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Observer Design using T-S Fuzzy Systems for pressure estimation in hydrostatic transmissions

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Abstract

Hydrostatic transmissions, also called hydrostatic gears, have been widely used in mobile working machines and off-road vehicles such as construction and agricultural machines. This kind of transmission offers important advantages like continuously variable transmission with high power density, maximum tractive force at low speeds and reversing without changing gear. The automatic electronic control of hydrostatic transmissions, which depend on a number of measurable values, has become more common in industrial practice. To ensure the reliability and safety at least a two-channel redundant system for the measuring channels is required.
In this paper, a general model-based approach using a Takagi-Sugeno (T-S) fuzzy observer for analytical redundancy of the oil pressure measuring process in hydrostatic transmissions is developed. It has been shown by experimental results that this approach can be used to estimate the pressure values under varying load conditions and different driving situations.

1. Introduction

Off-road vehicles, special construction and agricultural machinery are characterized by their mobility in different terrains and maximum performance under arbitrary load conditions. To enable the mobility of off-road vehicles the drive train of those machinery requires a continuously variation of the transmission ratio without interruption of tractive forces, high tractive forces at low speed and fast reversing operation. Drive trains with automatic controlled hydrostatic transmissions fulfil these demands, which are used more and more for mobile applications. Its usage allows a compact vehicle design, based on the possibility of a flexible arrangement of the transmission components.

The control system of hydrostatic transmissions depends on a number of measurable values such as the speeds of engine and hydrostatic motor, displacement of the hydrostatic pump and motor, different oil pressures in the closed circuit, and the position of the drive pedal. In modern mobile working machines, it is standard practice that the entire control of hydrostatic components, including safety-relevant functions such as traction force control or hydrostatic braking, is carried out by programmable electronic control units (ECUs) to an increasing extent. To ensure the system integrity of these safety-relevant functions, at least a two-channel redundant system for the measuring channels is required [1].
The main disadvantages of full redundant systems in standard applications are increasing costs and complexity without an increase of functionality of the working machine and finally for the customer. Mathematical models of hydrostatic transmissions reduce the need for measuring devices. In its simplest form this implies the use of a mathematical model running in real-time with the plant and driven by the same input signal as the plant. An extension of this is the observer-based approach involving feedback of the differences between the actual measured and calculated outputs [9].
Due to the nonlinear dynamics of the pressure evolution and the dependence on variable diesel engine speed a linear observer will not be able to reconstruct the oil pressure measuring process. A model-based approach using a Takagi-Sugeno (T-S) fuzzy observer for analytical redundancy is developed on the basis of this fact. It is shown by simulation studies and experimental results that this approach can be used to estimate the pressure values under varying load conditions.
A number of investigations on modeling hydrostatic transmissions with a variable displacement pump and a fixed displacement motor have been made: Firstly, in the early 80's Rydberg [10] presented a nonlinear simulation model con-

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sidering leakage flow losses. Research projects in the 90's such as [5], [11], used time-variable linear models for adaptive control concepts. Wochnik [16] developed a nonlinear state space model including nonlinear dynamics of the displacement unit of the pump and the main hydraulic circuit.
In order to investigate the steady state and dynamic characteristics, Huhtala [3] developed a nonlinear model with steady state loss models of *both displacement machines*, a variable displacement pump and motor. He uses command generators to determine the desired set values of the transmission input speed and the vehicle speed.
The concept of T-S fuzzy observer design in combination with state feedback controller by using Linear Matrix Inequalities (LMI) approach is considered for example in [7], [17], [13] and [4]. But, up to now just a few applications use this novel design approach in the context of analytical redundancy and fault tolerant control of nonlinear plants, refer to [6] and [8].
This paper is organized as follows: Firstly, in Section 2 a nonlinear state-space model of hydrostatic transmissions with a variable displacement pump and a variable displacement motor based on [12] is shortly presented. The nonlinear state-space system is transformed into a Takagi-Sugeno fuzzy system whereby the nonlinear terms are transferred into weighting functions using the sector nonlinearity approach [15]. After this, in Section 3, a reduced-order T-S observer design using LMI-based conditions is considered in detail. Finally, it has been shown by experimental results that, first, the proposed T-S model description of the plant is capable to represent the effective nonlinearities and, second, the designed T-S observer can be used for analytical redundancy under varying load conditions.

