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Adaptive feedforward control using a gaussian process and a recursive least squares algorithm for a hydraulic axial piston pump

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***Abstract*— Feedforward control of hydraulic systems is a huge benefit to their performance and has been a research topic for many years focusing on the differential equations of the pump in order to implement pressure control or flow control laws. Considering a servo-hydraulic system which is acutated by an operator, it is inevitable to firstly calculate the required flow to obtain a desired system behavior. A good measure for a suitable pump flow regarding a given input signal by an operator is the resulting pressure drop across the actuated valve. In this paper an adaptive feedforward controller is developed using a gaussian process and a recursive least squares algorithm to calculate the needed flow more accurately resulting in a desired pressure drop repeatedly. The results are then implemented to the hydraulic system and the tracking behavior of the real system is evaluated. This is done using setpoint changes of the operator input. The measurement results for the dynamic actuation of a cylinder are shown and a comparison between the gaussian process and the recursive least squares algorithm is made. With the adaptive feedforward controller the pressure drop can be set more precisely allowing an efficient operation of the overall hydraulic system.**

I. INTRODUCTION

Automation in hydraulic applications increases a lot considering automated movement of mobile working machines as seen in [2], [9], but also within their underlying hydraulic system. The change of hydromechanical controllers, which were state of the art for many years, to electrohydraulical controllers holds huge potential but due to the very fast dynamic of hydraulic systems it comes along with many challenges. The electrohydraulical actuation of servo valves considering e. g. the joystick input of an operator is subject to static friction problems [10] causing hysteresis effects and a change in the overall dynamic of the system since the transfer behavior of the electrical actuation is notable slower than the hydromechanical controller for the valve lifts. The hydraulic axial piston pump is the most used in mobile working machines and therefore is part of many publications reaching from solely modeling and dynamical examination to their feedforward and feedback control. Efficiently supplying hydraulic energy consisting of the hydraulic volume flow and the hydraulic pressure is the foundation of efficiently operating the entire hydraulic system of mobile working machines. Typical hydraulic systems can be subdivided into positive and negative flow control with both having their advantages and disadvantages. Reaching load-independent movements, negative flow control is to be used, where the active load pressure p_{LS} is available as a feedback and the volume flow of the hydraulic pump is controlled to obtain a system pressure p_{HP} having a constant offset to p_{LS}. This offset $\Delta p = p_{\mathrm{HP}} - p_{\mathrm{LS}}$ is necessary to overcome hydraulic friction and is the design parameter for the velocities of the actuated cylinders. In the state of the art, a hydromechanical pressure compensator valve being preloaded with the offset Δp is used to control the flow of the hydraulic pump, which is feasible because the high pressure dynamics yield a high bandwith within the hydromechanical controller. This pressure drop is a very important design parameter in the negatively controlled hydraulic systems since it determines the dynamic of the surpassed hydromechanical controller. For modern electrohydraulical actuated pumps, the desired pressure drop Δp can be set by using knowledge of the system and the common orifice equation to calculate and set the necessary volume flow. With the modern electrohydraulic controller the volume flow can be chosen arbitrarily without interfering with the dynamic behavior of the actuated piston which is beneficial since it is the main design parameter considering energy efficiency. As already mentioned, with the electrohydraulical controller knowledge of the current orifice must be known to set the desired volume flow. Unfortunately this orifice cross-section in the overall view of the hydraulic system is not available and the parameters are also varying over states of the hydraulic system as for example the viscosity of the hydraulic oil, being dependent on the temperature as well as the type of oil used, and therefore must be adapted during the operation of the hydraulic system. As it has been shown in many publications (e. g. [6], [8]), to accurately control the volume flow of an axial hydraulic piston pump a feedforward controller delivers the best performance. Also many publications are available for the control of the directional valves and controlling the pressure drop by acuating this valve as in [15] or [14]. Valve identification for directional valves has been performed offline within an experimental setup for example by Tørdal et al. [11] focusing on its dynamics. Other works as Valdiero et al. focus on the identification of the deadzone of the hydraulic valve [12]. Therefore the work of this contribution provides exact setpoints for an existing feedforward controller as seen in [6], calculated using a gaussian process as well as a recursive least squares algorithm. At first the governing system equations will be described and the

