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Controlling Uncertainty in Hydraulic Drive Systems by means of a Soft Sensor Network

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ABSTRACT

High power density, high reliability and good controllability for varying load requirements are typical characteristics of hydraulic drive systems used for power transmission in stationary and mobile applications. Furthermore, hydraulic systems are usually safety related systems. Consequently, the handling of uncertainties in hydraulic systems is essential. A major source of uncertainty is, in particular, the wear induced change of the system behavior. Nowadays, the most common way to face uncertainty is the oversized system design to ensure reliable system operation. However, the uncertainty remains. In the first part of the paper we present a general approach to face uncertainty by means of a soft sensor network. Soft sensor networks make it possible to gather system information redundantly. In this way the occurrence of data conflicts are allowed which serve as an indicator of uncertainty. The resolution of these conflicts either lead to increased confidence for the model-based system information or allows the detection of changing component characteristics. The application of a soft sensor network to a hydraulic drive system is illustrated and discussed in the second part of this paper.

Keywords: *control, uncertainty, hydraulic drive systems, soft sensor, network*

1. INTRODUCTION

Uncertainty in the usage phase of a technical component or a technical system can lead to downtime and, thus, is closely connected to additional expenses. To reduce costs and save resources there is a necessity to control uncertainty during the operation of a technical system. For this purpose the Collaborative Research Centre (CRC) 805 "Control of Uncertainty in Load Carrying Structures in Mechanical Engineering" of Technische Universität Darmstadt develops methodological and technological solutions to describe, quantify and control uncertainty. In this context, a new approach based on a soft sensor network was developed which provides a high potential to face and control uncertainty during operation.

In this paper, firstly, we present our general approach and, secondly, illustrate its application on the example of a hydraulic drive system. Our key research question is: How can the uncertainty of a hydraulic drive system be controlled by means of a soft sensor network? Since hydraulic drive systems are usually safety related systems the control of uncertainty is of major interest. For this purpose various sources of uncertainty as well as the control of uncertainty are discussed.

2. SOFT SENSOR NETWORK

Soft sensor is the short version of software sensor and represents a cyber physical system that measures a subset of state variables $X_{i,\mathrm{m}}$ of a process and, on this basis, computes unknown state variables X_c of this process. For this purpose process models that describe the mathematical relationship $X_c = f(X_{i,\mathrm{m}})$ are needed. These models can be subdivided into the following three main categories: (i) physical models, (ii) data driven (statistical) models and (iii) models based on machine learning algorithms (e.g. artificial neural networks). In control theory a soft sensors is equivalent to an observer. From the numerous publications that deal with soft sensors, Fortuna et al. [1], Chéruy [2] and Luttmann et. al. [3] give a useful generic functional principle of a soft sensor, summarized in figure 1.

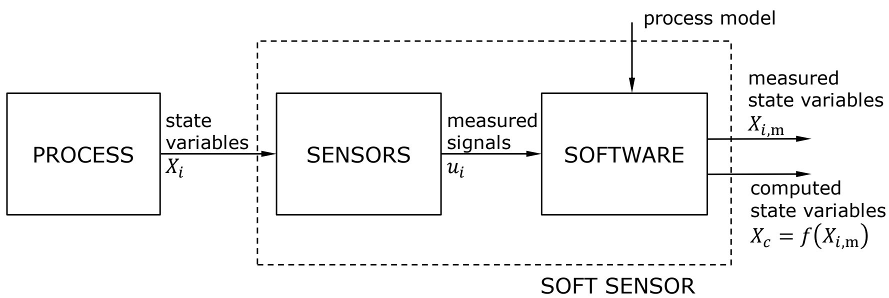

Fig. 1 Generic functional principle of a soft sensor

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 state variables for condition monitoring and controlling, and 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 are found in various fields of applications, e.g., manufacturing or chemical industry. A new field of application are fluid systems. 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 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 pump industry. The pump manufacturers *Grundfos* and *KSB* developed the *Alpha 3series* [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.

