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Parameter Evaluation and Control in an Electro-Hydraulic System Using an Advanced Least Squares Method

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***Abstract*— Electro-hydraulic systems are characterized by high complexity and nonlinearity, caused by the dynamic interactions between the fundamental quantities that determine their operation and control. The present study proposes a method for adaptive parameter estimation using an advanced method of least squares (A-LS) (Advanced Least Squares), applicable to nonlinear dynamical systems. The paper presents a mathematical model describing the dynamics of the electro-hydraulic system, as well as an approach for adaptive parameter estimation using Recursive Least Squares (RLS) in combination with the Stochastic Gradient Method (SGD). The main goal is to minimize errors between measurement results and predicted model values, ensuring high accuracy and stability under variable operating conditions. The results of the simulations show that the use of RLS for angular velocity estimation and SGD for adaptive load torque correction allows for effective noise suppression in measurements and precise tracking of system dynamics. The proposed approach provides a basis for optimizing electro-hydraulic systems through adaptive methods and can be useful for applications requiring high accuracy and reliability.**

Keywords*— *Electro-hydraulic system; Recursive least squares; Stochastic gradient descent; dynamic parameter estimation.

I. Introduction

Electro-hydraulic systems play an essential role in several industrial and engineering applications requiring high accuracy, reliability, and efficiency in motion control [1-5]. These systems combine the advantages of electrical and hydraulic technologies, providing high drive power in compact dimensions and good dynamic performance [6-10]. They are also widely used in robotics, automation, aviation systems, digital program control (CNC), heavy industry, and mobile hydraulics, where precise control of forces and movements is required [11-20].

Among the main advantages of electro-hydraulic systems are a high power-to-weight ratio, the ability to smoothly adjust the movement and a large output force. Additionally, they can operate under extreme loads and are suitable for applications requiring the ability to transmit large forces and power in compact sizes. Another important advantage is the high efficiency of power transmission and the ability to work with several types of loads, including intermittent dynamic loads. These systems can be integrated with advanced control algorithms, such as adaptive and predictive regulators, which further improves their flexibility and energy efficiency [21, 22].

Despite these advantages, electro-hydraulic systems also have significant drawbacks that can limit their accuracy and stability. A major problem is the nonlinearities that arise because of the dynamic interactions between pressure, flow, and load. Factors such as changes in temperature, mechanical backlash and viscosity of the working fluid also contribute to the complex behaviour of the system. In addition, noises appear in the measuring circuits of the system, which can reduce the quality of control and lead to significant errors in the evaluation of parameters. Another important disadvantage is the delay in the dynamic response of the system, which can lead to undesirable transients and instability in case of sudden changes in the load [23, 24].

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To overcome these shortcomings, various methods of correction and optimization have been proposed. These include the Kalman filter and its advanced versions, including the Extended Kalman Filter (EKF) and the Advanced Kalman Filter (UKF), which can be used to optimally filter measurements and reduce the impact of noise. Another alternative technique is the Wiener filter, which provides optimal linear filtering of the signal in the presence of white noise. In some cases, nonlinear adaptive methods are also applied, such as filters based on the Monte Carlo method (Particle Filters) and methods based on neural networks, which provide greater flexibility when working with dynamically changing systems [25-27].

This article proposes an advanced method for adaptive parameter estimation based on the Least Squares method with recursive correction (RLS) and the stochastic gradient method. Compared to the above methods, RLS offers more efficient processing of parametric estimates in real time and does not require prior noise statistical information, as is required with the Kalman filter. In addition, the stochastic gradient method provides rapid adaptation to changing dynamic external loads without incurring significant computational costs typical of nonlinear filters. The purpose of this method is to minimize errors between measured and predicted values, ensuring higher accuracy and stability under changes in operating conditions. The method combines adaptive algorithms to estimate parameters, considering dynamic influences on the system, and is particularly suitable for applications where external forces and moments change in real time.

This article will present a detailed analysis of the electro-hydraulic system, develop the mathematical model for adaptive parameter assessment and analyse the effectiveness of the proposed methodology through a simulation model.

II. Materials and Methods

A. Description of the electro-hydraulic system

The electro-hydraulic system developed in this work is a set of mechanical, hydraulic, and electronic components that work together to provide high-precision motion control. In Fig. 1, its schematic diagram is presented. At the heart of the system is the induction motor 1, whose operation is controlled by frequency control 10. This control allows for a change in the frequency and voltage of the current supplied to the motor, which provides precise control of speed and torque. The induction motor is connected to the hydraulic pump 2, which converts mechanical energy into hydraulic energy, creating flow rate and pressure. These parameters, in turn, determine the operation of the hydraulic motor 4, which converts hydraulic energy back into mechanical energy, driving the output shaft and overcoming the external load 8.

