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Electro-Hydraulic System Optimization Through an Advanced Kalman Filter

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***Abstract*— This paper presents a mathematical model of the Kalman Extended Filter (EKF) for estimating dynamic states in an electro-hydraulic system. The main goal is to increase the accuracy and stability of estimates in the presence of noise and nonlinearities in the dynamics of the system. EKF combines information from hydraulic motor shaft angular velocity measurements and the pressure difference between its inlet and outlet to provide reliable estimates of basic dynamic system parameters, including the current angular velocity and the moment created by the external load. Simulation studies demonstrate the advantages of the EKF compared to a system without a filter, emphasizing the importance of tuning the covariance matrices Q and R to achieve a balance between response speed and filter stability. The developed model shows high applicability for real electro-hydraulic systems, while offering the possibility of adaptation to other nonlinear dynamic systems.**

Keywords*— *Electro-hydraulic system; Extended Kalman Filter (EKF); nonlinear dynamics; optimization algorithm.

I. Introduction

Electro-hydraulic systems are important components in industrial and mobile technology because they provide high power, flexibility and efficiency. They combine the advantages of electric and hydraulic drives, providing high concentrated power, smooth speed and torque control, as well as the ability to operate under heavy loads [1-4]. In addition, electro-hydraulic systems offer high energy efficiency, thanks to the ability to adjust the pressure and flow rate according to the requirements of the application [5-7].

Thanks to these advantages, electro-hydraulic systems are widely used in various industrial and transport sectors [8-12]. They are used in robotic production lines, heavy construction machinery, aviation and automotive systems, as well as in automated processes in mechatronics [13-20]. Their ability to provide a stable and controlled flow of energy makes them indispensable for tasks requiring high accuracy and reliability [21, 22].

Despite their many advantages, electro-hydraulic systems also have some significant disadvantages that make their optimization and control difficult. One of the main problems is the presence of nonlinearities arising because of variations in pressure, temperature and dynamic loads [23]. These factors lead to non-linear behaviour of the system, which can lead to efficiency losses, instability, and degraded control accuracy. In addition, electro-hydraulic systems are often subject to noise and uncertainties related to sensor measurements and dynamic changes in the operating environment.

To overcome these shortcomings, various methods of data processing and management optimization are applied. Among the most used are different types of Kalman filters, which offer effective algorithms for assessing the state of the system in the presence of noise and uncertainty. The traditional Kalman Advanced Filter (EKF) is widely used in technical systems for processing nonlinear processes, offering reliable state assessment in the presence of noises and uncertainties. However, when the system's nonlinearities are significant, these methods can encounter difficulties related to loss of accuracy and numerical instability.

The present study proposes the use of an extended Kalman filter (EKF) as a method for data processing and control optimization in an electro-hydraulic system. The EKF uses a linear approximation through Jacobian

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matrices, which allows the evaluation of nonlinear processes through first-order approximation. This article discusses the application of EKF to evaluate and correct the parameters of the electro-hydraulic system and its integration with a PID regulator for optimized control, to minimize errors and improve its efficiency. The main objective of the study is to demonstrate the effectiveness of EKF for signal processing in nonlinear electro-hydraulic systems.

II. Materials and Methods

A. Description of the electro-hydraulic system

The electro-hydraulic system has been developed with the aim of providing high-precision motion control through the combined use of hydraulic and electrical components. The main idea behind this system is the transformation of electrical energy into hydraulic, which allows for effective control of the angular velocity and torque of the output shaft. By integrating various sensors and controls, the system can adapt its operation to loads and dynamic changes in conditions.

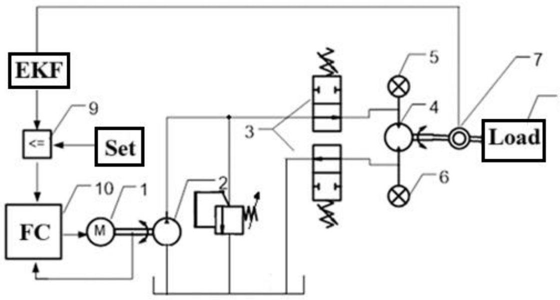

Fig. 1. Structural diagram of the electro-hydraulic system.