An essential prerequisite for the implementation of soft sensors is the affordable computer hardware. Firstly, to collect measuring signals and, secondly, to gain useful information out of these signals based on the models of the soft sensors. In recent years powerful computer hardware and micro controllers have become available on a very low budget. The most famous representative of this family is the *Raspberry Pi*, which is developed by the *Raspberry Pi foundation* [13]. The credit card sized system on a chip offers everything a basic desktop computer does. Additionally, it has a programmable general purpose in- and output pins that allow communication with the environment, e.g. sensors or analog to digital converters. The cheapest model is available for only 5 $. Nevertheless, it is emphasized that soft sensor models do not necessarily rely on local computing devices, e.g. a Raspberry Pi, but can also be stored and executed via cloud computing. It allows the collection, computing and provision of data. If the process requires real time estimates, e.g. control purposes, there exists a wide variety of cheap micro controllers, for example the *Arduino* [14]. Unlike the Raspberry Pi they don't bring a complete operating system, but they are robust and easy to use. Hence, the cost efficient availability of electronic components offers the possibility to create a soft sensor network out of multiple soft sensors.

In contrast to the presented soft sensor concepts our approach aims at calculating single system state variables redundantly. This needs a soft sensor network which consists of multiple soft sensors calculating the same system state variables. One the one hand redundant data can increase the quality of information of our system. However, this only applies if the data is consistent. On the other hand redundant data based on heterogeneous sources without any knowledge of their uncertainty often leads to conflicts and contradictory statements, so called "data induced conflicts". The idea is to use such data induced conflicts as an indicator for uncertainty. Hence, as a first step, one needs to allow data induced conflicts. In the present case data induced conflicts are caused by inconsistent data from different soft sensors. The source of such data conflicts may have different reasons: (i) A measuring sensor breaks down or becomes defective. (ii) The inconsistent data is a result of model uncertainties of the soft sensors. (iii) Single system components characteristics change, e.g., due to wear. As a second step these conflicts need to be solved. In particular in the usage phase of a technical system the data induced conflicts are relevant to security and their resolution has the highest priority. First of all the source of the conflict needs to be found out. For this purpose physical or experience-based boundary conditions have to be checked. Furthermore the analysis of time courses of each soft sensor is necessary. Secondly, the data induced conflict needs to be solved. One promising way to respond to data induced conflict based on changing system behavior is to adapt the model of the soft sensor. The resolution either leads to greater confidence for the model-based system state variables or allows the detection of changing components characteristics. The benefit of our approach is as follows: On the one hand, the detection of a changing system behavior can be used for predictive maintenance which leads to a reduction of operational costs. On the other hand, soft sensors enable the monitoring of the time-varying system state, e.g., energy supply of a hydraulic accumulator, and allow an anticipation of future operating strategies. In this context, Utz et. al. [15] demonstrated the use and advantage of the anticipation of future operation strategies for hydraulic drive systems based on a known energy supply. In this regard, the *Hybrid Air* concept of the *PSA Groupe* is another well-known example.

Figure 2 shows our generic approach to aggregate system information based on a soft sensor network. In the first step the soft sensors measure electric signals and gain data based on their implemented models. In the second step all the data of the various single soft sensors needs to be merged and analyzed. This data base allows data induced conflicts whose resolution leads to information on the system status and to the control of uncertainty.