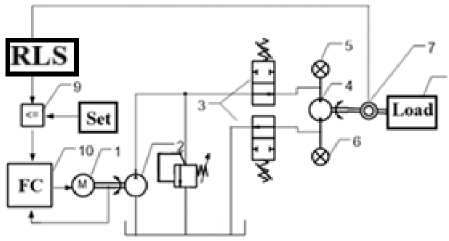

Fig. 1. Schematic diagram of electro-hydraulic drive system.

The system is equipped with measuring sensors that provide information about the change in the main values in the system. Pressure sensors 5 and 6 are installed at the inlet and outlet of the hydraulic motor, which measure the inlet and outlet pressure. In addition, to measure the angular velocity, a tach generator 7 is installed to the shaft of the hydraulic motor. The system also contains ON/OFF valves 3, which control the flow of hydraulic fluid, as well as a tuning unit 9, where the signals from the developed control optimization filter are transmitted.

B. Development of the RLS mathematical model for adaptive parameter estimation

The mathematical model is based on the differential equation describing the dynamics of the electro-hydraulic system:

$$T_{hid}(t) = J_l \cdot \dot{\omega}_l(t) + B_l \cdot \omega_l(t) + T_L(t), \qquad (1)$$

where: $T_{hid}(t)$ - the moment that reaches the shaft of the hydraulic motor; J_l - Inertial moment of the hydraulic motor shaft; B_l - Coefficient of friction in the hydraulic motor; $T_L(t)$ - the external load applied to the shaft of the hydraulic motor.

Equation (1) describes the balance of torques, considering inertial forces, frictional losses, and the influence of external load. This approach is standard for modeling dynamic systems and allows analysing the influence of various parameters on the behaviour of the system.

The torque generated by the hydraulic motor can be determined from the equation.

$$T_{hid}(t) = \frac{V_d}{2\pi} \cdot \Delta P(t) = T_{hid}(t) = \frac{V_d}{2\pi} \cdot [P_{in}(t) - P_{out}(t)], \qquad (2)$$

where V_d - The displacement of the hydraulic motor (the volume of fluid moved per revolution); $P_{in}(t)$ и $P_{out}(t)$ – the inlet and outlet pressure of the hydraulic motor, measured now of time t.

To apply the method for adaptive estimation of parameters based on the method of least squares, it is necessary to bring equation (1) into a discrete form and conform to the structure of the iterative procedure, i.e.

$$\omega_l(k+1) = \omega_l(k) + \Delta t \cdot \frac{V_d}{2\pi \cdot J_l} \cdot [P_{in}(k) - P_{out}(k)] - \Delta t \cdot \frac{B_l}{J_l} \cdot \omega_l(k) - \Delta t \cdot \frac{T_L(k)}{J_l}, \quad (3)$$

The external load $T_L(k)$ it is usually not a constant value, and its accurate prediction of each step of the iterative procedure can provide useful information for the effective control of the electro-hydraulic system. In this work, a method for determining the current values of the external load, based on iterative optimization, is adopted. Since $T_L(k)$ Equation (3), the method for iterative optimization can be based on this dependence, minimizing the difference between the predicted $\omega_l^{pred}(k)$ and the measured angular velocity $\omega_l^{meas}(k)$. The error between the predicted and measured angular velocity is determined by the difference.

$$e(k) = \omega_l^{meas}(k) - \omega_l^{pred}(k), \quad (4)$$

where $\omega_l^{meas}(k)$ - the measured angular velocity in step k; $\omega_l^{pred}(k)$ - the predicted angular velocity from the model.

The aim is to determine this value of $T_L(k)$, where the error $e(k)$ will have a minimum value. To iteratively update $T_L(k)$ In this work, the method of gradient descent was used (SGD), which in this case has the form.

$$T_L(k+1) = T_L(k) - \eta \cdot \frac{\partial E}{\partial T_L}, \quad (5)$$

where η is the coefficient of learning (learning rate), and $E(T_L)$ is determined by the expression.

$$E(T_L) = \frac{1}{2} \cdot \sum_{k=1}^{N} \left[\omega_l^{meas}(k) - \omega_l^{pred}(k)\right]^2 = \frac{1}{2} \cdot \sum_{k=1}^{N} e(k)^2, \quad (6)$$

where $E(T_L)$ - the sum of the squares of the errors and shows how well the moment of the load $E(T_L)$ approach the actual behaviour of the system.

