Development of a Multi-Factor Control System for the Electric Drives of Pumping Units in Coal Mining Quarries Utilizing an Extended Kalman Filter

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Abstract: - This study presents the development of an intelligent sensorless control system for a pumping unit driven by an asynchronous motor under variable hydraulic load conditions. The proposed approach integrates an electromechanical motor model based on the Park–Gorev transformation with a hydraulic load model and applies an extended Kalman filter (EKF) for real-time estimation and prediction of stator current and rotor speed. Unlike conventional systems, the method eliminates the need for pressure and flow sensors by relying solely on electrical measurements. Simulation and experimental results demonstrate high accuracy, with deviations below 5%. The developed model improves energy efficiency, enhances system reliability, and enables stable operation under fluctuating conditions, making it suitable for industrial pumping applications.

Key-Words: - Asynchronous motor, Pumping unit, Extended Kalman filter, Park-Gorev equations.

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1 Introduction

Improving the energy efficiency of industrial electric drives remains a paramount objective in light of escalating demands for sustainable development, cost efficiency, and compliance with environmental standards, [1]. Pumping units hold a pivotal role in the energy dynamics of mining enterprises, facilitating the extraction of groundwater and wastewater, ensuring consistent water discharge, and ensuring operational safety, [2]. According to industrial energy audits, the proportion of energy consumption attributable to pump units can reach 30–40% of the total electricity usage within an enterprise, [3]. In light of the above, even slight enhancements in pump management efficiency can yield significant economic and operational benefits.

Nonetheless, the management of pump installations in quarry environments is fraught with challenges. The main load on the electric drive arises from hydraulic resistance, which depends on variables such as water level, viscosity, density, and dynamic flow alterations, [4]. The abovementioned parameters are inherently variable and cannot be accurately described through fixed characteristics. That being said, the control system must exhibit a high degree of adaptability and possess the ability to anticipate the behavior of the system in real-time mode.

Currently, a variety of technical solutions exist, including intelligent pumps, frequency-regulated drives, and programmable logic controllers, [5]. However, the majority of these systems require the deployment of external sensors for monitoring pressure, flow rate, water level, and rotational speed. The financial burden of these sensors, along with their installation and maintenance, is often comparable to the cost of the pump equipment itself, particularly in environments that are polluted, corrosive, or difficult to access. What is more, even with the integration of sensors, many prevailing solutions fail to deliver the required level of accuracy and response time, [6], [7]. Notably, in unstable operating conditions such as a sudden surge in pressure or cavitation phenomena [8], [9], deviations in control can lead to engine overload or diminish operational efficiency.

Against this backdrop, intelligent control methods [10], [11] based on the internal parameters of the electric drive, such as currents and magnetic fluxes, without the use of additional sensors [12], have acquired particular relevance. Nonetheless, the scientific literature reveals a limited number of studies that explore the potential for predicting the state of the pumping unit solely based on engine parameters. This is particularly pertinent for asynchronous machines, which are predominant in industrial applications, [13]. Additionally, the issue of integrating the electromechanical and hydraulic models [14] remains inadequately explored, with the majority of algorithms failing to accommodate real-time variable loads, [15].

Thus, there exists a pressing scientific and technical imperative for the development of novel approaches that will enable: the elimination of external sensors without compromising accuracy; the consideration of hydraulic load dynamics; the prediction of latent parameters of the electric drive; and the reduction of overall energy consumption within the system. This study endeavors to address these challenges by constructing an integrated model of the pumping unit utilizing an extended Kalman filter (EKF) that operates exclusively on the basis of electromechanical measurements. The novelty of this study resides in the development of an adaptive control system based on the prediction of the stator current of an asynchronous motor through the extended Kalman filter. This innovation facilitates the omission of traditional level and pressure sensors while still maintaining the accuracy of the pump's workload assessment. Research hypothesis: The idea of the research posits that the analysis of the electromechanical parameters of the motor itself may suffice for the precise control of the pumping system under unstable operating conditions.

The purpose The main purpose of this study is to enhance the energy efficiency and reliability of pump units by implementing a predictive control system grounded in stator current and a mathematical model of the electric drive. To accomplish this objective, the following tasks were delineated:

1. Construct a mathematical model of an asynchronous electric motor for a pumping unit, taking into account the hydraulic load.
2. Develop an algorithm for forecasting the stator current utilizing an extended Kalman filter.
3. Compare the simulation outcomes with empirical data and assess the accuracy of the proposed approach.
4. Evaluate the feasibility of employing the proposed system for sensorless control of pumps in coal mining environments

2 Problem Formulation

Methods of prediction and sensorless control of electric drives utilizing the Kalman filter have garnered substantial attention in recent years. The study referenced in [16] delineates the online estimation of electrical and mechanical parameters of an asynchronous motor through the application of the Kalman filter, which has significantly enhanced the precision of the machine's state identification. In [17], the researchers dealt with a compensation mechanism for inverter nonlinearities within sensorless control systems, thereby achieving remarkable control accuracy.