2. Modeling of Hydrostatic Transmissions

2.1. Description and nonlinear physical model

Figure 1 shows the configuration of a typical hydrostatic transmission. The combustion engine is connected to a hydraulic displacement pump (axial piston type), which is operated in a closed oil circuit with a hydraulic displacement motor. The motor is connected to a mechanical gear, which drives the axle of the vehicle.
The pressure level between the pump and the motor varies for each individual hose (pipe), depending on the operating range such as acceleration, near-constant speed or deceleration and parameters of the vehicle. The output speed of the hydrostatic transmission in Figure 1 is controlled by an electronic control unit (ECU) as follows: The current drive pedal position and selection of driving direction is converted by the ECU into electrical signals for controlling the electrohydraulic displacement elements. The displacement elements can be adjusted independently. Due to the displacement variation the desired transmission gear ratio can be adjusted, the volume flow and the load pressure in the closed oil circuit change and so do speed and torque of the hydromotor.
The hydrostatic transmission dynamics can be represented by a nonlinear fourth order state-space model [12] :

$$\begin{aligned}
\dot{x}_1 &= -\frac{1}{T_{u_P}}\, x_1 + \frac{k_P}{T_{u_P}}\, u_1 \\
\dot{x}_2 &= -\frac{1}{T_{u_M}}\, x_2 + \frac{k_M}{T_{u_M}}\, u_2 \\
\dot{x}_3 &= \frac{10}{C_H}\left(\tilde{V}_{\max_P}\, x_1\, \omega_P - \tilde{V}_{\max_M}\, x_2\, x_4 - k_{\text{leak}}\, x_3\right) \\
\dot{x}_4 &= \frac{i_g^2 i_a^2 \eta_g \eta_{mh} \tilde{V}_{\max_P} 10^{-4} x_2\, x_3 - \tilde{d}_{vc} i_a^2 x_4 - M_{L_w} i_g i_a}{J_v}
\end{aligned} \tag{1}$$

with the state vector

$$\boldsymbol{x} = [\, x_1\,,\, x_2\,, x_3\,, x_4\,]^T := [\,\tilde{\alpha}_P\,,\,\tilde{\alpha}_M\,, \Delta p\,, \omega_M\,]^T \tag{2}$$

and the input vector

$$\boldsymbol{u} = [\,u_1\,,\,u_2\,]^T := [\,u_P\,,\,u_M\,]^T \tag{3}$$

The symbols are explained in Table 1.

Table 1. Vehicle driveline parameters

Symbol	Description	Value	Unit
x_1	hydropump angle	$\in \{-1, 1\}$	-
x_2	hydromotor angle	$\in \{0, 1\}$	-
x_3	pressure difference	-	$[\mathrm{N/m^2}]$
x_4	hydromotor speed	-	$[\mathrm{rad/s}]$
u_1	control signal hydropump	$\in \{-1, 1\}$	-
u_2	control signal hydromotor	$\in \{0, 1\}$	-
T_{u_P}	time constant hydropump	0.13	[s]
T_{u_M}	time constant hydromotor	0.22	[s]
k_P	static gain of pump displacement	241.67	-
k_M	static gain of motor displacement	283.33	-
k_{leak}	leakage coefficient	0.14	$[\mathrm{mm^3/sbar}]$
C_H	hydraulic capacitance	1840.8	$[\mathrm{mm^5/N}]$
$\tilde{V}_{\max_P}$	max. displacement volume hydrop.	145	$[\mathrm{cm^3}]$
$\tilde{V}_{\max_M}$	max. displacement volume hydrom.	170	$[\mathrm{cm^3}]$
ω_P	hydropump speed	-	$[\mathrm{rad/s}]$
J_v	moment of inertia vehicle	16512	$[\mathrm{Nms^2}]$
i_g	transmission ratio	-6.12	-
i_a	axle ratio	-23.3	-
η_g	gearbox efficiency	0.98	-
η_{mh}	hydromechanical efficiency	0.697	-
$\tilde{d}_{vc}$	viscous damping coefficient	0.33	[N m s]
M_{L_w}	external load torque on wheel	-	[Nm]