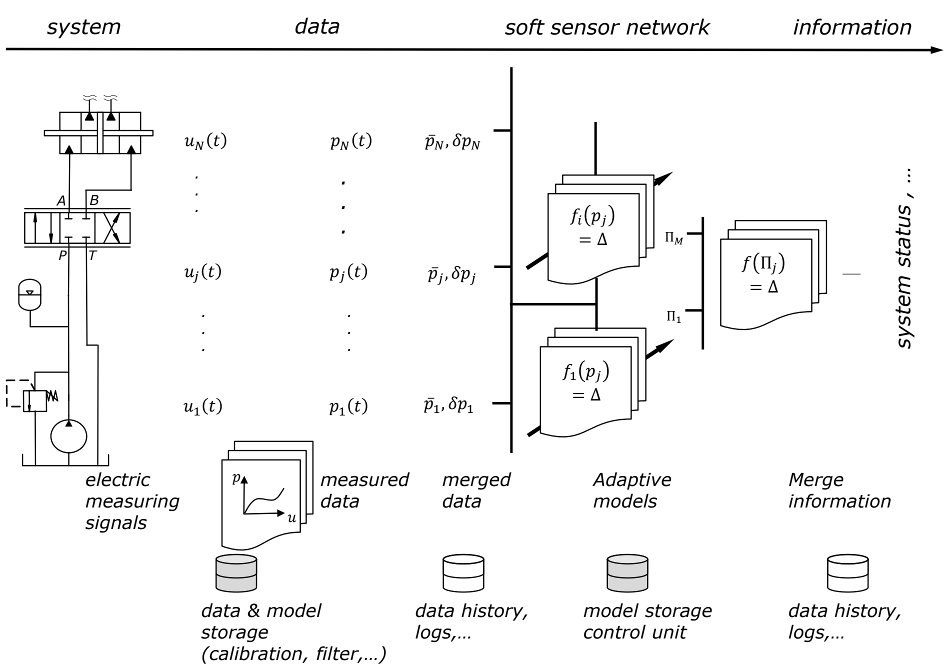

Fig. 2 Generic approach to aggregate system information based of a soft sensor network

3. APPLICATION OF A SOFT SENSOR NETWORK TO A HYDRAULIC DRIVE SYSTEM

Hydraulic drive systems are used for power transmission in stationary and mobile applications, e.g., in construction machinery or upper class vehicles [16]. These systems are characterized by their high power density, high reliability and good controllability for varying load requirements. The essential components of a hydraulic drive system are a positive displacement pump to convert mechanical power into hydraulic power, a valve to control the volume flow rate and a hydraulic motor to convert hydraulic power back into mechanical power. Usually hydraulic drive systems also include a hydraulic accumulator. Hydraulic accumulators can fulfill different functions. They may serve to store energy storage, to cover a high volume flow rate demand, to compensate leakage or to absorb pressure pulsations.

Since hydraulic drive systems fulfill an important role to realize functions of superior applications they are usually considered as safety related systems. For this reason, the control of uncertainty is of major interest. Besides the two sources of uncertainty of the soft sensors, the breakdown of a measuring sensor and consequently of the soft sensor and the model uncertainty which is known in the case of validated physical models, the third source of uncertainty, the wear induced change of the components characteristics is in the focus of the following considerations. The detection of a changing system behavior at an early stage makes predictive maintenance possible and helps to prevent the failure or down time of the hydraulic drive system. On the other hand it means to control uncertainty and to make fixed maintenance intervals superfluous at the same time. By this means, the maintenance costs can be reduced significantly. Another source of uncertainty we focus on is the availability of the energy supply when using a hydraulic accumulator as an energy storage. Usually the energy content of the hydraulic accumulator remains unknown as the metrological determination is too cost expensive and, thus, the anticipation of future operation strategies is not possible.

Nowadays, the most common way to face uncertainty is the oversized system design to ensure reliable system operation. However the uncertainty is not controlled but remains and, consequently, costs may increase. In the following, axiomatic models of the mentioned components of a hydraulic drive system are presented. All these models serve as a basis of a soft sensor network enabling the calculation of the volume flow rate redundantly. As discussed earlier in this paper, the metering of the volume flow rate is costly and, hence, usually not carried out. The redundant calculation of the volume flow rate in turn pursues the aim of enabling the occurrence of data induced conflicts and by this means of controlling uncertainty.