In [18], the application of an adaptive Kalman filter in the control of a permanent magnet synchronous motor (PMSM) was examined, validating its efficacy under fluctuating load conditions. The research presented in [19] employed a nonlinear variant of the Kalman filter – the Unscented Kalman Filter (UKF) – as a component of the model predictive control for a PMSM, demonstrating its advantages in maintaining stability. Similarly, in [20] the control mechanisms of a seven-phase asynchronous motor were explored, emphasizing the system's stability in the absence of a speed sensor.

In [21], the authors implemented a self-adaptive parameter estimation horizon methodology, underscoring the significance of real-time model correction. The study in [22] proposed an enhanced technique for back-EMF estimation for the control of a BLDC motor in electric vehicles, based on adaptive PFC and current prediction.

The investigation in [23] delves into on the estimation of operational points of a pump system's electric drive, utilizing pressure and inverter data. Next, in [24] the authors optimized the computational implementation of PFC for embedded microcontrollers, rendering it applicable in industrial real-time systems. The research detailed in [25] successfully realized sensorless control of a synchronous reluctance motor based on PFC, affirming the method's effectiveness in torque control. Furthermore, in [26] adaptive PFC was employed in navigation tasks, demonstrating the method's universality across various application domains. In addition, the work presented in [27] proposed an energy-efficient control system for pump systems, focusing on performance optimization.

Consequently, the analysis of the literature substantiates the extensive application of PFC and other predictive methods in electric drive control systems. Nevertheless, the majority of existing research predominantly concentrates on synchronous motors (PMSM, BLDC) or on speed control. In contrast, the utilization of PFC for estimating stator current in asynchronous pump system motors remains a relatively underexplored domain. Moreover, the existing studies rarely take into account the hydraulic component of the load, which constrains the models' accuracy under variable conditions. These limitations underscore the necessity for constructing an integrated model that encompasses both the electromechanical and hydraulic components, employing RF methods to predict latent parameters. It is precisely the solution of these challenges that the current research delves into.

3 Methods and Materials

3.1 Research Procedure

This study was conducted with the aim of enhancing the energy efficiency of pumping units employed in coal mining quarries. The main purpose was to develop a mathematical model of an asynchronous electric motor integrated with a pumping unit. Additionally, it was intended to implement the RFK algorithm for forecasting the stator current and assessing the system's condition under varying load conditions. The study was conducted in three stages:

1. Building a mathematical model of an asynchronous motor, taking into account the electromechanical and hydraulic characteristics of the pumping unit.
2. Implementing a numerical algorithm for predicting the state utilizing RFK, based on the discrete formulation of the Park-Gorev equations.
3. Verifying the model and comparing simulation results with experimental data regarding measured stator currents.

All calculations were performed at the research laboratory of industrial electric drive systems. The software implementation of the RFK model and algorithm was carried out within the MATLAB/Simulink environment.

3.2 Sampling

The research object was a typical pumping unit utilized for water drainage within a coal mining quarry. An asynchronous machine with a short-circuited rotor, possessing a power output of 15 kW and a rated frequency of 50 Hz, was selected for simulation in conjunction with a centrifugal pump. This type of equipment is extensively utilized across industrial sectors and reflects the most common operational conditions. The number of tests and simulation iterations conducted exceeded 50, thereby enabling a comprehensive evaluation of the stability of the RFK algorithm under a variety of load conditions, including fluctuations in water level, variations in network resistance, as well as changes in liquid viscosity. The rationale for selecting this specific pump model lies in its widespread application and the availability of reference experimental data for subsequent verification.

3.3 Methods

In this study, the preliminary stage of developing a mathematical model for the electric drive and pump units involves equations that delineate the dynamics of the pump. The pump unit comprises an asynchronous motor featuring a short-circuited rotor. As part of the study, a simulation was executed for the GFm32-160B electric pump drive, which possesses a power rating of 2.2 kW. The GFm32-160B pump model facilitates a detailed analysis of the system's dynamics and incorporates all necessary parameters for optimizing the performance of the pumping unit. The principal task is to integrate the electromechanical and hydraulic components of the pump, for which the Park-Gorev equation is used, [28].

$$\begin{bmatrix} \psi_{ds} \\ \psi_{qs} \end{bmatrix} = \begin{bmatrix} L_s & 0 \\ 0 & L_s \end{bmatrix} \begin{bmatrix} i_{ds} \\ i_{qs} \end{bmatrix} + \begin{bmatrix} M & 0 \\ 0 & M \end{bmatrix} \begin{bmatrix} i_{dr} \\ i_{qr} \end{bmatrix}, \tag{1}$$

where ψ_{ds}, ψ_{qs} – flux linkage along the axes d and q; i_{ds}, i_{qs} – stator currents; i_{dr}, i_{qr} – rotor currents; L_s – stator inductance; M – mutual inductance.