The schematic diagram of the electro-hydraulic system is presented in Fig. 1. The induction motor 1 creates a torque on its output shaft, to which the hydraulic pump is connected 2. The pump converts mechanical energy into hydraulic energy, creating a flow of working fluid under a certain pressure. This flow is fed to the hydraulic motor 4, which converts hydraulic energy back into mechanical energy, driving its output shaft and overcoming the external load 8. To measure and control the main quantities, measuring sensors are integrated into the system. Pressure sensors 5 and 6 are located respectively at the inlet and outlet of the hydraulic motor, measuring the created inlet and outlet pressure after energy conversion. In addition, to record the angular velocity of the output shaft of the hydraulic motor, tach generator 7 is installed. The system is controlled by frequency control 10 with a built-in PID regulator, which regulates the supplied voltage and frequency to the induction motor depending on the measured values of angular velocity and pressure. At the same time, the data processing unit 9 receives signals from the Extended Kalman Filter (EKF), which improves the accuracy of current measurements and provides the necessary algorithm for optimized system control.

B. EKF mathematical model for estimating hydraulic motor dynamics

The main goal of the EKF mathematical model is to provide reliable estimates of the angular velocity of the hydraulic motor shaft and of the moment created by the external load, combining information from angular velocity measurements and the pressure difference at the inlet and outlet of the hydraulic motor. Since the system is non-linear, EKF uses a first-order approximation to linearize the equations. The equation defining in nonlinear form the model of dynamics in the system has the following form:

$$x(k+1) = f[x(k), u(k)] + \omega(k), \tag{1}$$

where: $f[x(k), u(k)]$ is a function describing the nonlinear dynamics in the system; $x(k)$ are the values of the state vector in the step k; $\omega(k)$ is the noise defined in the kth step of the dynamic model.

Usually, the vector of control $u(k)$ contains input quantities that affect the dynamics of the system. In the case under consideration, the dynamics of the hydraulic motor is mainly determined by the pressure difference ΔP between its entrance and exit. Since $\Delta P(k)$ directly affects the generated torque, it is taken as a control variable. Thus, the control vector in the EKF model is defined as: $u(k) = \Delta P(k)$. This allows the EKF to use the measured pressure values to correct condition predictions.

To relate the real state in the system to the values of the measured quantities, the EKF is based on the nonlinear form of the measurement equation:

$$y(k) = h[x(k)] + v(k), \tag{2}$$

where: $h[x(k)]$ is the nonlinear relationship between the vector of states and the vector of measurements; $v(k)$ is the noise (errors) in the measurements.

The State Vector $x(k)$ contains the main dynamic variables of the hydraulic motor that EKF needs to evaluate. In the model under consideration, these are the angular velocity of the hydraulic motor shaft $w_l(k)$ and the moment of external load $T_L(k)$. These values determine the dynamics of the system, affect the behaviour of the hydraulic motor and can be set by:

$$x(k) = \begin{bmatrix} w_l(k) \\ T_L(k) \end{bmatrix}. \tag{3}$$

The measurement vector $y(k)$ consists of quantities that are measured directly in the system. In this case, these are the angular velocity of the shaft $w_l(k)$, measured by the tach generator and the pressure difference $\Delta P(k)$, whose current values are determined by the pressure sensors located at the inlet and outlet of the hydraulic motor. These dimensions are used to correct the EKF forecasts, and the vector looks like this:

$$y(k) = \begin{bmatrix} w_l^{meas}(k) \\ \Delta P^{meas}(k) \end{bmatrix}, \tag{4}$$

where: $w_l^{meas}(k)$ is the measured value of the angular velocity of the hydraulic motor shaft in the kth step; $\Delta P^{meas}(k)$ – The measured value of the pressure difference between the inlet and outlet of the hydraulic motor in the kth step.