Pelz et al. [17] developed a semi-analytical and type independent model that calculates the volume flow rate as a function of the pressure, rotating speed and working fluid properties. Typical working fluids are hydraulic oils that follow the Arrhenius equation giving a relationship between the viscosity and temperature. The model can be both applied to hydraulic pump and hydraulic motors. Furthermore it is possible to take manufacturing tolerances into account. The model of Vergé et. al. [18] also can be used to calculate the volume flow rate through a valve and, in addition, is able to take wear into account. The physical model of Pelz and Buttenbender [19] is based on the conservation equation for mass and energy, and thus, allows the calculation of the time varying energy content of the hydraulic accumulator. In summary, these scale models serve as a basis of a soft sensor network and only require the inexpensive measurement of the pressure, rotating speed and temperature. Besides enabling data induced conflicts, the soft sensor network provides the opportunity to calculate the energy content of the pressure accumulator and allow the anticipation of future operation strategies for hydraulic drive systems. The soft sensor network representing a virtual image of the real or technical system, in this case the hydraulic drive system, is shown in figure 3.

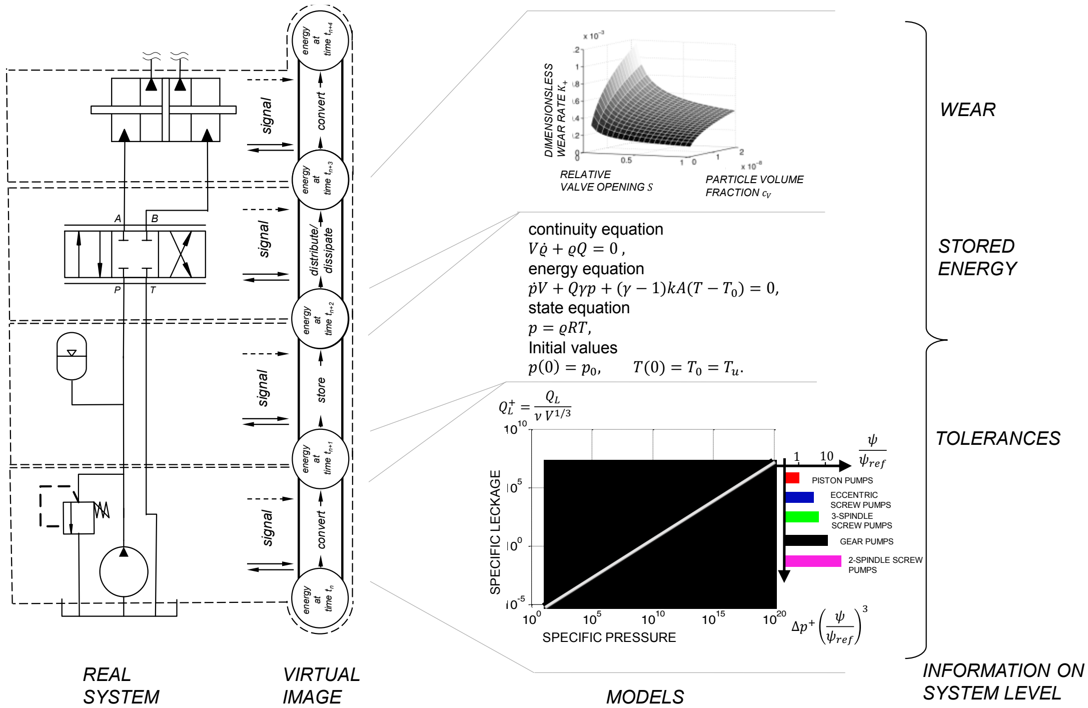

Fig 3 Soft sensor network of a hydraulic drive system

In the following, the occurrence of data induced conflicts due to wear, both in the valve and pump are illustrated in figure 4a and 4b, respectively. Both figures show the model curves of the pump and the valve which are used to calculate the volume flow rate as a function of the measured pressure. If no wear occurs 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 one single component, its characteristic curve will change, and consequently, the operation point will change as well. In the case of a worn out valve, the volume flow rate will increase (fig. 4a), in the case of a worn out pump, the volume flow rate will decrease (fig. 4b). In addition, the model curve will not represent the worn out component behavior anymore and lead to an incorrect