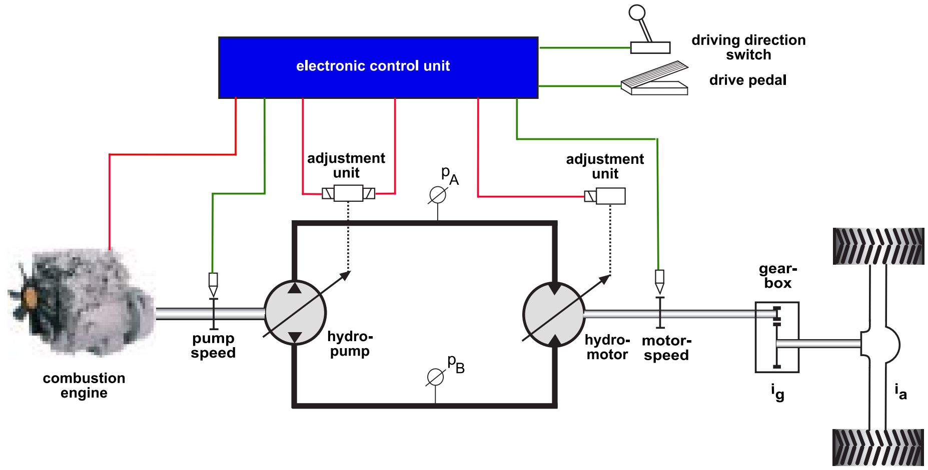

Figure 1. Electro-hydraulic hydrostatic transmission in off-road vehicles

2.2. Model in T-S Fuzzy System Form

The accurate transformation of nonlinear differential equation systems into a T-S fuzzy system in standard form

$$\dot{\boldsymbol{x}} = \sum_{i=1}^{N_r} h_i(\boldsymbol{z})\, \boldsymbol{A}_i\, \boldsymbol{x} \;+\; \sum_{i=1}^{N_r} h_i(\boldsymbol{z})\, \boldsymbol{B}_i\, \boldsymbol{u} \tag{4}$$

$$\boldsymbol{y} = \sum_{i=1}^{N_r} h_i(\boldsymbol{z})\, \boldsymbol{C}_i\, \boldsymbol{x} \tag{5}$$

with $\boldsymbol{z} \in \mathbb{R}^l$ is given if the nonlinearities can be replaced by sector nonlinearities. However this transformation is not bijective. This means that different T-S fuzzy systems can be accurately derived from a given nonlinear differential equation system. This degree of freedom will be used to meet an essential requirement for the observer synthesis. Yoneyama et al. [17] showed that the separation principle holds if all variables in $\boldsymbol{z}$ can be measured. Otherwise a separate observer design based on LMI-methods is not realizable using the following design approach. Based on this requirement a T-S fuzzy system for reconstructing the pressure difference ($\Rightarrow x_3 \neq z_j$ for $j = 1, \ldots, l$) is carried out in two steps.
First step: Because of linear inputs $\boldsymbol{u}$ in (1) the nonlinearities can be expressed by

$$\boldsymbol{A}(x_2, \omega_P) = \begin{bmatrix} -\frac{1}{T_{u_P}} & 0 & 0 & 0 \\ 0 & -\frac{1}{T_{u_M}} & 0 & 0 \\ 0 & 1 & & \\ \frac{10\tilde{V}_{\max_P}\omega_P}{C_H} & 0 & \frac{-10k_{\text{leak}}}{C_H} & \frac{-10\tilde{V}_{\max_M} x_2}{C_H} \\ 0 & 0 & \gamma x_2 & -\frac{d_{vc}}{J_v} i_a^2 \end{bmatrix} \tag{6}$$

with

$$\gamma = \frac{1}{J_v}\, i_g^2\, i_a^2\, \eta_g\, \eta_{mh} \tilde{V}_{\max_P}\, 10^{-4} \tag{7}$$

The variables ω_P and x_2 in (6) are bounded. Therefore they can each be replaced by a linear combination of the sector functions w_{j1} und w_{j2}:

$$z_j = f_j(z_j) = \underline{f}_j \underbrace{\frac{\bar{f}_j - z_j}{\bar{f}_j - \underline{f}_j}}_{=w_{j1}(z_j)} + \bar{f}_j \underbrace{\frac{z_j - \underline{f}_j}{\bar{f}_j - \underline{f}_j}}_{=w_{j2}(z_j)} \tag{8}$$

$$\text{with} \quad \underline{f}_j := \min[z] \quad \text{and} \quad \bar{f}_j := \max[z] \,.$$