It should be mentioned that the corresponding matrices are used to determine the values of the stator and rotor inductances of an asynchronous motor. They take into account the mutual inductances between the stator and rotor windings, as well as the self-inductances of each winding. The abovementioned inductances can be described using matrices that define the inductive connections in the system, [29], [30], [31].

$$L_s = L_0 \cdot \begin{bmatrix} 1+2\sigma_s & -\cos(\theta_r) & -\cos(\theta_r + \frac{2\pi}{3}) \\ -\cos(\theta_r) & 1+2\sigma_s & -\cos(\theta_r - \frac{2\pi}{3}) \\ -\cos(\theta_r + \frac{2\pi}{3}) & -\cos(\theta_r - \frac{2\pi}{3}) & 1+2\sigma_s \end{bmatrix} \quad (2)$$

$$L_r = L_0 \cdot \begin{bmatrix} 1+2\sigma_r & -\cos(\theta_r) & -\cos(\theta_r + \frac{2\pi}{3}) \\ -\cos(\theta_r + \frac{2\pi}{3}) & 1+2\sigma_r & -\cos(\theta_r - \frac{2\pi}{3}) \\ -\cos(\theta_r) & -\cos(\theta_r - \frac{2\pi}{3}) & 1+2\sigma_r \end{bmatrix}$$

where L_0 is the nominal inductance; σ_s – stator scattering coefficient; σ_r – rotor dissipation coefficient; θ_r – the electrical angle of the rotor.

In essence, the electromagnetic torque of an asynchronous motor can be calculated utilizing the matrix expression, taking into account the currents and inductances in the stator and rotor.

$$M = \frac{3}{2} \cdot \frac{p}{2} (\psi_{ds} \cdot i_{qs} - \psi_{qs} \cdot i_{ds}) \quad (3)$$

where p is the number of pole pairs.

The hydraulic component of the pump can be described through a series of equations that include fluid motion equations and equations relating hydraulic and mechanical parameters. Let us consider the basic equations that delineate the hydraulic processes occurring within the pump [17]. (3)

$$\frac{dQ}{dt} = \omega (H_0 \frac{r_2^2}{i_g^2} - x_1 H_{CT} - x_1 (a_n - a_p)^2) \quad (4)$$

where dQ/dt – change in pump productivity over time; ω – angular rotation speed of the motor; $H0$ – nominal pressure at zero productivity; r_2 – impeller radius; i_g – gear ratio between the motor and the pump; x_1 – constant; H_{CT} – water rise height; a_n, a_p – hydraulic resistance.

For *forecasting* of the state of the asynchronous motor as part of the pumping unit is applied *Extended Kalman filter (EKF)*. In the present study special attention is paid to the prediction of stator currents. Essentially, it is these parameters that are sensitive to changes in external load, caused by changes in the water level and its viscosity during the pumping process. The prediction of the stator current allows for the implementation of intelligent control of the pumping unit without the use of water level sensors, based solely on the parameters of the electric drive. Since the implementation of the EKF is carried out in digital form, the continuous model based on the *Park-Gorev* equations is discretized in time. Consequently, the system can be presented as follows:

$$x(t_{k+1}) = A_d \cdot x(t_k) + B_d \cdot u(t_k), \quad (5)$$

where *x(tk)* – state vector; A_d – discrete state matrix; B_d – discrete control matrix; *u(tk)* – control moment vector.

$$y(t_k) = C(t_k) \cdot x(t_k), \quad (6)$$

where *y(tk)* – measured value vector; *C(tk)* – output matrix.

$$A_d \approx I + A(t) \cdot T, \quad (7)$$

where *A(t)* – the matrix of the system in discrete time; *T* – step; *I* – identity matrix.

$$B_d \approx B(t) \cdot T \quad (8)$$

where *B(t)* – the control matrix in continuous time.

The RKF algorithm consists of two stages: *extrapolation and correction. Extrapolation* is performed on the basis of a discrete mathematical model of an asynchronous electric motor (equations (5)–(6)) to predict the state of the system, while the correction refines the estimate using the measured stator currents. The current paper proposes to modify the standard state vector estimation equation (equation (14)) by introducing an additional estimate of the rotor flux vector. Given the above, the RLC uses both the measured stator currents and the rotor flux estimate to more accurately determine the state of the system.