If we apply an inverse relation to equation (1) and write it from a discrete procedure in continuous time, we get an equation describing the evolution of the state vector $x(t)$

$$\dot{x}(t) = f[x(t), u(t)] + \omega(t). \quad (5)$$

The basic equation for the dynamics of a hydraulic motor is:

$$J_l \cdot \dot{w}_l(t) = T_{hid}(t) - T_L(t) - B_l \cdot w_l(t), \quad (6)$$

where: J_l – Inertial moment of the hydraulic motor shaft; B_l - resistance moment coefficient; $T_L(t)$ – the moment created by the external load; $T_{hid}(t)$ - the torque generated by the hydraulic motor.

The torque generated by the hydraulic motor $T_{hid}(t)$ It depends on the pressure difference between the inlet and outlet of the motor and is proportional to the working volume of the motor. This relationship can be expressed by the following formula:

$$T_{hid}(t) = \frac{V_d}{2 \cdot \pi} \cdot \Delta P(t), \quad (7)$$

where: V_d is the volume of hydraulic fluid that passes through the engine in one full revolution of the shaft.

After substituting (7) in (6), the expression

$$\dot{w}_l(t) = \frac{V_d}{2 \cdot \pi \cdot J_l} \cdot \Delta P(t) - \frac{T_L(t)}{J_l} - \frac{B_l}{J_l} \cdot w_l(t). \quad (8)$$

In the model under consideration, we assume that the load moment $T_L(t)$ changes slowly within short time intervals. This assumption is justified because in most practical applications of hydraulic motors, the external load does not undergo rapid changes in very short intervals. Usually, load changes are due to mechanical loads or external forces that act with smooth dynamics.

As a result, in small time intervals, we can assume that the derivative of the load moment is approximately zero:

$$\dot{T}_L(t) \approx 0. \quad (9)$$

This assumption facilitates mathematical modeling and improves the stability of the EKF by allowing the filter to predict states more efficiently under conditions of smooth load changes.

Thus, the dynamic model of the EKF system is written as:

$$\dot{x}(t) = \begin{bmatrix} \dot{w}_l(t) \\ \dot{T}_L(t) \end{bmatrix} = \begin{bmatrix} \frac{V_d}{J_l \cdot 2 \cdot \pi} \cdot \Delta P(t) - \frac{B_l}{J_l} \cdot w_l(t) - \frac{T_L(t)}{J_l} \\ 0 \end{bmatrix} + \begin{bmatrix} \omega_w(t) \\ \omega_T(t) \end{bmatrix}, \quad (10)$$

Where: $\omega_w(t)$ – noise and errors in the model related to angular velocity dynamics; $\omega_T(t)$ - the noise and errors in the model that occur when determining the external load.

Since EKF works in an iterative structure, it is necessary to bring the matrix equation (10) into discrete time, i.e.

$$w_l(k+1) = w_l(k) + \Delta t \cdot \left[\frac{V_d}{J_l \cdot 2 \cdot \pi} \cdot \Delta P(t) - \frac{B_l}{J_l} \cdot w_l(t) - \frac{T_L(t)}{J_l}\right] + \Delta t \cdot \omega_w(t), \quad (11)$$

$$T_L(k+1) = T_L(k) + \Delta t \cdot \omega_T(t).$$

Equations (11) represent the discrete dynamical model for EKF. In addition, in the discretization of the load torque equation $T_L(k+1)$ the added random component $\omega_T(t)$ is multiplied by Δt, since it derives from its derivative. But the load moment itself $T_L(k)$ it is not multiplied by the discrete of time, because in the model it is assumed that it changes slowly, and its derivative is approximately zero.

To be able to use EKF to estimate the states of the system, it is necessary to define the mathematical relationship between the measured quantities and the real states. This connection allows the filter to adjust its predictions using the available measurement information. In the model under consideration, the measured parameters include the angular velocity of the hydraulic motor shaft and the pressure difference between the inlet and outlet of the motor, which are used to update the states in the EKF. Angular velocity $w_l^{meas}(k)$ is measured by the tach generator and therefore:

$$w_l^{meas}(k) = w_l(k) + v_w(k), \quad (12)$$

where: $v_w(k)$ - noise and errors made in angular velocity measurement.