As a result, the following system matrix is given

$$\boldsymbol{A}(z_1, z_2) = \begin{bmatrix} -\frac{1}{T_{u_P}} & 0 & 0 & 0 \\ 0 & -\frac{1}{T_{u_M}} & 0 & 0 \\ \frac{10\tilde{V}_{\max_P} f_2(z_2)}{C_H} & 0 & \frac{-10k_{\text{leak}}}{C_H} & \frac{-10\tilde{V}_{\max_M} f_1(z_1)}{C_H} \\ 0 & 0 & \gamma f_1(z_1) & -\frac{d_{vc}}{J_v} i_a^2 \end{bmatrix} . \tag{9}$$

Second step: Now the variables in (9) can be extracted and concentrated into the so-called membership functions $h_i(\boldsymbol{z})$, $i = 1, \ldots, N_r$. They result from the combination of $l = 2$ linear combinations of the sector nonlinearities with $N_r = 2^l = 4$.

$$\{w_{11}, w_{12}\} \times \{w_{21}, w_{22}\}$$

The membership functions can be calculated from the product of the sector functions $w_{jk}(z_j)$ for $k = 1, 2$, see [12]:

$$h_1(z_1, z_2) = w_{11}(z_1) \cdot w_{21}(z_2) \,,\; \ldots \,,$$
$$h_4(z_1, z_2) = w_{12}(z_1) \cdot w_{22}(z_2) \quad .$$

All time invariant system matrices can be described in a compact form:

$$\boldsymbol{A}_i = \begin{bmatrix} -\frac{1}{T_{u_P}} & 0 & 0 & 0 \\ 0 & -\frac{1}{T_{u_M}} & 0 & 0 \\ \frac{10\tilde{V}_{\max_P}*_2}{C_H} & 0 & \frac{-10k_{leak}}{C_H} & \frac{-10\tilde{V}_{max_M}*_1}{C_H} \\ 0 & 0 & \gamma *_1 & -\frac{d_{vc}}{J_v} i_a^2 \end{bmatrix} \tag{10}$$

where $*_1 \in [\underline{x}_2, \bar{x}_2]$ und $*_2 \in [\underline{\omega}_P, \bar{\omega}_P]$.
By disregarding external loads M_{L_w} this leads to the following T-S-fuzzy model for the observer design

$$\dot{\boldsymbol{x}} = \sum_{i=1}^{4} h_i(z_1, z_2)\, \boldsymbol{A}_i\, \boldsymbol{x} \;+\; \boldsymbol{B}\, \boldsymbol{u} \tag{11}$$

with $z_1 := x_2,\ z_2 := \omega_P$, the input matrix

$$\boldsymbol{B} = \begin{bmatrix} \frac{k_P}{T_{u_P}} & 0 \\ 0 & \frac{k_M}{T_{u_M}} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \tag{12}$$

and the output equation

$$\boldsymbol{y} = \boldsymbol{C}\, \boldsymbol{x} \qquad \text{with} \qquad \boldsymbol{C} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}. \tag{13}$$

Remark: The T-S fuzzy system (11) fulfills the requirement of measurable variables in $\boldsymbol{z}$. Therefore the system is suitable for an observer based monitoring of the pressure difference x_3.

3. Takagi-Sugeno Fuzzy Observer Design

3.1. Reduced-order observer structure

For a nonlinear dynamic system described by the T-S fuzzy model (11) a fuzzy observer can be designed to reconstruct the full state vector. In the considered application we take the advantages of the fact that just one state, the pressure difference, have to be estimated. Hence the order of the observer is reduced by the number of sensed states respectively outputs. This enables, in the following, a reduction of the LMI-based design problem and improved the robustness of the estimated pressure difference against load variation. The state vector is partitioned into two parts: $\boldsymbol{x}_a = [\,\tilde{\alpha}_P\,,\, \tilde{\alpha}_M\,, \omega_M\,]^T$, which is directly measurable, and $\boldsymbol{x}_b = \Delta p$, which represents the remaining state variable that has to be estimated. The system matrices of each linear model are accordingly partitioned:

$$\begin{bmatrix} \dot{\boldsymbol{x}}_a \\ \dot{\boldsymbol{x}}_b \end{bmatrix} = \begin{bmatrix} \boldsymbol{A}_{i_{aa}} & \boldsymbol{A}_{i_{ab}} \\ \boldsymbol{A}_{i_{ba}} & \boldsymbol{A}_{i_{bb}} \end{bmatrix} \begin{bmatrix} \boldsymbol{x}_a \\ \boldsymbol{x}_b \end{bmatrix} + \begin{bmatrix} \boldsymbol{B}_{i_a} \\ \boldsymbol{B}_{i_b} \end{bmatrix} \boldsymbol{u} \tag{14}$$