calculation of the volume flow rate in each worn out component. Consequently, the calculation of the volume flow rate based on the pump and valve model will differ and will cause a data induced conflict. In both cases, the volume flow rate $Q_{\mathrm{P,m}}$ calculated by pump model will be higher than the volume flow rate $Q_{\mathrm{V,m}}$ calculated by the valve model.

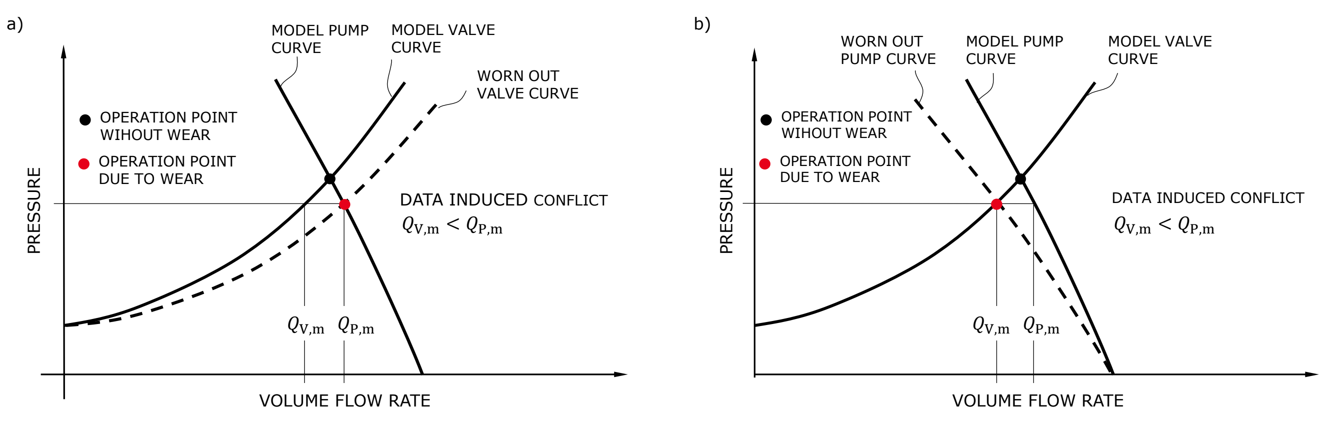

Fig 4 Data induced conflicts due to wear in the pump or valve

To resolve the presented data induced conflict, an analysis of the time courses of each component is a promising strategy. On the basis of the time courses a changing component characteristic needs to be detected and the worn out component needs to be identified. Subsequently, the model curve of the worn out component has to be adapted using the characteristic curves of the remaining components.

4. CONCLUSION

In this paper a general approach to control uncertainty in technical systems based on a soft sensor network is presented and different sources of uncertainty are discussed. A soft sensor network enables the redundant calculation of system state variables and, thus, allows the occurrence of data induced conflicts. Following the approach these data induced conflicts are an indicator of uncertainty. The resolution of the data induced conflicts leads to information on the system status and to the control of uncertainty. Controlling uncertainty makes predictive maintenance possible and helps to prevent the failure or down time of the technical systems. At the same time, it makes fixed maintenance intervals superfluous and leads to a reduction of maintenance costs. The approach is illustrated on a hydraulic drive system. For this specific application another source of uncertainty, the energy content of a hydraulic accumulator, can also be controlled by means of a soft sensor network.

Following the presented approach, the next step is the experimental validation of the soft sensor network by means of the presented hydraulic drive systems. Further research needs to focus on the resolution of data induced conflicts. 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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