The pressure difference $\Delta P^{meas}(k)$ is measured by the sensors located at the inlet and outlet of the hydraulic motor, and the relationship with the moment generated by the hydraulic motor is determined by (7), i.e.

$$\Delta P(k) = \frac{2 \cdot \pi}{V_d} \cdot T_{hid}(k), \quad (13)$$

Considering the basic equation for the dynamics of a hydraulic motor (6) and after bringing the dependencies into discrete time, we get:

$$\Delta P^{meas}(k) = \frac{2\cdot\pi}{V_d} \cdot \left[T_L(k) + J_l \cdot \frac{w_l(k) - w_l(k-1)}{\Delta t} + B_l \cdot w_l(k)\right] + v_P(k), \quad (14)$$

where: $v_P(k)$ is the noise and errors made when measuring pressure differences.

Then, the final form of the measurement model will be:

$$y(k) = \begin{bmatrix} w_l^{meas}(k) \\ \Delta P^{meas}(k) \end{bmatrix} = \left\{ \begin{matrix} w_l(k) \\ \frac{2\cdot\pi}{V_d} \cdot \left[T_L(k) + J_l \cdot \frac{w_l(k) - w_l(k-1)}{\Delta t} + B_l \cdot w_l(k)\right] \end{matrix} \right\} + \begin{bmatrix} v_w(k) \\ v_P(k) \end{bmatrix}. \quad (15)$$

In this way, the measurement model for EKF relates the measured quantities to the real states, considering both the non-linear dependencies in the system and the influence of noise in the measurements.

In EKF, Jacobian matrices are used to perform linearization of the nonlinear dynamic and measurement model. These matrices represent the local derivatives (gradients) of the respective functions relative to the states of the system. The Jacobian of the dynamic model $F(k)$ describes how small changes in states $x(k)$ affect the prediction of states in the next iteration, i.e.

$$F(k) = \frac{\partial f(x,u)}{\partial x}. \quad (16)$$

In addition, the Jacobian (16) is used to update the state covariance matrix.

For its part, the Jacobian of the measuring model $H(k)$ shows how the measured quantities depend on the current states, and its general form is:

$$H(k) = \frac{\partial h(x)}{\partial x}. \quad (17)$$

It is necessary to note that the matrix $H(k)$ participates in the calculation procedure for specifying the gain in the EKF filter by determining the weight of the measurements in the forecast correction.

The Jacobian matrix $F(k)$ can be presented in an expanded form as follows:

$$F(k) = \frac{\partial f(x,u)}{\partial x} = \begin{bmatrix} \frac{\partial f_1}{\partial w_l} & \frac{\partial f_1}{\partial T_L} \\ \frac{\partial f_2}{\partial w_l} & \frac{\partial f_2}{\partial T_L} \end{bmatrix}, \quad (18)$$

where f_1 is the equation for $w_l(k+1)$ в (11); f_2 is the equation for $T_L(k+1)$ in (11).

After calculating the partial derivatives of (18), the following final form for the matrix is obtained $F(k)$:

$$F(k) = \begin{bmatrix} 1 - \Delta t \cdot \frac{B_l}{J_l} & -\frac{\Delta t}{J_l} \\ 0 & 1 \end{bmatrix}. \quad (19)$$

From (15), the following two components can be determined that are necessary to determine the elements of the Jacobian matrix of the measurement model $H(k)$:

$$h_1 = w_l(k), \quad (20)$$

$$h_2 = \frac{2\cdot\pi}{V_d} \cdot \left[T_L(k) + J_l \cdot \frac{w_l(k) - w_l(k-1)}{\Delta t} + B_l \cdot w_l(k)\right].$$