$$\boldsymbol{y} = \begin{bmatrix} \boldsymbol{E}^{(n-p)\times(n-p)} & \boldsymbol{0}^{(n-p)\times p} \end{bmatrix} \begin{bmatrix} \boldsymbol{x}_a \\ \boldsymbol{x}_b \end{bmatrix} \tag{15}$$

with $n = 4$ and $p = 1$ wherein $\boldsymbol{E}$ is the identity matrix with ones on the main diagonal and zeros elsewhere. Based on this, the well known reduced-order observer structure [2] for linear time invariant systems can be written as

$$\begin{aligned} \dot{\boldsymbol{x}}_c = & \,(\, \boldsymbol{A}_{i_{bb}} \, - \boldsymbol{L}_i \boldsymbol{A}_{i_{ab}}\,)\, \hat{\boldsymbol{x}}_b \\ & + (\, \boldsymbol{A}_{i_{ba}} \, - \boldsymbol{L}_i \boldsymbol{A}_{i_{aa}}\,)\, \boldsymbol{y} \\ & + (\, \boldsymbol{B}_{i_b} \, - \boldsymbol{L}_i \boldsymbol{B}_{i_a}\,)\, \boldsymbol{u} \end{aligned} \tag{16}$$

$$\hat{\boldsymbol{x}}_b = \boldsymbol{x}_c + \boldsymbol{L}_i\, \boldsymbol{y} \tag{17}$$

Remark: To get around the difficult of derivative of measurement in reduced-order observer the new state $\boldsymbol{x}_c$ is defined.

Using the idea of Parallel Distributed Compensation (PDC) scheme [14] for nonlinear systems represented by T-S fuzzy models, the nonlinear observer dynamics will then be a weighted sum of the individual linear observers (16)

$$\begin{aligned} \dot{\boldsymbol{x}}_c = & \sum_{i=1}^{N_r} h_i(\boldsymbol{z}) \;\; (\, \boldsymbol{A}_{i_{bb}} \, - \boldsymbol{L}_i \boldsymbol{A}_{i_{ab}})\, \hat{\boldsymbol{x}}_b \\ & + \sum_{i=1}^{N_r} h_i(\boldsymbol{z}) \;\; (\, \boldsymbol{A}_{i_{ba}} \, - \boldsymbol{L}_i \boldsymbol{A}_{i_{aa}})\, \boldsymbol{y} \\ & + \sum_{i=1}^{N_r} h_i(\boldsymbol{z}) \;\; (\, \boldsymbol{B}_{i_b} \, - \boldsymbol{L}_i \boldsymbol{B}_{i_a})\, \boldsymbol{u} \end{aligned} \tag{18}$$

$$\hat{\boldsymbol{x}}_b = \boldsymbol{x}_c + \sum_{i=1}^{N_r} h_i(\boldsymbol{z}) \boldsymbol{L}_i\, \boldsymbol{y} \tag{19}$$

The weighting functions $h_i(\boldsymbol{z})$ with $\boldsymbol{z} = [\,\tilde{\alpha}_M\,,\, \omega_P\,]^T$ in (18) and the number of linear models with $N_r = 4$ are the same as in the original plant model (11).

3.2. LMI-based observer design

For the following T-S fuzzy observer design, it is assumed that the fuzzy system model is locally observable, i.e. all $(\boldsymbol{A}_{i_{bb}}, \boldsymbol{A}_{i_{ab}})$, $i = 1, \ldots, N_r$ pairs are observable. If the estimation error is defined by

$$\boldsymbol{e}_b = \boldsymbol{x}_b - \hat{\boldsymbol{x}}_b \tag{20}$$

the dynamics of the error are given by substracting

$$\dot{\boldsymbol{x}}_b = \sum_{i=1}^{N_r} h_i(\boldsymbol{z})\, [\boldsymbol{A}_{i_{bb}}\, \boldsymbol{x}_b + \boldsymbol{A}_{i_{ba}}\, \boldsymbol{x}_a + \boldsymbol{B}_{i_b}\, \boldsymbol{u}\,] \tag{21}$$

from (18) with (19) to get

$$\dot{\boldsymbol{e}}_b = \sum_{i=1}^{N_r}\sum_{j=1}^{N_r} h_i(\boldsymbol{z})h_j(\boldsymbol{z})\left[\boldsymbol{A}_{i_{bb}} - \boldsymbol{L}_i\,\boldsymbol{A}_{j_{ab}}\right]\boldsymbol{e}_b \qquad (22)$$