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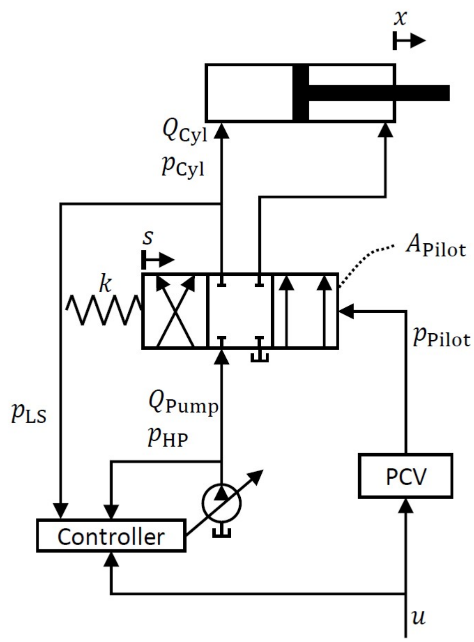

Fig. 1. Sketch of a negatively controlled hydraulic system with user input u to the pump controller and the pressure control valve (PCV) setting the pressure p_{Pilot}. In the center $4/3$ valve with 4 inlets and 3 positions with valve lift s, which is set by the pilot pressure and the spring, allowing volume flow Q_{Pump} to pass to the cylinder with cylinder position x and the pressure p_{Cyl} is seen. Additionally, the feedback of p_{HP} and p_{LS} is shown.

calculation of data points will be shown, afterwards the two algorithms will be proposed. This paper concludes with showing measurement results using the adaptive feedforward controller and a comparison between the algorithms and the performance of the final feedforward controller.

II. System description and creation of training data

A. System description of the negatively controlled hydraulic system

Firstly, an introduction to the hydraulic system will be given and an awareness for the importance of good valve characteristics will be made. Here the dynamics of the hydraulic system will shortly be introduced and the dependency of supply volume flow and the aforementioned resulting pressure drop is explained.

In order to simplify the sketch of the hydraulic system, Fig. 1 only shows the pressure and the volume flow for the base chamber of the double-acting cylinder. It can be seen in Fig. 1, following the actuation signal of an operator u to a pressure control valve (PCV), the pilot pressure $p_{\text{Pilot}}(u)$ is set to move the valve against a spring. The counterforce of the spring, with spring rate k, results in $F_{\text{Spring}} = k \cdot s$ and the resulting force of p_{Pilot} and an area A_{Pilot} result overall in the external forces acting on the valve lift s. Due to friction of the plunger with mass m_{Plunger} in the valve housing the second order dynamic resulting of the governing differential equation given in (1) can be assumed to be strongly damped and the valve dynamic is assumed to be very fast.

$$\ddot{s} = \frac{1}{m_{\text{Plunger}}} \cdot \left(p_{\text{Pilot}} \cdot A_{\text{Pilot}} - k \cdot s - F_{\text{Friction}}(\dot{s})\right) \quad (1)$$

Therefore calculating the steady state $\ddot{s} = \dot{s} = 0$ results in a linear function

$$s(u) = \frac{A_{\text{Pilot}}}{k} \cdot p_{\text{Pilot}}(u). \quad (2)$$

Since it was assumed that $F_{\text{Friction}}(\dot{s})$ is only dependent on $\dot{s}$, static friction is not considered and the aforementioned hysteresis effects are not modeled. In the real system no information regarding the hysteresis effect is available and in addition to the here proposed feedforward control law, a feedback control law or a feedback control law combined with a disturbance observer needs to be designed to obtain good tracking behavior despite the obvious model uncertainties. The travel of s yields an orifice cross section A_{Valve}, which lets the supply volume flow Q_{Pump} pass to the actuated cylinder. The flow through the orifice can be assumed as turbulent flow [3] and with the contraction coefficient c_v and a desired pressure drop Δp_{des} across the valve, the desired supply volume flow $Q_{\text{Pump,des}}$ is obtained to

$$Q_{\text{Pump,des}} = c_v \cdot A_{\text{Valve}}(s) \cdot \sqrt{\Delta p_{\text{des}}}. \quad (3)$$