The gradient descent method is preferred in this case over other optimization approaches, as it provides an effective approximation to the optimal solution without the need for prior information about the statistical properties of noise in the system. In addition, gradient descent allows for rapid adaptation to dynamically changing conditions, making it suitable for real-time applications. Compared to methods such as Newtonian optimization, which require the calculation of the second derivative (Hessian matrix), gradient descent is a significantly more computationally efficient approach and can be easily implemented in adaptive algorithms.

The aim is to determine the values of $T_L(k)$, that minimize the function $E(T_L)$. Since the partial derivative $\frac{\partial E}{\partial T_L}$ is a function of the error $e(k)$ It follows that if the error is positive (the predicted speed is less than the measured one), and it is necessary to increase the $T_L(k)$. If the error is negative, the value of the $T_L(k)$. This procedure gradually adjusts the $T_L(k)$, докато грешката стане близка до нула. However, the gradient method does not always guarantee reaching a global minimum. Depending on the initial conditions and characteristics of the error function $E(T_L)$, the algorithm can fall into local minima or have slow convergence, especially if the surface of the error function contains plateau or pronounced minima. To improve convergence, techniques such as adaptive learning factor or the addition of dynamic acceleration in gradient descent are often used in practice to avoid stagnation at negligible local minimums and accelerate reaching the global minimum. In the current study, however, the focus is on the accuracy of load torque estimation, rather than on accelerating convergence. In addition, the adopted adaptive assessment method ensures stable behaviour even in the absence of additional acceleration techniques. It is therefore necessary to determine the gradient in terms of $T_L(k)$, i.e., how the change in the moment created by the external load affects the error. For this purpose, the differentiation rule can be used:

$$\frac{\partial E}{\partial T_L} = \sum_{k=1}^{N} e(k) . \frac{\partial e(k)}{\partial T_L}. \quad (7)$$

Since the algorithm being developed works in an iterative procedure, it is more appropriate to use the stochastic gradient method instead of the full gradient, which includes a sum of all iterations (which would be slower and more complex), which updates the parameter step-by-step, using only the current error:

$$T_L(k+1) = T_L(k) - \eta \cdot \frac{\partial e(k)}{\partial T_L(k)} \cdot e(k). \quad (8)$$

The sum in (8) is dropped because the method makes the correction of each iteration using the instantaneous error $e(k)$, instead of waiting for the accumulation of information from all previous steps. This is the main advantage of the Stochastic Gradient Method (SGD) over the classical gradient descent, which uses the average of all errors to update the parameters. Although SGD allows for faster adaptation to current changes in the system and can find an approximation to the optimal solution significantly earlier, it can lead to increased variability in parameter updates. For this reason, the stability of the algorithm depends on the correct choice of the learning factor η. To determine the partial derivative of the $e(k)$ error from the moment created by the load in the kth iteration, the following equation can be used:

$$\frac{\partial e(k)}{\partial T_L(k)} = \frac{\partial}{\partial T_L(k)} \left[\omega_l^{meas}(k) - \omega_l^{pred}(k)\right]. \quad (9)$$

Since $\omega_l^{meas}(k)$ does not depend on $\partial T_L(k)$, the derivative is converted to:

$$\frac{\partial e(k)}{\partial T_L(k)} = -\frac{\partial \omega_l^{pred}(k)}{\partial T_L(k)}. \quad (10)$$

Equation (3) shows that the only term dependent on $\partial T_L(k)$, e $-\Delta t \cdot \frac{T_L(k)}{J_l}$. Therefore:

$$T_L(k+1) = T_L(k) + \eta \cdot \frac{\Delta t}{J_l} \cdot e(k). \quad (11)$$

Formula (11) is the iterative formula for updating the load moment, based on the stochastic gradient method (SGD), which performs a step-by-step update (on each iteration) using only the current error $e(k)$, which makes the algorithm faster and more adaptable. Here we correct $T_L(k)$ at each step, so the mistake $e(k)$ decrease.