If the error dynamics (22) is stable, the state estimation will converge asymptotically to the real state. An observer with converging state estimation can also be referred to as a stable observer. The stability of the above error dynamics is verified by the following theorem:

Theorem 1: The fuzzy observer (18), (19) is globally asymptotically stable if a common positive definite matrix $\boldsymbol{P} > \boldsymbol{0}$ exists such that

$$\begin{aligned} &\boldsymbol{A}_{i_{bb}}^T\boldsymbol{P} + \boldsymbol{P}\boldsymbol{A}_{i_{bb}} - \boldsymbol{A}_{j_{ab}}^T\boldsymbol{N}_i^T - \boldsymbol{N}_i\boldsymbol{A}_{j_{ab}} + 4\alpha\boldsymbol{P} \\ &+\boldsymbol{A}_{j_{bb}}^T\boldsymbol{P} + \boldsymbol{P}\boldsymbol{A}_{j_{bb}} - \boldsymbol{A}_{i_{ab}}^T\boldsymbol{N}_j^T - \boldsymbol{N}_j\boldsymbol{A}_{i_{ab}} < \boldsymbol{0}\,, \end{aligned}$$

$$\boldsymbol{A}_{i_{bb}}^T\boldsymbol{P} + \boldsymbol{P}\boldsymbol{A}_{i_{bb}} - \boldsymbol{A}_{i_{ab}}^T\boldsymbol{N}_i^T - \boldsymbol{N}_i\boldsymbol{A}_{i_{ab}} + 2\alpha\boldsymbol{P} < \boldsymbol{0} \qquad (23)$$

for $i, j = 1, ..., N_r$ where $\boldsymbol{N}_i = \boldsymbol{P}\,\boldsymbol{L}_i$.

The matrices $\boldsymbol{P}$ and $\boldsymbol{N}_i$ can be found by using convex optimization techniques if the Linear Matrix Inequalities (23) have a feasible solution for a given decay rate $\alpha \in \mathbb{R}^+$. The $i = 1, \ldots, N_r$ observer gains can then be obtained as $\boldsymbol{L}_i = \boldsymbol{P}^{-1}\boldsymbol{N}_i$. The proof of this theorem follows directly from the proof of the full T-S observer theorem in [15]. For this particular application based on the T-S fuzzy model (11), the driveline parameters (Table 1) and a desired decay rate $\alpha = 2$ the following solution is obtained as

$$\boldsymbol{P} = 2.6282 \cdot 10^{-2}$$

$$\begin{aligned} \boldsymbol{N}_1 &= \left[\begin{array}{ccc} 0 & 0 & -9.0124 \cdot 10^{-5} \end{array}\right]\,, \\ \boldsymbol{N}_2 &= \left[\begin{array}{ccc} 0 & 0 & -2.1937 \cdot 10^{-6} \end{array}\right]\,, \\ \boldsymbol{N}_3 &= \left[\begin{array}{ccc} 0 & 0 & -4.5062 \cdot 10^{-5} \end{array}\right]\,, \\ \boldsymbol{N}_4 &= \left[\begin{array}{ccc} 0 & 0 & +5.7926 \cdot 10^{-6} \end{array}\right]\,, \end{aligned}$$

$$\begin{aligned} \boldsymbol{L}_1 &= \left[\begin{array}{ccc} 0 & 0 & -3.4291 \cdot 10^{-3} \end{array}\right]\,, \\ \boldsymbol{L}_2 &= \left[\begin{array}{ccc} 0 & 0 & -8.3468 \cdot 10^{-5} \end{array}\right]\,, \\ \boldsymbol{L}_3 &= \left[\begin{array}{ccc} 0 & 0 & -1.7145 \cdot 10^{-3} \end{array}\right]\,, \\ \boldsymbol{L}_4 &= \left[\begin{array}{ccc} 0 & 0 & +2.2040 \cdot 10^{-4} \end{array}\right]\,. \end{aligned}$$