This matrix has the following form:

$$H(k) = \frac{\partial h(x)}{\partial x} = \begin{bmatrix} \frac{\partial h_1}{\partial w_l} & \frac{\partial h_1}{\partial T_L} \\ \frac{\partial h_2}{\partial w_l} & \frac{\partial h_2}{\partial T_L} \end{bmatrix}. \quad (21)$$

Then, the full form of the matrix $H(k)$ will be:

$$H(k) = \begin{bmatrix} 1 & 0 \\ \frac{2\cdot\pi}{V_d} \cdot \left(\frac{J_l}{\Delta t} + B_l\right) & \frac{2\cdot\pi}{V_d} \end{bmatrix}. \quad (22)$$

Among the elements of the matrix $H(k)$, the calculation of $\frac{\partial h_2}{\partial w_l}$ requires special analysis because it contains a difference between states from two consecutive iterations. In this case, the partial derivative of $J_l \cdot \frac{w_l(k) - w_l(k-1)}{\Delta t}$ to $w_l(k)$ determines the attitude $J_l/\Delta t$, since the derivative of $w_l(k-1)$ is equal to 0, because it is a value from the previous iteration and does not depend on the current state $w_l(k)$.

In the EKF, covariance matrices $Q(k)$ and $R(k)$ are essential for assessing uncertainty in the dynamic and measurement model. They are related to dynamic noise and deviations in the theoretical model, respectively $\omega(k)$ and noise and errors in measurement procedures $v(k)$. The covariance matrix of dynamic noise $Q(k)$ defines the statistical characteristics of the uncertainties in the model related to the dynamics of angular velocity and the moment created by the external load. In general, this matrix has extra diagonal elements that determine the correlation between the individual noise components. In the model under consideration, however, the noises $\omega_w(k)$ and $\omega_T(k)$ are considered uncorrelated because angular velocity dynamics errors and load moment uncertainties originate from different physical sources. This allows simplification of the covariance matrix $Q(k)$, Assuming as diagonal with the following form:

$$Q(k) = \begin{bmatrix} \sigma^2_{\omega_w}(k) & 0 \\ 0 & \sigma^2_{T_L}(k) \end{bmatrix}, \tag{23}$$

where: $\sigma^2_{\omega_w}(k)$ is the variance characterizing uncertainties and random variations in angular velocity dynamics $w_l(k)$, caused by model inaccuracies, nonlinear effects and external interference; $\sigma^2_{T_L}(k)$ is the dispersion that determines the deviations in the dynamics of the load moment $T_L(k)$, which may result from random external influences, changes in mechanical loads or unidentified variations in the characteristics of the system.

In the present paper, the variance $\sigma^2_{\omega_w}(k)$ is calculated dynamically by analysing the differences between measured and predicted angular velocity values in separate time intervals. This involves calculating the mean and standard deviation of these differences, and the variance can be adjusted adaptively as the characteristics of the system change. By analogy, the variance $\sigma^2_{T_L}(k)$ is estimated based on variations in the load time, analysing the deviations between the calculated and real values for different operating modes.

The covariance matrix of the measuring noise $R(k)$ describes the errors and noises made when measuring angular velocity and pressure difference. In this work, it is accepted that measurement errors $v_w(k)$ and $v_P(k)$ are uncorrelated because the tach generator and pressure sensors work on different principles and measure physically independent quantities. Therefore, the matrix $R(k)$ It has the following diagonal view:

$$R(k) = \begin{bmatrix} \sigma^2_{v_\omega}(k) & 0 \\ 0 & \sigma^2_{v_P}(k) \end{bmatrix}, \tag{24}$$

where $\sigma^2_{v_\omega}(k)$ is the variance characterizing errors in angular velocity measurement $w_l(k)$, caused by external interference and errors of the tach generator; $\sigma^2_{v_P}(k)$ is the variance determining the errors in measuring the pressure difference $\Delta P(k)$, which can arise from the sensitivity of sensors, temperature fluctuations, noises in electronic circuits or dynamic effects in the hydraulic system.

