta_{vol} := \frac{Q}{nV}, \qquad Re := \frac{nV^{2/3}}{\nu}, \qquad Q_L^+ := \frac{Q_L}{\nu V^{1/3}}, \qquad \Delta p^+ := \frac{\Delta p}{\nu^2 \varrho V^{-2/3}}. \tag{7}$$

Equation (2) represents a soft sensor for the pump characteristic and is mathematically described by

$$\eta_{vol} = 1 - \frac{L}{Re}\; (\Delta p^+ \psi^3)^m \tag{8}$$

with the empiric pump parameters L and m. Hence, the volume flow rate is represented by the dimensionless volumetric efficiency of the pump. Furthermore, the effect of wear in the pump can be described by an increase of the relative gap ψ, that leads to a higher internal leakage. Consequently, the relative gap ψ is uncertain and needs to be determined during operation.

At the same time, the unknown system environment of the pump can be modelled by a generic resistance

$$\Delta p = \frac{\varrho}{2} \zeta' \left(\frac{Q}{A}\right)^2 \tag{9}$$

with a loss coefficient ζ' and the unknown cross section A. Equation (5) describes the pressure loss in the system environment as a quadratic dependence of the volume flow rate. By means of dimensional analysis the generalized loss coefficient is defined as

$$\zeta := \zeta' \frac{V^{4/3}}{A^2} \tag{10}$$

and leads to a dimensionless representation of the generic resistance

$$\Delta p_+ = \frac{1}{2} \zeta\, Re^2 \eta_{vol}^2 \tag{11}$$

with the known dimensionless numbers of equation (7). The unknown cross section A does not occur anymore. The effect of wear in the system environment can be described by a change of the generalized resistance ζ. Like the relative gap ψ of the pump, the generalized resistance ζ is uncertain and needs to be determined during operation.

At this point, there are two soft sensors, equation (8) and equation (11), that contain the three unknowns: Firstly, the volume flow rate Q or volumetric efficiency η_{vol}, secondly, the relative gap ψ and, thirdly, the generalized resistance ζ.

Thus, one further equation is necessary to complete the equation system allowing the calculation of the three unknowns during operation. For this purpose, the model of the hydro-mechanical efficiency η_{mh} of the pump by Pelz et. al /13/ can be applied

$$\eta_{mh}^{-1} = 1 + \frac{2\pi}{1 - \kappa_+}\left(C + R_\mu \frac{Re}{\Delta p^+ \psi} + R_\varrho \frac{Re^2}{\Delta p^+}\right) \tag{12}$$

with the known dimensionless compressibility κ_+ of the working fluid. The dimensionless numbers are defined as

$$\eta_{mh} := \frac{\Delta p V n}{P_S}, \qquad \kappa_+ := \kappa \Delta p / 2. \tag{13}$$

C, R_μ and R_ϱ are empiric pump parameters. The relative gap ψ occurs in the model of the hydro-mechanical efficiency as well, as equation (12) shows.

4.2 Fusion to a self-aware and environmental-aware pump

The soft sensor network based on the three soft sensors, i.e. equation (8), (11) and (12), now allows the sequential calculation of the three unknowns, the volumetric efficiency η_{vol}, the relative gap ψ and the generalized resistance ζ during operation. The approach is as follows:

4. The relative gap ψ is calculated from equation (12) on the basis of the known empiric pump parameter, the geometric volume, the measured quantities, i.e. pressure, temperature, rotating speed and shaft power. The working fluid properties, i.e. viscosity, density and compressibility, have to be calculated from rheological models, e.g. the Arrhenius law, and the temperature.
5. The volumetric efficiency η_{vol} is calculated from equation (8) and the known relative gap ψ.
6. The generalized resistance ζ is calculated from equation (11) and the known volumetric efficiency η_{vol}.

Within this framework, the pump manufacturer is able to monitor and describe the condition of his pump quantitatively by means of the relative gap ψ and, at the same time, knows if the pump or the system environment causes a malfunction, i.e. providing an unspecified volume flow rate.