The estimation of the predicted state is as follows:

$$x(t_{k+1}) = \begin{bmatrix} \psi_{r\alpha}(t_{k+1}) \\ \psi_{r\beta}(t_{k+1}) \\ i_{s\alpha}(t_{k+1}) \\ i_{s\beta}(t_{k+1}) \end{bmatrix} + A_d \begin{bmatrix} \psi_{r\alpha}(t_k) \\ \psi_{r\beta}(t_k) \\ i_{s\alpha}(t_k) \\ i_{s\beta}(t_k) \end{bmatrix} + B_d \begin{bmatrix} u_{s\alpha}(t_k) \\ u_{s\beta}(t_k) \end{bmatrix}, \quad (9)$$

The update of the covariance matrix of the error:

$$P(t_k) = P(t_{k+1}) - K(t_k) \cdot H(t_k) \cdot P(t_{k+1}). \quad (10)$$

Kalman coefficient:

$$K(t_k) = P(t_{k+1}) \cdot H(t_k)^T \cdot \left[H(t_k) \cdot P(t_{k+1}) \cdot H(t_k)^T + R\right]^1. \quad (11)$$

The update of the state vector with correction:

$$(t_k) = x(t_{k+1}) \cdot K(t_k) \cdot \left[y(t_k) \cdot x(t_{k+1})\right] \quad (12)$$

where $u_s(t)$ – input voltages; $P(t)$ – covariance matrix of the error estimate; $K(t)$ – Kalman gain matrix; R – measurement noise; $H(t)$ – gradient matrix; Q – process noise.

The extended Kalman gain equation:

$$K(t_k) = P(t_{k+1}) \cdot H^T(x(t_{k+1})) \cdot \left[H(x(t_{k+1})) \cdot P(t_{k+1}) \cdot H(x(t_{k+1}))^T + R\right]^1. \quad (13)$$

The state vector update:

$$x(t_k) = x(t_{k+1}) + K(t_k) \cdot \left[y(t_k) - H(x(t_{k+1})) \cdot x(t_{k+1})\right] \quad (14)$$

The observation matrix:

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix} \quad (15)$$

The covariance matrix update:

$$P(t_k) = P(t_{k+1}) - K(t_k) \cdot H(x(t_{k+1})) \cdot P(t_{k+1}). \quad (16)$$

The process noise covariance matrix Q and the measurement noise covariance matrix R were selected based on experimental observations and characteristics of the measurement system. The R matrix reflects the variance of the stator current measurement noise, while the Q matrix takes into account the uncertainties of the mathematical model associated with the nonlinearity of the hydraulic load and variations in the parameters of the electric drive.

The initial error covariance matrix $P(t_0)$ was set diagonal with increased initial values, which corresponds to the lack of a priori information about the state of the system during startup. During operation, the EKF recursively corrects $P(t_k)$, which leads to a gradual decrease in the estimation uncertainty.

Sensitivity analysis showed that moderate variations in the values of Q and R do not lead to a loss of filter convergence, which confirms the robustness of the proposed algorithm.

The prediction algorithm is implemented based on the extended Kalman filter, the structure of which is shown in Figure 1 (Appendix).

Figure 1 (Appendix) shows the structure of the EKF algorithm, which consists of two main stages - state prediction and estimation correction based on measurement results. Such a structure provides recursive refinement of the system state in discrete time.

3.4 Tools

MATLAB/Simulink tools were used for numerical simulation and algorithm implementation – for building the engine and pump model, discretizing equations, implementing the EKF, and visualizing results. All tools and methods were used in conjunction, providing a holistic system for intelligent control of the pumping unit without the use of physical pressure or flow sensors.

3.5 Stability and Convergence Analysis of the Discrete EKF-Based Model

The stability of the proposed discrete electromechanical model in combination with the extended Kalman filter (EKF) is an important condition for its reliable operation under variable hydraulic loads. The dynamics of the system in discrete time is determined by the state transition matrix A_d, obtained by discretizing the Park-Gorev equations.

The local stability of the discrete model was assessed by analyzing the eigenvalues of the matrix A_d. For the nominal operating modes considered in this study, all eigenvalues of A_d are located inside the unit circle, which indicates the local asymptotic stability of the linearized system near the operating point.

As for the state estimation process using the EKF, for nonlinear systems, global stability guarantees, as a rule, cannot be rigorously proven. However, under standard assumptions regarding the boundedness of disturbances, a small discretization step, and the presence of excitation at the input of the system, the EKF ensures the boundedness of the estimation error covariance. In the proposed model, the covariance matrix P_k remains positive definite and bounded throughout the simulation time.

4 Results

An integrated model of the pumping unit (Figure 2, Appendix) was built based on the equations delineated in Section 3, taking into consideration electromechanical and hydraulic processes, as well as the digital control system.