In practical applications, the variances of measuring noise $\sigma^2_{v_\omega}(k)$ and $\sigma^2_{v_P}(k)$ can be determined by statistical analysis of measurement results. One of the most common approaches is to calculate the standard deviation of the errors between the repeatedly measured values and their filtered estimates. This method allows adaptive updating of the covariance matrix in real time, which is why it is used in the present work.

In the structure of the Kalman Advanced Filter (EKF), the first step is prediction (Prediction Step of the status):

$$x^-_{k+1} = f(x_k, u_k). \tag{25}$$

In this phase, a prediction of the states of the system for the next iteration is performed using the nonlinear dynamic model. This allows the expected state values to be calculated in advance before making an adjustment based on the new measurements. Mathematically, this step is defined in a general form by equation (1), and for the specific system - by the already derived discretized equations for dynamics (11). For a more compact representation, these equations can be written in matrix form:

$$x^-_{k+1} = \begin{bmatrix} w_l^-(k+1) \\ T_L^-(k+1) \end{bmatrix} = \begin{bmatrix} w_l(k) \\ T_L(k) \end{bmatrix} + \Delta t \cdot \begin{bmatrix} \frac{V_d}{J_l \cdot 2 \cdot \pi} \cdot \Delta P(k) - \frac{B_l}{J_l} \cdot w_l(k) - \frac{T_L(k)}{J_l} \\ 0 \end{bmatrix}. \tag{26}$$

Along with the prediction of states, EKF also calculates the covariance error matrix of the model, which characterizes the uncertainty in the predicted state. This matrix P^-_{k+1} is updated by linear approximation using the Jacobian matrix $F(k)$ and the covariance matrix of dynamic noise $Q(k)$:

$$P^-_{k+1} = F(k) \cdot P_k \cdot F^T(k) + Q(k). \tag{27}$$

Gain $K(k)$ ensures the optimal combination of forecast values and current measurements by calculating according to the following formula:

$$K(k) = P^-_k \cdot H^T(k) \cdot [H(k) \cdot P^-_k \cdot H^T(k) + R(k)]^{-1}, \tag{28}$$

where: $H(k)$ – the Jacobian matrix of the measurement model, defined by (22); $R(k)$ – the covariance matrix of errors and noises allowed in the measurement of angular velocity and pressure difference determined by (24).

The correction of the predicted state is based on the difference between the current values of measured quantities $y(k)$ and their predicted values $h(x^-_k)$:

$$x_{k+1} = x^-_{k+1} + K(k) \cdot [y(k) - h(x^-_k)]. \tag{29}$$

Equation (29) has the following matrix form:

$$\begin{bmatrix} w_l(k+1) \\ T_L(k+1) \end{bmatrix} = \begin{bmatrix} w_l^-(k+1) \\ T_L^-(k+1) \end{bmatrix} + \begin{bmatrix} K_{11}(k) & K_{12}(k) \\ K_{21}(k) & K_{22}(k) \end{bmatrix} \cdot \left\{ \begin{bmatrix} w_l^{meas}(k) \\ \Delta P^{meas}(k) \end{bmatrix} - \begin{bmatrix} w_l(k) \\ \frac{2 \cdot \pi}{V_d} \cdot \left[T_L(k) + J_l \cdot \frac{w_l(k) - w_l(k-1)}{\Delta t} + B_l \cdot w_l(k) \right] \end{bmatrix} \right\}, \tag{30}$$

where $K_{11}(k)$, $K_{12}(k)$, $K_{21}(k)$, $K_{22}(k)$ are values obtained in the kth iteration when solving the matrix equation (28).

After the state correction, the EKF updates the covariance matrix P_{k+1}^{-}, by refining the assessment of state uncertainty after the inclusion of the new measurements:

$$P_{k+1} = [I - K(k) \cdot H(k)] \cdot P_{k+1}^{-}, \quad (31)$$

where: I is the single matrix.

III. Results and Discussion

A. Evaluation of EKF performance based on simulation studies

To evaluate the effectiveness of the developed EKF model, a simulation model was created in the MATLAB/Simulink programming environment. The simulations include the dynamic system of the hydraulic motor, measuring noises, as well as the application of EKF for state assessment. Some of the simulation results are shown in figures 2 and 3.