In summary, the presented soft sensor network consists of five layers and represents the above presented approach from simple data measurement to a self-aware and environmental-aware pump. According to Figure 4, the five layers of the soft sensor network are (i) the supply of additional information, eq. rheology, (ii) the problem condensation by means of dimensional analysis, (iii) the domain specific knowledge of fluid systems, (iv) the equation solver and (v) the presentation of problem specific key performance indicators (KPI) in a cockpit to the manufacturer or operator.

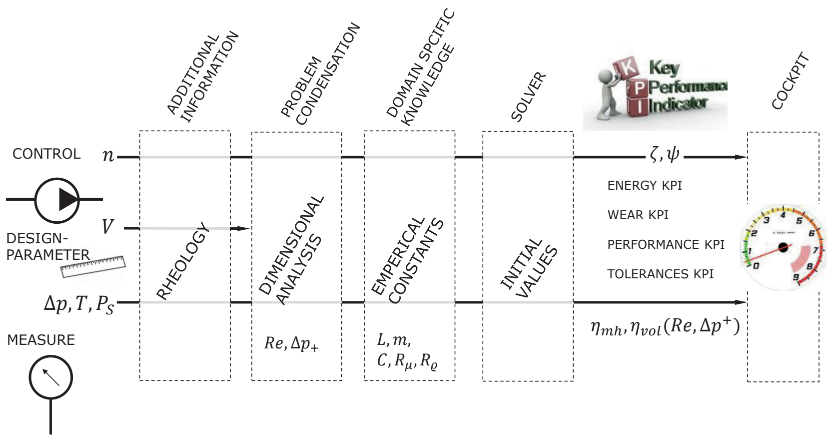

Figure 4: Application of the filter disks (Figure 1) resulting in five layers of a soft sensor network for ζ and ψ.

The approach to a self-aware pump was also examined experimentally on a test bench by means of two identical screw pumps: One screw pump without wear and one screw pump with modified gaps, according to typical signs of wear /18/. The examination includes the measurement of characteristic curves, i.e. pressure and volume flow rate, at a constant rotating speed for two different oils. Furthermore, the sequential calculation of the two unknowns of the worn out pump, i.e. the relative gap ψ and the volume flow rate Q, is performed. On this basis, a validation of presented approach according the self-aware pump is possible. Figure 5 shows the validation results by means of the measured characteristics curves of both, the screw pump without wear and the worn out screw pump, and the calculated characteristic curve of the worn out pump by the soft sensor. The soft sensor and measured values show a very good correlation in the case of an oil with a kinematic viscosity of 22 cSt, as shown in Figure 5a). The calculated and measured values in the case of an oil with a kinematic viscosity of 54 cSt show a slight deviation, but still underline the application ability of the approach under the named conditions.

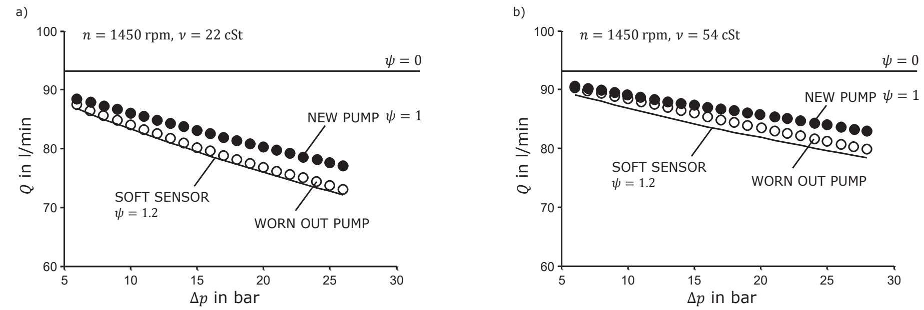

Figure 5: Validation of soft sensor network approach on screw pump with and without wear.

5 System level – data aggregation in hydraulic systems using soft sensor networks

As already mentioned, hydraulic systems face a high cost pressure on the market. Installation and maintenance require highly qualified professionals. Thus, not only the initial purchase and installation costs, but also the operating and maintenance costs are of high interest. Against this background, predictive maintenance is closely connected to significant cost saving potential /19/. Since these cost saving will occur over the operating time, the advantage is not directly seen by the customer. Thus, additional costs for predictive maintenance solutions are rarely accepted on the market.