Figure 2 (Appendix) illustrates an integrated mathematical model of an induction motor and pump, in which the hydraulic load directly affects the electromagnetic torque and stator current. This allows for variable operating modes to be taken into account without the use of additional sensors.

Using a developed mathematical model of the GFm32-160B pump's electric drive, the values of the stator and rotor current, electromagnetic torque, and angular rotation speed of the motor were determined. The experimental data obtained during the testing process were juxtaposed to the simulation results to verify the accuracy of the computational model. According to the mathematical model, in the initial phase of starting up the stator current reached a peak of 37 A, which is comparable to the experimental value of 39.2 A. The starting time in both cases was from 0.3 to 0.5 seconds (Figure 3, Appendix).

Figure 3 (Appendix) shows the experimental data for measuring the stator current of the asynchronous electric motor of the GFm32-160B pump unit under conditions of variable hydraulic load. As can be seen, characteristic fluctuations in the current amplitude are observed, caused by changes in the water level and the corresponding increase in resistance at the pump outlet. These data were used to verify the model and adjust the PFC algorithm.

The comparison shown in Figure 3 (Appendix) demonstrates a high agreement between the results of mathematical modeling and experimental data. The relative deviation of the maximum stator current in the transient mode does not exceed 5%, while in the steady state the difference is within the measurement error.

Comparative calculations between experimental and simulated values of the stator current and angular speed were carried out to quantitatively assess the accuracy of the proposed mathematical model. The calculation of relative errors showed a high degree of agreement between the model and the real data. The summary results are presented in Table 1 (Appendix).

It should be noted that during the experiments, challenges emerged in accurately measuring the precise instantaneous values of the GFm32-160B pump's electric drive speed, whereas the results derived using the mathematical model exhibited high accuracy in displaying all corresponding values. Consequently, the nominal angular velocity was found to be identical in both cases (Figure 4, Appendix).

Figure 4 (Appendix) illustrates the data pertaining to the variation in the angular velocity of the pump unit's electric drive during both simulation and experimental procedures. It can be seen that the values derived from the mathematical model (a) exhibit a commendable concordance with the experimental findings (b). The maximum deviation between the curves does not exceed 5%, thereby confirming the adequacy and validity of the developed model.

In addition to the comparative analysis of the analytical and experimental models (Table 2, Appendix), the characteristics of the variations in magnetic flux linkages pertaining to the rotor and stator of the GFm32-160B pump motor were examined through the mathematical model. It should be noted that empirical measurement of these parameters was not possible to measure due to the challenges associated with accessing the necessary equipment and the inherent limitations of the technical means available for accurately measuring these parameters.

Figure 5 (Appendix) shows the dynamics of the stator current of the asynchronous motor, calculated using equation (2) without the application of the RFK. At the initial moment of time (up to ~4 seconds), a pronounced transient process is observed with current fluctuations in a wide range of ±40. Following this, the system enters a steady state, and the current stabilizes around zero with slight fluctuations. The yellow area reflects the range of calculated current values during the simulation process, demonstrating the model's behavior under transient and steady-state conditions.

Figure 6 (Appendix) shows the dynamics of the stator current of an asynchronous motor after the application of the RKF. In the initial phase (up to ~3 seconds), a transient process is observed with current fluctuations within ±40, after which the current quickly stabilizes, demonstrating the stability of the model. Compared to the previous graph without RKF, a significant reduction in the scatter of values and a decrease in fluctuations in the steady state can be noted. The green area illustrates the smoothed current estimates obtained as a result of filtering, which confirms the effectiveness of RKF in suppressing noise and increasing the accuracy of predicting the dynamics of the stator current (Figure 7, Appendix).

Figure 7 (Appendix) shows the result of stator current prediction using EKF. Compared with the unfiltered signal (Figure 6, Appendix), a significant reduction in variance and noise suppression is observed after the transient process is completed. This confirms the effectiveness of EKF in reducing the estimation error and increasing the stability of the prediction.

As a result of the study, an integrated mathematical model of the pumping unit was developed, encompassing both electromechanical and hydraulic components. The implemented RKF algorithm facilitated accurate predictions of the stator current and rotor angular velocity based on a minimal set of input parameters. The simulations conducted validated that the proposed system guarantees stable operation of the electric drive under varying loads and enables the elimination of additional pressure and flow sensors. The discrepancy between the simulated and experimental data was less than 5% for angular velocity and less than 2% for stator current, underscoring the high accuracy of the constructed model. Hence, the employed approach significantly streamlines the structure of the control system while enhancing its energy efficiency through predictive control.