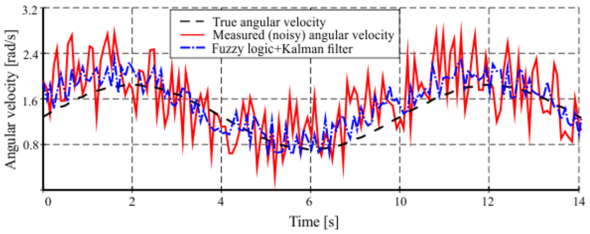

Fig. 2. Fig. 2: Change in the angular velocity of the hydraulic motor shaft with EKF set with preset values of Q and R.

The curves in Fig. 2 represent the change in angular velocity of the hydraulic motor shaft in two operating modes. In the first mode, the system works without turning on the EKF module, and the angular velocity is determined directly from the measured values (red curve). In this case, the noise in the measurements has a significant impact, resulting in deviations from the true value (the black broken curve). In the second mode, EKF is applied, and the resulting filtered value is represented by the blue curve. The figure shows that although the EKF reduces some of the noise, the result is not optimal due to incorrect adjustment of the filter parameters. In this case, the covariance matrices Q and R are selected with preset values, but without additional adjustment to the actual measurements, which limits the efficiency of the filter.

In Fig. Figure 3 shows the results after optimization of the covariance matrices Q and R. In this case, the filtered value (blue curve) is significantly closer to the true angular velocity (black dashed line), while the measurement noise is suppressed. This demonstrates the importance of proper adjustment of dies Q and R on the effectiveness of the EKF. In the optimized configuration, the die Q is tuned to reflect the dynamic uncertainties in the model, and R has been corrected based on empirical data from the measurement system, thus reducing correction errors.

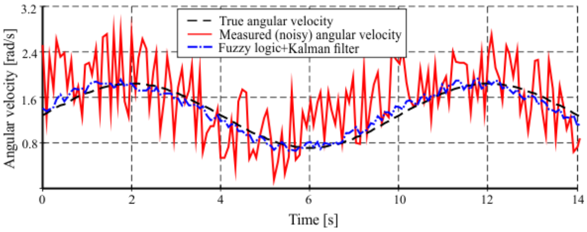

Fig. 3. Fig. 3: Angular velocity change with optimized covariance matrices Q and R in EKF.

Gain also plays an essential role in this iterative process K, which determines to what extent the measured values correct the predicted state. At optimal settings, the gain provides a balance between the predicted and measured values, which greatly improves the accuracy of the estimate. In the first case (Fig. 2) K is not optimally adjusted, resulting in less noise suppression, while in the second case (Fig. 3) an adaptive tuning method was used, resulting in a significantly better match to the actual dynamics of the system.

The results of simulation studies show that EKF can effectively reduce the influence of noise and improve the accuracy of the evaluated parameters, but its effectiveness is highly dependent on the adjustment of the covariance matrices Q and R, as well as the correct choice of gain K.

IV. Conclusions

In this work, a mathematical model of an extended Kalman filter (EKF) has been developed for evaluating dynamic states in an electro-hydraulic system. The main goal is to ensure higher accuracy and stability of estimates in the presence of noise and nonlinearities in the dynamics of the system. The model combines information from angular velocity and pressure difference measurements to provide reliable estimates of this output shaft speed and the torque created by the external load.

Simulation studies have shown that EKF significantly improves the accuracy of the evaluated parameters compared to a system without a filter. Along with this, these studies have shown the importance of tuning covariance matrices Q and R, which directly determine the accuracy and stability of the EKF. By optimizing these matrices, an optimal balance was achieved between the speed of reaction and the stability of the filter.

The practical significance of the developed model is expressed in its applicability for real electro-hydraulic systems, while at the same time it can be adapted for other nonlinear dynamic systems. The results obtained demonstrate the potential of EKF to improve the accuracy and stability of control systems under noise and dynamic load conditions.

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