While section 4 is discussing the use of soft sensors on the component level, for fluid systems containing multiple hydraulic components, the application and connection of soft sensors on every component, i.e. a soft sensor network, is useful. As Aristotele's proverb has it "the whole is greater than the sum of its parts", data of all single soft sensors need to be merged and are supposed to generate additional information. This is of high interest, since additional information on the system level comes "for free" without the need of additional sensor equipment. Consequently, the question raises "how can additional information on the system level be generated and used for predictive maintenance?"

Under the assumption of a constant density of the working fluid and no external leakage, the volume flow rate represents a conservation variable of each fluid system. Thus, the volume flow rate is an information carrier between the corresponding soft sensors and allows its redundant calculation by different soft sensors. Now two scenarios are possible: Firstly, the calculated data is consistent and verified. Secondly, contradictory statements about the volume flow rate occur. Such contradictory statements are called data induced conflicts and can have different reasons: (i) A measuring sensor breaks down or becomes defective. (ii) The inconsistent data results from model uncertainties of the soft sensors. (iii) Single system components characteristics change due to wear. Hence, a data induced conflict is an indicator for uncertainty in the fluid system. On the other side, the resolution of a data induced conflict provides a basis for predictive maintenance, e.g. the identification of a worn out component before breakdown.

The following approach is developed within the Collaborative Research Center 805 "Control of Uncertainties in Load-Carrying Structures in Mechanical Engineering" at the Technische Universität Darmstadt. The first step is obvious. Data induced conflicts have to be allowed by means of redundant data acquisition of a soft sensor network. In the second step, the cause of the data induced conflict has to be classified into (i) sensor break down, (ii) soft sensor uncertainty or (iii) component characteristic change. The following action depends on the classification of the conflict. In the first case, a sensor breakdown is usually identified by the time history of the sensor. If the signal suddenly changes or interrupts, either the sensor needs to be replaced or the soft sensor must ignore it. In the second case, soft sensors need to be based on validated models meaning the model uncertainty is known and quantified. Thus, a data induced conflicts caused by model uncertainty can be identified and has to be accepted. The third case occurs as soon as the two previous cases are excluded. The worn out component needs to be identified, monitored and replaced or repaired before its breakdown. At the same time, its soft sensor model needs to be adapted to the changed characteristic (as shown in section 4 of this paper). The identification process of the worn out component requires the resolution of the data induced conflicts, which is still a subject of current research.

As a proof of concept for data induced conflicts, the change of a component characteristic due to wear is discussed by means of a simple fluid system consisting a pump and a valve. The data induced conflict due to wear in the valve is illustrated in Figure 6. Figure 6 shows the qualitative characteristics of the pump and the valve which are used to calculate the volume flow rate as a function of the measured pressure. In addition, the known measurement and model uncertainties are taken into account. Without wear the intersection of the model curves will determine the operation point. In this case, the calculated flow volume rate of both pump and valve model will be equal. However, if wear occurs in the valve, its characteristic curve will change, and, consequently, the operation point will change as well. The volume flow rate increases and the initial model curve will not represent the valve behaviour anymore. This leads to an incorrect calculation of the volume flow rate by the soft sensor of the valve. Consequently, the calculation of the volume flow rate based on the pump Q_{P} and the valve Q_{V} will differ and a data induced conflict occurs.

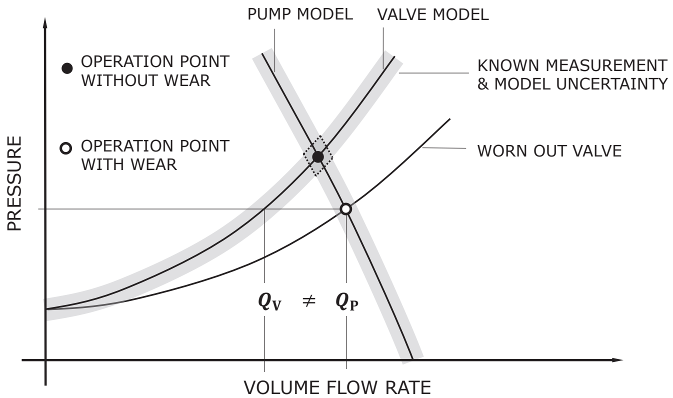

Figure 6: Data induced conflict due to a worn out valve.