An important parameter in gradient descent is the learning coefficient η, which specifies the update step of a moment defining the external load $T_L(k)$ in each iteration. Choosing the appropriate value for this coefficient is essential for the speed and stability of adaptation. If η is too small ($\eta \leq 0.01$), the update of the $T_L(k)$ will be conducted too slowly, which can lead to a significant delay in the algorithm's response to real changes in the system. In such cases, error correction will be insufficiently effective, and the process may require too many iterations to reach an optimal result. If η has too much value ($\eta \geq 0.1$), algorithm will make aggressive adjustments that can lead to variations around the real value of the $T_L(k)$ or even to instability of adaptation. In this case, the load torque will fluctuate unnaturally with each step, and unwanted fluctuations in the system may occur. The experience gained from various applications shows that the initial value of $\eta = 0.05$ is a good compromise between quick adaptation and stability. Depending on the dynamics of the system, this parameter can be further adjusted experimentally to ensure optimal behaviour.

The vector form of the least squares method model, which minimizes errors between measured and predicted values, is as follows:

$$\omega_l(k+1) = \Phi(k) \cdot \theta + \varepsilon(k), \quad (12)$$

where: $\Phi(k)$ is a matrix of regressors; θ is the vector with the parameters of the system; $\varepsilon(k)$ – The error of the model in the kth step.

In this work, in contrast to the classical method of least squares (MLS), which is used to identify constant parameters, we apply MLS for dynamic estimation of the angular velocity of the shaft of a hydraulic motor $\omega_l(k)$ and the moment of external load $T_L(k)$. This is achieved by minimizing error $\varepsilon(k)$, defined as the difference between the measured and predicted angular velocity value:

$$\sum_k \varepsilon^2(k) = \sum_k [\omega_l^{meas}(k+1) - \Phi(k) \cdot \theta]^2. \quad (13)$$

For the display of $\Phi(k)$ and θ, We bring equation (3) to the following form, considering that $T_L(k)$ is evaluated separately by an iterative procedure for the Stochastic Gradient Method (SGD):

$$\omega_l(k+1) = \left(1 - \Delta t \cdot \frac{B_l}{J_l}\right) \cdot \omega_l(k) + \Delta t \cdot \frac{V_d}{2\pi \cdot J_l} \cdot [P_{in}(k) - P_{out}(k)]. \quad (14)$$

The Regressor Matrix $\Phi(k)$ consists of the input values of the model, which determine the dynamics of the system, and serves as the basis for estimating the unknown parameters using the method of least squares. In contrast to the standard applications of the method of least squares, in this study the quantities that are evaluated dynamically are the angular velocity of the hydraulic motor shaft $\omega_l(k)$ and load torque $T_L(k)$, since they change over time and must be precisely defined for the management of the system. In connection with what has been said, the matrix $\Phi(k)$ It can be written as follows:

$$\Phi(k) = [P_{in}(k+1) - P_{out}(k+1) \quad \omega_l^{meas}(k+1)]. \quad (15)$$

In the present work, with sufficient accuracy for real-world applications, we assume that the measured value of angular velocity $\omega_l^{meas}(k)$ is used directly as an input dimension in the model. This decision is because sensor measurements, although subject to some errors, provide more reliable information about the actual dynamics of the system compared to the result of an accumulation of predicted values. The use of measured data prevents the accumulation of errors in the iteration process, which is especially important for the long-term stability of the model. Furthermore, this approach allows the method of least squares to be more precise in estimating angular velocity and load torque, without the need for additional filtering or adaptive algorithms to select optimal values. Therefore, the full form of the matrix (15) will be:

$$\Phi_N(k) = \begin{bmatrix} P_{in}(k+1) - P_{out}(k+1) & \omega_l^{meas}(k+1) \\ P_{in}(k) - P_{out}(k) & \omega_l^{meas}(k) \\ P_{in}(k-1) - P_{out}(k-1) & \omega_l^{meas}(k-1) \\ \vdots & \vdots \\ P_{in}(0) - P_{out}(0) & \omega_l^{meas}(0) \end{bmatrix}. \quad (16)$$

However, in the current recursive algorithm, to minimize computational complexity, we use only the matrix (15).

The Parameter Vector θ contains the constant physical coefficients of the system, which determine the relationship between the input quantities $P_{in}(k) - P_{out}(k)$ and $\omega_l(k)$ in the current iteration and output angular velocity $\omega_l(k+1)$ in the next iteration

$$\theta = \begin{bmatrix} \Delta t \cdot \frac{V_d}{2\pi \cdot J_l} \\ 1 - \Delta t \cdot \frac{B_l}{J_l} \end{bmatrix}. \quad (17)$$

To bring the algorithm to the concept of recursive evaluation of parameters, it is necessary to define the recursive gain factor $K(k)$:

$$K(k) = P(k) \cdot \Phi^T(k) \cdot [\lambda + \Phi(k) \cdot P(k) \cdot \Phi^T(k)]^{-1}, \quad (18)$$

where λ – weight factor (forgetting factor); $P(k)$ – covariance matrix of estimates.