As already made clear in the introduction the main issue is to derive reliable orifice cross-sections over the operating range of the valve. Here specifications by the manufacturer are often available but do not comprise additionally encountering reductions of the flow cross-section like the entrance to the casing in which the valve is built-in or orifices to introduce damping effects into the hydraulic channel. As it can be seen in Fig. 1 the load pressure p_{LS} and the pressure of the high pressure line p_{HP} are measured and the resulting pressure drop across the valve $\Delta p = p_{\text{HP}} - p_{\text{LS}}$ can be calculated. The dynamical equations

$$\begin{aligned} \dot{p}_{\text{HP}} &= \frac{E}{V_{0,\text{System}}} \cdot (Q_{\text{Pump}} - Q_{\text{Cyl}}), \\ \dot{p}_{\text{Cyl}} &= \frac{E}{V_{0,\text{Cyl}}} \cdot (Q_{\text{Cyl}} - A_{\text{Cyl}} \cdot \dot{x}) \end{aligned} \quad (4)$$

describe the pressure dynamics of the high pressure line $\dot{p}_{\text{HP}}$ and the pressure inside the base chamber of the cylinder $\dot{p}_{\text{Cyl}}$, using the bulk modulus E and the volume $V_{0,i}$, with $i = \{\text{HP, Cyl}\}$. It can be assumed that the dynamic of the pressure feedback p_{LS} is negligible and therefore $p_{\text{LS}} = p_{\text{Cyl}}$ holds. Another issue is that the volume flow of the pump Q_{Pump} can not be measured but due to the availabilty of good models of hydraulic axial piston pumps it can be estimated using an accurate nonlinear pump model

$$\begin{aligned} \dot{\boldsymbol{x}} &= f(\boldsymbol{x}, u_{\text{Pump}}), \\ \boldsymbol{x}(0) &= \boldsymbol{x}_0, \end{aligned} \quad (5)$$

which has been presented in an earlier publication [6]. Here $\boldsymbol{x}$ comprises the swash plate angle α which can be used calculating the volume flow

$$Q_{\text{Pump}} = \frac{V_{\text{Pump}}(\alpha)}{2\pi}\dot{\varphi}_{\text{Pump}}, \tag{6}$$

as seen additionally in [7], [3] with a known rotational speed $\dot{\varphi}_{\text{Pump}}$ of the pump. After an actuation of the operator the given supply volume flow passes through the orifice cross-section A_{Valve} and yields a pressure increase according to (4). This pressure shows oscillations coming from the oscillations of the cylinder speed $\dot{x}$, which will be seen later in the measurement results. The pressure drop across the valve follows the dynamic of the volume flows, because the pressure dynamic is very fast since the time constant of the differential equation reaches from 10^8 to 10^{10} and the time constants of the dynamic of the cylinder are much lower.

B. Creation of training data

Since the hydraulic system is understood now, this knowledge is used to create training data for the actual characteristic of the cross-section of the valve. The entire process will be explained and supported by exemplary figures of training data.