5 Discussion

The results obtained from this study elucidate the remarkable accuracy and stability of the proposed sensorless control model for a pump unit based on an asynchronous motor. A comparative analysis with existing scientific approaches facilitates an assessment of the contributions of this work to the advancement of the field. Some relevant study can be found in [32]. In the study [16], the authors implemented an online estimation of the parameters of an asynchronous motor utilizing a frequency converter. However, their model fails to incorporate the hydraulic load, in contrast to our approach, which regards the pump as a dynamic component.

In [17], the compensation for inverter nonlinearities in sensorless control systems was proposed, enhancing accuracy yet neglecting the integration of the drive model with the external load. On the other hand, our model encompasses the interaction between the pump and the drive, thus presenting a significant advantage. The study [18] introduced an adaptive Kalman filter for the control of a Permanent Magnet Synchronous Motor (PMSM). Although their approach demonstrates high accuracy, such methods are predominantly applicable to synchronous motors. We have substantiated that comparable efficiency can be achieved for asynchronous motors.

In [19], the authors used the Unscented Kalman Filter (UKF) as part of Model Predictive Control (MPC), yet their focus remained on the rotational speed, whereas our research prioritizes the prediction of the stator current, which serves as a more sensitive indicator of load variations. The authors in [20] investigated a seven-phase asynchronous drive, albeit without integrating a hydraulic model. In contrast, our study harmonizes electromechanical and hydraulic dimensions.

Yet another study [21] delves into the application of the Moving Horizon Estimation method and self-tuning, albeit with a focus on PMSM and necessitating complex optimization. Our implementation, in contrast, is more straightforward and suitable for systems that are more accessible in terms of design. In [22], the EKF was developed for BLDC control in electric vehicles, addressing comparable back-EMF estimation tasks. In our system, the stator current is estimated, which facilitates implementation, particularly under demanding operating conditions, such as those encountered in quarries.

The study [23] illustrates how pressure and inverter data can be used to estimate the load. However, our approach entirely eliminates the need for sensors and relies solely on electrical parameters, thereby streamlining the system. In [24], the emphasis was placed on the computational optimization of the EKF. Their approach corroborates the feasibility of such algorithms in real-time applications, which aligns with our solution, implemented in MATLAB/Simulink with potential for subsequent migration to embedded platforms.

In [25], sensorless control of Synchronous Reluctance Motors (SynRM) was executed. The objective in the said study bears similarity to ours, yet they did not simulate the interaction with a mechanical load. Our system encompasses a broader spectrum of parameters. In [26], the applicability of adaptive Power Factor Correction (PFC) in navigation systems was demonstrated. Despite the differing application, their algorithm substantiates the flexibility of the PFC approach, similar to our implementation in the pumping unit. In [27], an energy-efficient pump control system was proposed, though it lacks predictive algorithms and necessitates the use of sensors. Our work eliminates this dependency while enhancing accuracy.

It should be noted separately that the computational complexity of the proposed EKF algorithm is determined by the operations of matrix multiplication and inversion and has the order of $O(n^3)$, where n is the dimension of the state vector. Given the small number of state variables in the proposed model, the algorithm is suitable for implementation in real time and can be adapted for embedded microprocessor systems.

Thus, the majority of the reviewed studies either concentrate on synchronous machines, do not take into account the influence of external loads, or depend on pressure, speed, or position sensors. The system we propose amalgamates the advantages of predictive control with a sensorless approach, thereby expanding the horizons of existing solutions. This study is fully aligned with the established objective: the development of a control model for a pumping unit devoid of physical sensors. All designated tasks have been accomplished. The hypothesis regarding the feasibility of precise control predicated solely on electromechanical parameters has been experimentally validated. The proposed system holds promise for successful application in water drainage systems within coal mining quarries and can also be adapted to other industrial systems characterized by variable load.

6 Limitations

Despite the positive results, the developed control system possesses several limitations:

1. Complexity of parametric adjustment. For the model to function optimally, an accurate understanding of the parameters pertaining to the asynchronous motor and the pumping unit is imperative, including inductances, resistances, and moments of inertia. In the absence of reliable specifications, errors may occur during the identification process.
2. Sensitivity to external disturbances, such as sudden changes in fluid properties (in particular, viscosity and density), or instability in the power supply can reduce the accuracy of predictions without appropriate model adaptation.
3. High computational costs. The implementation of the extended Kalman filter algorithm necessitates substantial computational resources, particularly at high sampling frequencies, which may constrain its application within microcontroller systems characterized by limited performance capabilities.
4. The lack of feedback concerning actual pressure or flow rate can prove critical in emergency scenarios, where precise regulation of hydraulic parameters is essential, extending beyond mere monitoring of stator current.