4. Experimental validation

The designed observer is validated by means of a comparsion between a measured (x_3) and the observed pressure

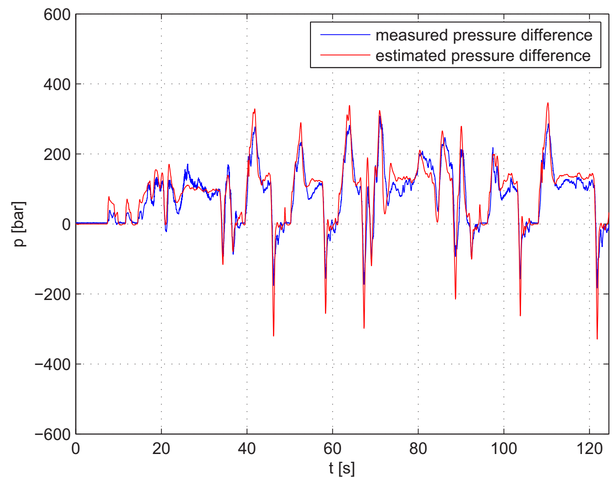

Figure 2. Measured and estimated pressure difference using the T-S observer (18), (19)

difference $(\hat{x}_3)$. The measurement was recorded during a test run with a standard wheel loader on a test track. The input signals of the observer law (18), (19) with $\boldsymbol{y} = \boldsymbol{x}_a = [\,x_1\,,\,x_2\,,\,x_4\,]^T$ are supplied by the measured hydropump angle x_1, hydromotor angle x_2 and the hydromotor speed x_4. The pressure difference signals are illustrated in Figure 2 and correspond to a driving cycle with acceleration and deceleration periods showed in Figure 4. The measured pressure difference varies in a full operation range of a forward vehicle motion. The plot of Figure 2 shows that the observer is able to reconstruct the pressure difference signal for the purpose of analytical redundancy. As a second proof of evidence the performance of the T-S fuzzy observer is compared with a linear observer based on just one linear state-space model $(i = 3)$ of the T-S fuzzy model. This submodel has the highest membership value e.g. between $t = 26\ldots34\,\mathrm{s}$ and is therefore the best linearized model for this time span. The results are illustrated in Figure 3. It is obvious, that the linear observer is unsuitable due to the strong nonlinear dynamics of hydrostatic transmissions.

5. Conclusion and Outlook

A model-based analytical redundancy concept for the reconstruction of pressure difference signals in hydrostatic transmissions was presented in this paper. Based on a T-S fuzzy model description of the nonlinear plant a reduced-order T-S observer was designed by solving an appropriate LMI condition. It was shown e.g. in [15] that those designed observers guarantee a global asymptotically stable error dynamics.