The presented approach was applied on a hydraulic test bench at the Chair of Fluid System at the Technische Universität Darmstadt. The test setup contained a screw pump operating against a worn out manual throttle valve. The measured variables are the rotating speed of the pump, pressure differences of the pump and the valve, valve lift as well as the working fluid temperature. The working fluid is a hydraulic oil (ISO VG 22).

The models used at the test bench are shown in Figure 7. The pump model (Fig 7a)) calculates the internal leakage of pump (see Section 4.1.). Taking the rotating speed and geometric volume into account, equation (5) determines the volume flow rate. Pelz et. al show the derivation and calibration of the model in /13/. Figure 7b) shows the characteristic curve of the valve for different valve lifts h. Figure 7 c) and d) illustrate the dependence of the viscosity and density from the temperature, respectively. The viscosity is calculated by the Arrhenius law and the density is calculated by a trivial interpolation of measured values.

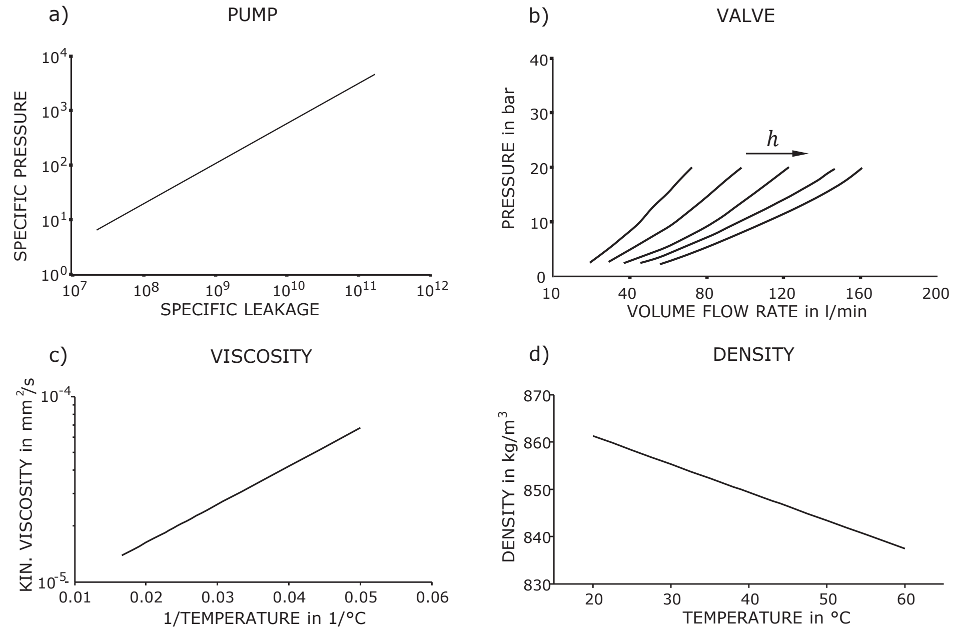

Figure 7: Models used at the test setup.

The measured volume flow rate of both soft sensors, the pump and the valve, for different operating points is shown in Figure 8. The error bars describe the model and measurement uncertainty. For the operating points 1 to 4 the difference between the two soft sensors exceeds the corresponding uncertainty and, thus, a data induced conflict occurs and indicates a worn out component, which, in this example, is the valve. Consequently, the measurements show, that the concept of data induced conflicts is applicable to hydraulic systems.