7 Recommendations

Drawing upon the conducted research, the following recommendations and directions for further work can be formulated:

1. Development of adaptive mechanisms for real-time auto-tuning of model parameters will enhance the system's resilience to fluctuations in environmental and equipment characteristics.
2. Optimization of the Extended Kalman Filter (EKF) algorithm to diminish computational volume, including by simplifying matrix operations or the transitioning to lower-order filters, is an urgent task. This will facilitate the method's adaptation for embedded control systems.
3. Integration with Supervisory Control and Data Acquisition (SCADA) systems and digital twins will empower the proposed model to function as a component of more sophisticated automated control systems for pumping stations.
4. The adaptation of the algorithm for diverse types of equipment, including fans, compressors, or drives within heating and water supply systems, has a high potential for practical application.
5. The introduction of fault detection and diagnosis based on the deviation of predicted parameters from actual values can increase the reliability and safety of operations.

8 Conclusion

Modern pumping installations, particularly within the context of coal mining, require a significant degree of adaptability and energy efficiency. Conventional control methods rely heavily on a large number of sensors, which complicates the system architecture and increases operational costs. Given the above, the advancement of intelligent control strategies that can deliver precision and dependability with a minimal suite of measuring instruments has become an urgent task.

The mathematical model of the GFm32-160B electric pump drive has demonstrated adequacy and high accuracy in assessing the main parameters of the system. By employing RLC to predict stator currents, magnetic flux linkages, and motor angular velocity, a deviation of no more than 5% from experimental data was achieved. The proposed approach has shown that it is feasible to provide a reliable evaluation of the drive's condition, even in the absence of direct measurements of torque or magnetic flux linkages. Nonetheless, it was observed that despite the model's efficacy, it does not take into account the D matrix and the mutual inductances between the stator and rotor, which could potentially introduce inaccuracies.

The developed system is applicable for controlling pumping units across various sectors, including the mining industry, water supply, thermal power engineering, and other sectors where optimization of energy consumption and enhancement of equipment reliability are required. The capacity to dispense with costly pressure and flow sensors renders the proposed method particularly appealing in environments characterized by heightened vibration, pollution, or constrained maintenance opportunities. Looking ahead, it is expedient to refine the mathematical model by taking into account the D matrix and the mutual inductances between the stator and rotor windings to increase accuracy under extreme operating conditions. Another promising avenue of exploration lies in the development of an adaptive version of the RLC algorithm, capable of autonomously adjusting filter parameters in response to fluctuating conditions. Particular emphasis should be placed on the evolution of embedded computing solutions with low power consumption to facilitate the implementation of such systems at the industrial automation level.

References:

[1] Baranidharan, M., Kanna, R.R., Singh, R.R. Energy Saving on Industrial Drive Technologies-Past, Present, and Future Perspective. *IOP Conference Series: Materials Science and Engineering,* Vol. 906, No. 1, 2020. https://doi.org/10.1088/1757-899X/906/1/012005

[2] d'Obyrn, K., Kamiński, P., Cień, D., Jendrysik, S., Prostański, D. Hydrogeological and Mining Considerations in the Design of a Pumping Station in a Shaft of a Closed Black Coal Mine. *Energies*, Vol. 17, No. 13, 2024, art. 3297. https://doi.org/10.3390/en17133297

[3] Wang, F., Qiao, Y., Zhou, H., Wu, J., Xu, B. An Independent Electro-Hydraulic Variable Speed Drive to Improve Energy Efficiency of Electric Wheel Loader Working System. *IEEE Transactions on Vehicular Technology*, Vol. 73, No. 12, 2024, pp. 18250-18265. https://doi.org/10.1109/TVT.2024.3438268

[4] Husain, I., Ozpineci, B., Islam, M. S., Gurpinar, E., Su, G. J., Yu, W. et al. Electric drive technology trends, challenges, and opportunities for future electric vehicles. *Proceedings of the IEEE*, Vol. 109, No. 6, 2021, pp. 1039-1059. https://doi.org/10.1109/JPROC.2020.3046112

[5] Chowdhury, S., Xue, L., Rahman, D., Sahu, R. Electric drive technology trends, challenges, and opportunities for future electric vehicles. *Proceedings of the IEEE*, Vol. 109, No. 6, 2021, pp. 1039-1059. https://doi.org/10.1109/JPROC.2020.3046112

[6] Nemoto, K., Kang, D., Kambayashi, I., Tsuru, W., Watanabe, S., Yokota, K. Stability Analysis of Cavitation Surge in Hydraulic System Considering Response Delay of Cavitating Pump. *International Journal of Fluid Machinery and Systems*, Vol.15, No. 4, 2022, pp. 401-410. https://doi.org/10.5293/IJFMS.2022.15.4.401