The weighting factor controls the speed of adaptation of the algorithm. Lower values of λ (close to 0.95) give more weight to new measurements, which makes the algorithm more adaptable to changes in system dynamics. Higher values (close to 1) reduce the impact of new data and retain more information than previous estimates, resulting in a smoother correction. Since the processes in the electro-hydraulic system do not change abruptly over time, a value is assumed in this work $\lambda = 0.99$, which provides a good balance between stability and adaptability of the algorithm.

Since the moment created by the external load $T_L(k)$, is determined by a separate stochastic gradient method (SGD), the recursive algorithm (RLS) includes the estimation of angular velocity $\omega_l(k)$ and the pressure difference $P_{in}(k+1) - P_{out}(k+1)$. This allows for more precise adaptive estimation since the dynamics of the system are directly dependent on these two parameters as well.

The use of RLS for $\omega_l(k)$ and SGD for $T_L(k)$ is justified by the different update mechanisms. RLS minimizes accumulated errors, while SGD makes quick corrections step-by-step. The inclusion of $T_L(k)$ in RLS would lead to a conflict between the two methods, which may reduce the effectiveness of adaptive assessment. The vector of the evaluated parameters is:

$$X(k) = \begin{bmatrix} \widehat{\omega}_l(k) \\ \Delta\hat{P}(k) \end{bmatrix}, \quad (19)$$

where $\widehat{\omega}_l(k) = \omega_l^{pred}(k)$ is the estimation of the angular velocity of the hydraulic motor shaft in the kth step; $\Delta\hat{P}(k)$ is the estimation of the difference between the inlet and outlet pressure of the hydraulic motor in the kth step.

In the adaptive estimation of these parameters, it is necessary to derive a corresponding covariance matrix that defines the uncertainty in the estimates:

$$P(k) = \begin{bmatrix} \sigma_\omega^2 & 0 \\ 0 & \sigma_{\Delta P}^2 \end{bmatrix}, \quad (20)$$

where σ_ω^2 is the variance of errors in angular velocity estimation; $\sigma_{\Delta P}^2$ is the variance of errors in the pressure difference estimate.

Initially, the variances in the $P(k)$ is set with high values, which allows the algorithm flexibility in initial iterations, and subsequently the values are dynamically updated, which leads to a decrease in uncertainty over time.

The recursive formula for updating grades is:

$$X(k+1) = X(k) + K(k) \cdot \delta(k), \quad (21)$$

where the error vector $\delta(k)$ It has the following form:

$$\delta(k) = \begin{bmatrix} \omega_l^{meas}(k+1) - \widehat{\omega}_l(k) \\ \Delta P^{meas}(k+1) - \Delta\hat{P}(k) \end{bmatrix}, \quad (22)$$

where $\omega_l^{meas}(k+1)$ is the measured value of the angular velocity in k+1 – iteration; $\Delta P^{meas}(k+1)$ is the measured value of the pressure difference in k+1 – iteration.

After each iteration, the covariance matrix $P(k)$ is updated to consider added information and thus reduce uncertainty in estimates. The update procedure is determined by the matrix equation:

$$P(k+1) = P(k) - K(k) \cdot \Phi(k) \cdot P(k). \quad (23)$$

This adjustment ensures that the algorithm remains adaptable to changes in system dynamics while improving the accuracy of angular velocity and pressure difference estimates.

III. Results and Discussion

A. Evaluation of the operability of the method through a simulation experiment

To evaluate the effectiveness of the proposed adaptive method for parameter estimation, a simulation model has been developed in the MATLAB/Simulink environment. The model includes the electro-hydraulic system from Fig.1 with a dynamically changing load and a mechanism for adaptive estimation of angular velocity and load torque. The presented results illustrate the behaviour of the system under conditions of changing input influences. The estimation of angular velocity is performed using the recursive least squares method (RLS), and the moment of external load is updated using the stochastic gradient method (SGD).