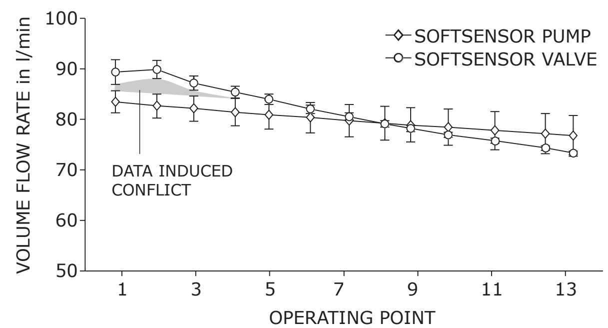

Figure 8: Measurement results for two different soft sensors, describing a pump and a valve.

However, in the experimental setup the worn out component is known and the resolution of the data induced conflicts is not necessary. In a predictive maintenance context, the solution of the data induced conflict is the key. That is why the collaborative research center 805 is carrying out further research on this subject focusing on the three promising approaches: (i) identification of anomalies in data time series, (ii) enabling further redundancies by other hydraulic components (e.g. accumulators, filters) and (iii) voting logics, as known from the aviation industry.

6 Conclusion

This paper presents new concepts of soft sensor networks demonstrating the capability of soft sensors to contribute to the digitalization in hydraulic applications. Hence, soft sensor network applications on three different levels, (i) sensor level, (ii) the component level and (iii) the system level, are presented by means of exemplary fluid systems. All soft sensors are based on physical modelling and, thus, clear fundamentals of engineering. On the sensor level, the focus is on the cost reduction saving expensive measurement equipment. On the component level, the implementation of a self-aware and environmental-aware pump is presented. Finally, on the system level, the advantageous use of data induced conflicts for predictive maintenance is discussed.

Following the presented concepts, the next steps are further experimental investigation of soft sensor networks as well as research on the resolution of data induced conflicts. Furthermore, an operational predictive maintenance application by means of an exemplary fluid system needs to be developed. To do so, further filter disks are applied to form a hybrid soft sensor, as shown in Figure 1. In this way, transparent and implemented approaches will support a common and target-oriented discussion. These investigations will be carried out within the framework of the Collaborative Research Centre (CRC) 805 "Control of Uncertainty in Load Carrying Structures in Mechanical Engineering" of Technische Universität Darmstadt.

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Nomenclature

The first column of the following table shows the symbols utilized for physical and mathematical quantities. The second column shows the meaning of each quantity. The dimension of each physical quantity is denoted in the third column, based on the generic quantities length (L), mass (M), time (T) and temperature (Θ).

Variable	*Description*	*Dimensions*
V	Volume	L^3
ϱ	density	ML^{-3}
t	Time	T
Q	Volume flow rate	$L^3\ T^{-1}$
$\dot{m}_{perm}$	Mass flow rate due to permeability	MT^{-1}
c_v	Heat capacity	$L^2T^{-2}\Theta^{-1}$
T	Temperature	Θ
c_p	Isobaric heat capacity	$L^2T^{-2}\Theta^{-1}$
k	Heat transfer coefficient	$MLT^{-3}\Theta^{-1}$
A	Surface Area	L^2
T_u	Ambient Temperature	Θ
p	Pressure	$ML^{-1}T^{-2}$
R	Gas constant	$L^2T^{-2}\Theta^{-1}$
n	Rotational speed	T^{-1}
Q_l	Internal leakage flow rate	L^3T^{-1}
ν	Kinematic viscosity	L^2T^{-1}
ψ	Relative gap	1
η_{vol}	Volumetric efficiency	1
Re	Reynolds number	1
Q_l^+	Specific internal leakage	1
Δp^+	Specific pressure difference	1
m	Empiric parameter	1
L	Empiric parameter	1
ζ'	Loss coefficient	1
η_{mh}	Hydro-mechanical effiency	1
κ_+	Dimensionless compressibility	1
C	Empiric pump parameter	1
R_μ	Empiric pump parameter	1
R_ϱ	Empiric pump parameter	1
P_S	Shaft power	ML^2T^{-3}
κ	Compressibility	$M^{-1}L^1T^2$
Q_P	Volume flow rate of the Pump	L^3T^{-1}
Q_V	Volume flow rate of the valve	L^3T^{-1}
h	Valve lift	L

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