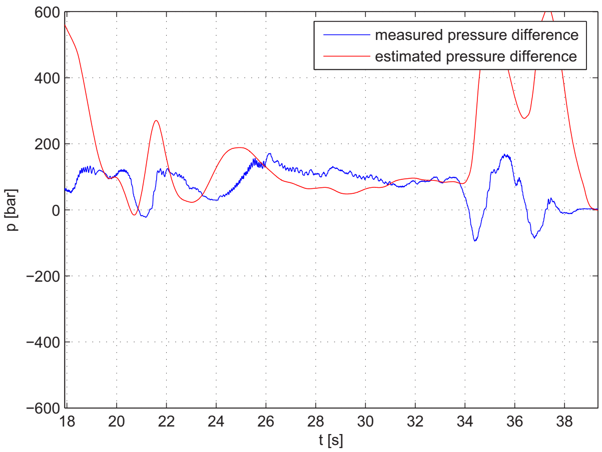

Figure 3. Measured and estimated pressure difference using a linear observer

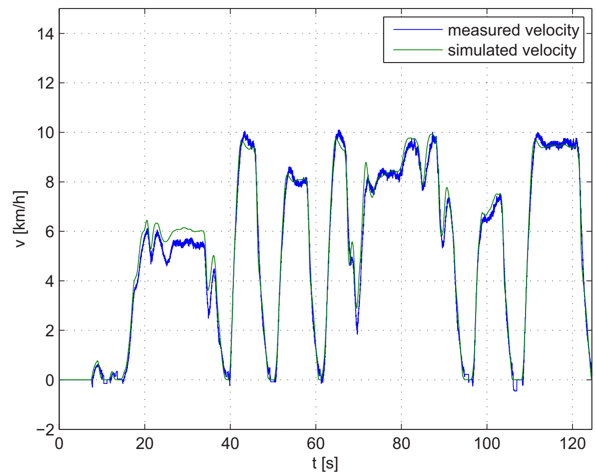

Figure 4. Measured and simulated velocity

The reduced-order T-S fuzzy observer was experimentally validated by means of a comparison between the measured and the reconstructed pressure difference signal. The presented figures clearly show that the observer is able to reconstruct the pressure difference signal for the purpose of analytical redundancy. This is the essential step for developing a model-based fault diagnosis system for mobile working machines. In a next step we will design further observers for monitoring the angles of the hydropump and the hydromotor. Based on this a dedicated observer scheme [9] for a sensor fault diagnosis and identification system (FDI) should be designed and tested on a real test vehicle.

References

[1] *IEC 61508, Functional safety of electrical / electronic / programmable electronic safety-related systems*. 2001.

[2] G. F. Franklin, J. D. Powell, and A. Emami-Naeini. *Feedback Control of Dynamic Systems*. Addision-Wesley Publishing Company, second edition, 1991.

[3] K. Huhtala. *Modelling of Hydrostatic Transmissions - Steady State, Linear and Nonlinear Models*. PhD thesis, Tampere, Finland, 1996.

[4] P. Korba, R. Babuska, H. B. Verbruggen, and P. M. Frank. Fuzzy Gain Scheduling: Controller and Observer Design based on Lyapunov Method and Convex Optimization. *IEEE Transaction on Fuzzy Systems*, 11(3):285–298, 2003.

[5] J. Lennevi, K. E. Rydberg, and J. O. Palmberg. Microprocessor control of hydrostatic transmissions adapting to driving conditions. In *11th Aachener Fluidtechnisches Kolloqium*, Aachen, Germany, 1994.

[6] C. J. Lopez-Toribio, R. J. Patton, and S. Daley. Takagi-Sugeno Fuzzy-Tolerant Control of an Induction Motor. *Neural Computing and Application*, 9:19–28, 2000.

[7] X. J. Ma, Z. Q. Sun, and Y. Y. He. Analysis and design of fuzzy controller and fuzzy observer. *IEEE Transactions on Fuzzy Systems*, 6(1):41–50, 1998.

[8] M. Oudghiri, M. Chadli, and A. E. Hajjaji. Control and Sensor Fault-Tolerance of Vehicle Lateral Dynamics. In *Proceedings of the 17th World Congress IFAC*, pages 123–128, 2008.

[9] R. J. Patton, P. M. Frank, and R. N. Clark. *Fault diagnosis in dynamics systems theory and application*. Prentice-Hall International, UK, 1989.

[10] K. E. Rydberg. *On performance optimization and digital control of hydrostatic drives for vehicle applications*. PhD thesis, Linköping Studies and Technology, No. 99, Linköping, Sweden, 1983.

[11] M. Sannelius. *On complex hydrostatic transmissions*. PhD thesis, Linköping Studies and Technology, No. 569, Linköping, Sweden, 1999.

[12] H. Schulte. Modeling of Hydrostatic Transmissions considering leakage losses. In *IFAC Workshop on Advanced Fuzzy-Neural Control Proceedings*, Valenciennes, France, 2007.

[13] K. Tanaka, T. Ikeda, and H. O. Wang. Fuzzy regulators and fuzzy observers: Relaxed stability conditions and LMI-based designs. *IEEE Transactions on Fuzzy Systems*, 6(2):1–16, 1998.

[14] K. Tanaka and M. Sugeno. Stability analysis and design of fuzzy control systems. *Fuzzy Sets and Systems*, 45:135–156, 1992.

[15] K. Tanaka and H. Wang. *Fuzzy Control Systems Design and Analysis*. John Wiley & Sons, New York, Chichester, 2001.

[16] J. Wochnik. *Modellbildung und nichtlineare Regelung dieselhydraulisch angetriebener Flurförderfahrzeuge (in German)*. PhD thesis, GH-Uni Duisburg, Germany, 1992.

[17] J. Yoneyama, M. Nishikawa, H. Katayama, and A. Ichikawa. Output stabilization of takagi-sugeno fuzzy systems. *Fuzzy Sets and Systems*, 111(2):253–266, 2000.