After an actuation of the valve by the operator input u, the electrohydraulical controller calculates a desired volume flow $Q_{\text{Pump,des}}$ as seen in (3). As an initial guess for the cross-section of the valve its characteristic given by the manufacturer is used, which is seen in Fig. 2. Here, the time dependence must be introduced, where k is the current value. With a known dynamic of the pump, a real $\Delta p_{\text{real}}(k)$, potentially differing from the desired $\Delta p_{\text{des}}(k)$ which is required to calculate the desired supply volume flow as in (3), is measured. Using these measurements and the model based volume flow $Q_{\text{Pump}}(k)$ a real cross-section of the valve $\tilde{A}(k)$ can be calculated using the known orifice equation (3) solved for A to

$$\tilde{A}(k) = \frac{Q_{\text{Pump}}(k)}{c_v \cdot \sqrt{\Delta p_{\text{real}}(k)}}. \tag{7}$$

Together with the available operator input $u(k)$, the calculated $\tilde{A}(k)$ creates a training tupel. In this case a *dSpace MicroAutoBox II* is used as a electronic control unit and analog digital converter with a sample frequency of 50 Hz, so training data is quickly gathered. The created trainings tupel are filtered regarding their plausability. The outlier detection is done via a distance-based approach, where a point is judged based on the distance to its neighbors. The assumption is that, the training data has a normal distribution around the true valve characteristic. Therefore outliers are far apart from their neighbors and have a very sparse neighborhood [4]. The distance-based approach is done only in one dimension along the cross-section for every value of $u \in \mathbb{Z}$. Here, a radius ε and a percentage π is defined. Further, a point p is considered an outlier if at most π percent of all outher points have a distance to p less than ε.

An exemplary training set is shown in Fig. 2. Here in gray the initial trainig data is shown and in yellow the filtered tupels. The black curve still shows the original

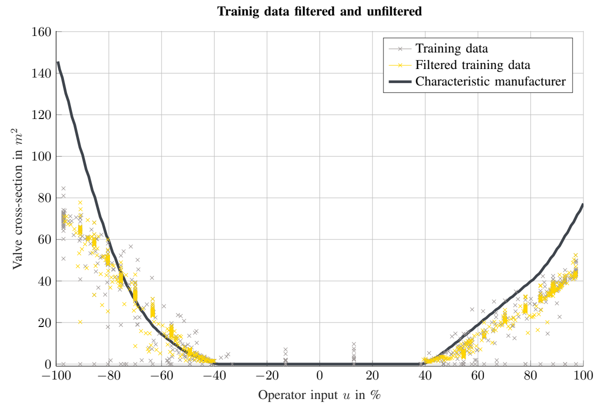

Fig. 2. Exemplary training data shown for the orifice. Every marker stands for one time step k. The accumulation of values in the vicinty of $|u| = 17\%$ origines from the prestress of the valve despite no given valve travel s.

valve characteristic given by the manufacturer. It can be seen, that the estimated tupels have lower values for the cross-section than the characteristic provided. This can be explained by the fact, that all additional orifices and flow resistances are lumped into the training data. This is a wanted effect and the prediction for $Q_{\text{Pump,des}}(k)$ is expected to meet with the desired pressure drop $\Delta p_{\text{des}}(k)$. The filtering works respectively well, but still has some potential. In the result section it will be seen, that the gaussian process has less problems with training data with large variances since it is a classification method on its own. The recursive least squares algorithm in contrast benefits largely from a good filtering method since it is very sensitive to outliers due to the quadratic penalty values during the optimization.

III. Design of the identification routines

Since the training data is now available, the two online identification routines are presented and the setting parameters are explained. First, the gaussian process is introduced and afterwards the recursive least squares algorithm is explained.

A. Gaussian process

Gaussian processes (GP), being part of the nonparametric supervised machine learning techniques, are used for regression and classification. A huge benefit is the prediction based on known training data and an information on the resulting uncertainty [13]. Given a random variable $f(u)$, a mean $\mu(u) = \mathrm{E}[f(u)]$ and a variance σ^2 can be calculated. Comparing random variables $f(u)$ and $f(u')$ the assumption is made that they have a higher correlation, if u and u' are closer. Thies yields the definition of a gaussian process

$$f(u) \sim \mathcal{GP}(\mu(u), l(u, u')), \tag{8}$$

with the function for the covariance as given in [5]

$$l(u, u') = \mathrm{E}[(f(u) - \mu(u))(f(u') - \mu(u'))]. \tag{9}$$

There exist various kernel functions coinciding with the covariance function $l(u, u')$ and for this work the squared exponential kernel as seen in [1] is used and can be written as

$$l(u,u') = \varphi_1^2 \exp\left(-\frac{\|u-u'\|^2}{2\cdot\varphi_2^2}\right). \tag{10}$$