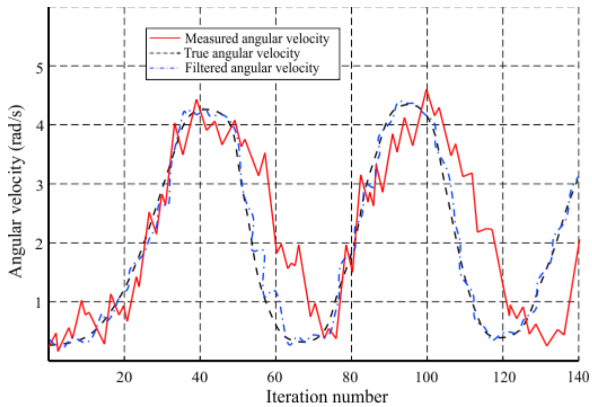

Fig. 2. Comparison of measured, true, and filtered angular velocity estimated by RLS with gradient correction.

In Fig. Figure 2 presents graphically the curves illustrating the measured angular velocity (the red curve), the true angular velocity (the black dotted curve) and the angular velocity estimated by the recursive method of least squares (the blue dotted curve). The graph shows that the measured angular velocity contains significant fluctuations and noise, which makes it difficult to use it directly for control. Despite these fluctuations, the estimation obtained by the recursive method of least squares follows the true angular velocity with high accuracy. This shows that the algorithm effectively eliminates measurement noise and provides accurate angular velocity determination in real time. The difference between the true and estimated angular velocity is minimal, demonstrating the good convergence of the algorithm. Even with sudden changes in movement, the filtered angular velocity remains stable and follows the dynamics of the system with a small delay.

The results confirm that the proposed methodology provides high accuracy and stability of the estimates, which is essential for the application of the method in electro-hydraulic systems. The successful noise suppression and elimination of parasitic oscillations makes the method suitable for managing dynamic processes where the reliability of assessments is critical.

The dynamics of the estimated load torque $T_L(k)$ is shown in Fig. 3. The curve is obtained using the stochastic gradient method (SGD). The graph shows how the moment created by the external load adapts with each iteration, gradually following the increasing trend of the actual load.

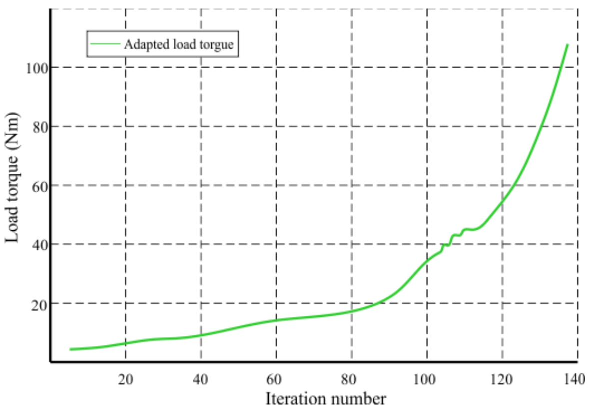

Fig. 3. Adaptive estimation of external load moment by stochastic gradient method (SGD).

In the initial iterations, the load torque is small and changes smoothly, which is the result of the initial uncertainty in the estimates. As the iterations progressed, the algorithm was able to track the change more accurately in load, ensuring a smooth and stable adaptation. At the end of the simulation, an increase in load torque was observed, indicating that the algorithm successfully identified changes in dynamic load.

The absence of significant variations and sharp deviations in the load estimate confirms the stability of the algorithm. This is especially important in applications where the load torque may vary due to external factors, such as changes in operating conditions or external interference.

The results obtained show that the combined use of RLS for angular velocity estimation and SGD for load torque estimation provides reliable and adaptive tracking of system dynamics. This approach allows for rapid adaptation to changing conditions, while maintaining stability and minimizing errors in estimates.

IV. Conclusions

This paper presents an advanced method for estimating parameters in an electro-hydraulic system based on the recursive least squares method (RLS) and the stochastic gradient method (SGD). Through the developed mathematical model and the simulations conducted, it was proved that the proposed methodology provides high accuracy in estimating the angular velocity of the hydraulic motor and the load torque, effectively suppressing noise in measurements.

The results of the simulation experiment confirm that the combined use of RLS and SGD results in reliable adaptation of real-time estimates, which is essential for dynamically changing workloads. The method offers stability and quick response of the system to variations in operating conditions, making it suitable for applications requiring high precision and adaptability.

The proposed approach can be further extended by applying nonlinear optimization techniques, as well as by integrating additional filtering methods to improve immunity to noise and uncertainties in the system.

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