Here φ_1 and φ_2 are the so called hyperparameters and are used to control the learning process. The squared exponential kernel is used since its output are function with a smooth course, which is reasonable considering the construction of the valve. As it can be seen in Fig. 2, the calculated cross-sections $\tilde{A}(k)$ are assumed to have an additive noise with normal distribution $\varepsilon_i = \mathcal{N}(0,\sigma_k^2)$. Introducing the model f_{GP} as a result of the gaussian process, a training tupel has the relation

$$\tilde{A}(k) = f_{\text{GP}}(u(k)) + \varepsilon_i. \tag{11}$$

Using the entire training data $\tilde{\boldsymbol{A}}$ and $\boldsymbol{u}$ and the covariance matrix

$$\boldsymbol{L}(\boldsymbol{u},\boldsymbol{u}) = \begin{bmatrix} l(u(k),u(k)) & \dots & l(u(k),u(n)) \\ \vdots & \ddots & \vdots \\ l(u(n),u(k)) & \dots & l(u(n),u(n)) \end{bmatrix}, \tag{12}$$

where n is the amount of training data, it can be written

$$\underline{\tilde{A}} \sim \mathcal{N}(0, \boldsymbol{L}(u,u) + \boldsymbol{\sigma}^2\boldsymbol{I}), \tag{13}$$

while assuming a zero-mean distribution. The bold notation is used to mark matrices, the underline marks vectorial variables, and $\boldsymbol{I}$ is the identity. The choice of the hyper-parameters is very important and is illustrated considering the kernel length φ_1: If it is chosen too small the gaussian process leads to overfitting, whereas if it is chosen too big, the gaussian process leads to underfitting of the trainig data. A good choice for the training data can be found iteratively and a good combination of φ_1 and φ_2 will be shown in the results section.

B. Recursive least squares algorithm

The recursive least squares algorithm is used to estimate linear parameters combined with ansatzfunctions. The ansatzfunctions are combined in the matrix $\boldsymbol{U}$ and the parametervector is described with $\boldsymbol{\Theta}$. The equation

$$\underline{\tilde{A}} = \boldsymbol{U}\cdot\boldsymbol{\Theta} \tag{14}$$

therefore describes the linear system of equations. The squared penalty of the optimization algorithm then is defined as

$$\min_{\boldsymbol{\Theta}} f(\Theta) = \min_{\boldsymbol{\Theta}} \|\tilde{\boldsymbol{A}} - \boldsymbol{U}\cdot\boldsymbol{\Theta}\|^2. \tag{15}$$

At time k the solution of the parameter vector $\underline{\Theta}(k)$ can be given by

$$\underline{\Theta}(k) = \left(\boldsymbol{U}^{\text{T}}(k)\cdot\boldsymbol{U}(k)\right)^{-1}\cdot\boldsymbol{U}(k)\cdot\underline{\tilde{A}}(k), \tag{16}$$

using the pseudoinverse of the non regular matrix $\boldsymbol{U}(k)$. Moving to the time $k+1$ the matrix $\boldsymbol{U}(k+1)$ and the vector $\boldsymbol{y}(k+1)$ can be given to

$$\begin{aligned} \boldsymbol{A}(k+1) &= \begin{bmatrix} \boldsymbol{A(k)} \\ A(k+1) \end{bmatrix}, \\ \boldsymbol{U}(k+1) &= \begin{bmatrix} \boldsymbol{U}(k) \\ \underline{U}^{\text{T}}(k+1) \end{bmatrix}. \end{aligned} \tag{17}$$

$\underline{U}(k+1)$ must be transposed when combined with the matrix $\boldsymbol{U}(k+1)$ since it is a vector and $\boldsymbol{U}(k)$ is a matrix. Combining (16) and (17) and introducing the update matrix $\boldsymbol{P}^{-1} = \boldsymbol{U}^{\text{T}}(k)\cdot\boldsymbol{U}(k)$ the update of $\underline{\Theta}(k+1)$ can be given to

$$\begin{aligned} \underline{\Theta}(k+1) &= \underline{\Theta}(k) \\ &\quad + \underline{\gamma}(k)\cdot\left(\tilde{A}(k+1) - \underline{U}^{\text{T}}(k+1)\cdot\underline{\Theta}(k)\right), \end{aligned} \tag{18}$$

with

$$\gamma(k) = \frac{\boldsymbol{P}(k)\cdot\underline{U}(k+1)}{1+\underline{U}^{\text{T}}(k+1)\cdot\boldsymbol{P}(k)\cdot\underline{U}(k+1)}. \tag{19}$$

The update of $\boldsymbol{P}(k+1)$ can then be calculated recursively to

$$\boldsymbol{P}(k+1) = \boldsymbol{P}(k) - \underline{\gamma}(k)\cdot\underline{U}^{\text{T}}(k+1)\cdot\boldsymbol{P}(k). \tag{20}$$

Comparing the course of the valve characteristic in Fig. **??**, it can be assumed that a polynom of fourth order is suitable to estimate the valve characteristic. When considering the proportional valve opening this can be modeled as a cylinder moving inside a tube increasing the orifice area. This process has an opening area with increasing gradient, then a linear phase, and an area where it's nearly completely opened which results in an area with decreasing gradient. The above mentioned vectors then build the optimization, according to (14),

$$\begin{bmatrix} \tilde{A}(0) \\ \tilde{A}(1) \\ \vdots \\ \tilde{A}(n) \end{bmatrix} = \begin{bmatrix} u(0)^4 & u(0)^3 & u(0)^2 & u(0) & 1 \\ u(1)^4 & u(1)^3 & u(1)^2 & u(1) & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ u(n)^4 & u(n)^3 & u(n)^2 & u(n) & 1 \end{bmatrix} \cdot \begin{bmatrix} \Theta_4 \\ \Theta_3 \\ \Theta_2 \\ \Theta_1 \\ \Theta_0 \end{bmatrix}. \tag{21}$$

IV. Results

Now the identification results and the resulting actuation of the cylinder via the operator input u is examined. Particular attention is payed to the resulting pressure drop Δp across the valve. First, the identification results of the gaussian process are shown, which also gives an additional information about the uncertainty, namely the 2σ interval. As it can be seen in the results of the gaussian process a very smooth curve is found, which suits the mechanical properties of the valve very well. The 2σ confidence interval is relatively large, but the results are very promising. As hyperparameter $\varphi_1 = 320$ and $\varphi_2 = 50$ have been chosen. This has been done without a hyperparameteroptimization, but with a iterative manual approach to validate the gaussian process on the training data. The predictive behavior of the

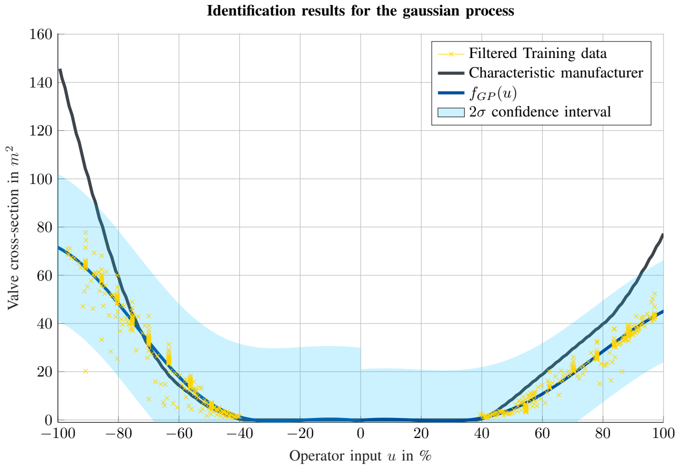

Fig. 3. Identification results off the gaussian process showing additionally the training data, the valve characteristic given by the manufacturer and the 2σ confidence interval.

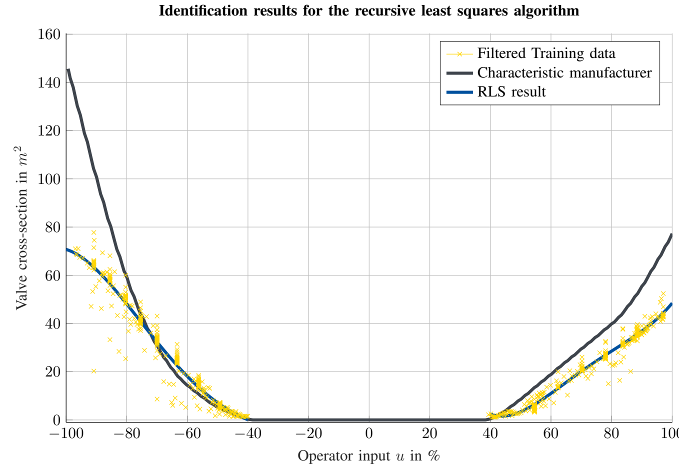

Fig. 4. Identification results off the recursive least squares algorithm showing additionally the training data, the valve characteristic given by the manufacturer.

gaussian process finds better results without filtering and with fewer data points. In our scenario in contrast the availabilty of data is not a big issue and the gaussian process needs more computational power than the recursive least squares algorithm. The gaussian process has however some benefits. Often the values at specific sampling points have a low variance, since they often occur during the operation of the machine. The gaussian process has the power to trust these values more, wheras the recursive least squares algorithm has limited options to manually adapt the weight of single identifcation tupels.

For the recursive least squares algorithm the performance can be seen in Fig. 4. Due to the outlier detection and the presence of many training tupel, the RLS performs also very well. The RLS is a very simple algorithm in terms of computational power and is very easy to implement online for the adaptive feedforward control of the hydraulic axial piston pump.

Since both algorithms come to the same result having the same training data, the results for the adaptive feedforward control of the pump will only be shown for the update of the valve characteristic via the recursive least squares algorithm.

In Fig. 5 a comparison between the feedforward controller based on the valve characteristic of the manufacturer is compared to the adaptive feedforward control, which had preceding to the validation multiple arbitrary movements to collect training data and converge. As mentioned before, regarding the sample frequency the collected trainig data enables the algorithm to converge quickly. It can be seen, that for the adaptive feedforward controller the desired Δp of $18\,\text{bar}$ is reached and set very well, whereas the non adaptive feedforward controller supplys too much volume flow, which then again results in a too high Δp. This can be explained, since the valve characteristic provided by the manufacturer does not comprise additional flow reductions and therefore the amount of supply volume flow is overestimated. As it can

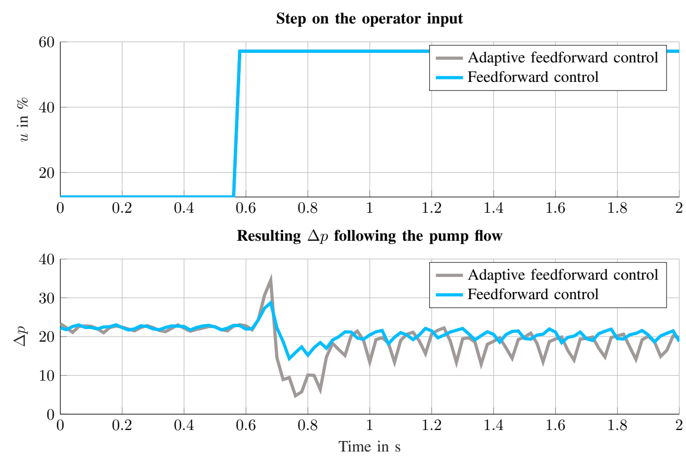

Fig. 5. Comparing the adaptive feedforward control without the adaption algorithm shows that the Δp is not met at desired pressure drop of $\Delta p_{\text{des}} = 18\,\text{bar}$.

be seen in Fig. 5 the operator input u is set to approximately $55\,\%$ and in comparison with Fig. 3 or Fig. 4 the deviation of the estimated valve characteristic and the manufacturers valve charcteristic is not as large as for example for an operator input of $80\,\%$. The oscillations in Fig. 5 of Δp origin from the discrete number of pistons within the hydraulic axial piston pump. The feedforward scheme uses the operator input as seen in the upper picture of Fig. 4. The feedforward controller then increases the supply volume flow which is stowed since the valve has not opened fully yet. This results in a pressure increase of p_{HP} and after the valve is opened (around $0.7\,\text{s}$) the volume results in an accelaration of the cylinder which results in a pressure drop of p_{HP} which can also be seen in Fig. 4 and 6. The pressure drop of the adaptive feedforward controller is higher, since the effects of the still closed valve are very similar, but when the valve is opened the adaptive feedforward controller in this case has a lower supply volume flow. This in turn results in the

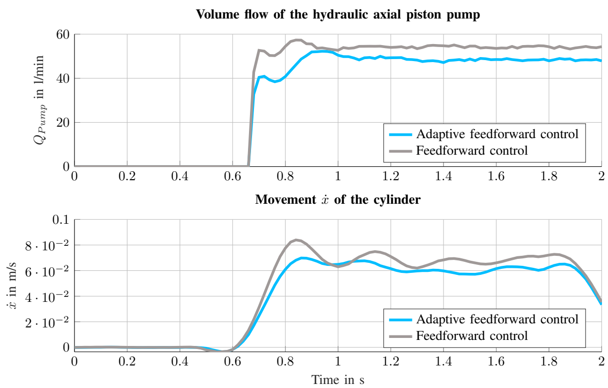

Fig. 6. Due to the overestimation of the feedforward controller without the adaption algorithm, the volume flow Q_{Pump} is too high, resulting in a too high pressure drop Δp and therefore a higher piston speed.

correct pressure drop Δp which can be seen when taking the mean betwenn 1 s and 2 s.

The issue which is depicted in Fig. 6 is that for automation of an mobile work machine using a hydraulic system a predictable and reliable speed must be present. If the valve characteristic is not representative and therefore the supplied volume flow is not suitable in regarde to the valve lift s the velocity can be set accurately. It can also be seen, that the feedforward control law itself is identical and only the desired supply volume flow $Q_{\text{Pump,des}}$ and hence the volume flow Q_{Pump} changes switching between the feedforward controller with and without the adaption algorithm.

V. Conclusion and Further Work

In this work two adaption algorithms have been showed in detail to improve the performance of a negativley controlled hydraulic system. The reliable supply and predictable behavior of the hydraulic system is crucial for subsequently implement control algorithms for automated piston control as seen for example in excavators. The outdated mechanical controller which has only the feedback loop makes it almost impossible to control the piston velocity well; especially if directional changes occur. With the contribution presented herein in combination with modern feedforward techniques for the hydraulic axial piston pump, the hydraulic system has been brought to a performance level with which the position control of the cylinder can be achieved with a much better tracking behavior. The comparison of the gaussian process with the recursive least squares algorithm does not yield huge differences which can be led back to the available data which has a very high quality. Regarding computational intensity the recursive least squares algorithm is a lot quicker and therefore was implemented on the real system to validate the improved performance. The control of the hydraulic system must be further improved and extended with a disturbance observer to be able to react on errors for example during the heat-up phase of the hydraulic oil. A feedback controller at this point is very cumbersome since the sample frequency of 50 Hz together with the dynamic of the pump delivers a very low bandwidth compared to the highly dynamic pressure equations.

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