[7] Han, Y., Zou, J., Presas, A., Luo, Y., Yuan, J. Off-design operation and cavitation detection in centrifugal pumps using vibration and motor stator current analyses. *Sensors*, Vol. 24, No. 11, 2024, art. 3410. https://doi.org/10.3390/s24113410

[8] Shi, G., Wang, S., Xiao, Y., Liu, Z., Li, H., Liu, X. Effect of cavitation on energy conversion characteristics of a multiphase pump. *Renewable Energy*, Vol. 177, 2021, pp. 1308-1320. https://doi.org/10.1016/j.renene.2021.05.119

[9] Fu, X., Li, D., Wang, H., Qin, D., Wei, X. Cavitation mechanism and effect on pump power-trip transient process of a pumped-storage unit. *Journal of Energy Storage*, Vol. 66, 2023, art. 107405. https://doi.org/10.1016/j.est.2023.107405

[10] Obidov, B. Intelligent electric drive control systems and artificial intelligence: An in-depth review. *Web of Discoveries: Journal of Analysis and Inventions*, Vol. 2, No. 9, 20254, pp. 1-6. http://webofjournals.com/index.php/3/article/view/1742 (Accessed Date: 21 Apr 2026).

[11] Abd-Elhaleem, S., Shoeib, W., Sobaih, A.A. Improved power management under uncertain driving conditions for plug-in hybrid electric vehicles via intelligent controller. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 24, No. 12, 2023, pp. 13698-13712. https://doi.org/10.1109/TITS.2023.3308509

[12] Balogun, A., Olajube, A., Awelewa, A., Okafor, F., Sanni, T., Samuel, I. A sensorless efficiency-optimizing vector control scheme for an induction motor drive. *Frontiers in Energy Research*, Vol. 12, 2024, art. 1406565. https://doi.org/10.3389/fenrg.2024.1406565

[13] Tran, M.Q., Elsisi, M., Mahmoud, K., Liu, M.K., Lehtonen, M., Darwish, M.M. Experimental setup for online fault diagnosis of induction machines via promising IoT and machine learning: Towards industry 4.0 empowerment. *IEEE access*, Vol. 9, 2021, pp.

115429-115441. https://doi.org/10.1109/ACCESS.2021.3105297

[14] Liu, Z., Sun, J., Yue, D., Zuo, X., Gao, H., Feng, K. A review on integral evolution of electro-hydraulic actuation in three momentous domains: aerospace, engineering machinery, and robotics. *Fourth International Conference on Mechanical Engineering, Intelligent Manufacturing, and Automation Technology (MEMAT 2023)*, Vol. 13082, 2024, pp. 141-159. https://doi.org/10.1117/12.3026210

[15] Lysiak, V., Oliinyk, M. Dynamic Modes of Synchronous Electric Drive with Centrifugal Hydraulic Load of Pump Station. *Energy Engineering and Control Systems*, Vol. 7, No. 1, 2021, pp. 48-55. http://nbuv.gov.ua/UJRN/eecs_2021_7_1_9

[16] Yildiz, R., Demir, R., Barut, M. Online estimations for electrical and mechanical parameters of the induction motor by extended Kalman filter. *Transactions of the Institute of Measurement and Control*, Vol. 45, No. 14, 2023, pp. 2725-2738. https://doi.org/10.1177/01423312231160582

[17] Et-taaj, L., Boulghasoul, Z., El Kharki, A., Elbacha, A. Improvement of sensorless control of induction motor by voltage source inverter nonlinearities compensation and extended Kalman filter. *Electrical Engineering*, Vol. 104, No. 5, 2022, pp. 3509-3521. https://doi.org/10.1007/s00202-022-01560-1

[18] Cui, J., Xing, W., Qin, H., Hua, Y., Zhang, X., Liu, X. Research on permanent magnet synchronous motor control system based on adaptive kalman filter. *Applied Sciences*, Vol. 12, No. 10, 2022, art. 4944. https://doi.org/10.3390/app12104944

[19] Janiszewski, D. Sensorless model predictive control of permanent magnet synchronous motors using an unscented kalman filter. *Energies*, Vol. 17, No. 10, 2024. https://doi.org/10.3390/en17102387

[20] Salem, E. Z. Speed sensorless control of seven phase asynchronous motor drive system using extended Kalman filter. International Journal of Electronics Letters, Vol. 10, No. 2, 2022, pp. 144-160 https://doi.org/10.1080/21681724.2020.1870720

[21] Chen, A., Chen, W., Wan, H. PMSM Sensorless Control Based on Moving Horizon Estimation and Parameter Self-Adaptation. *Electronics*, Vol. 13, No. 13, 2024. https://doi.org/10.3390/electronics13132444

[22] Inan, R. An Improved Model Predictive Current Control of BLDC Motor With a Novel Adaptive Extended Kalman Filter–Based Back EMF Estimator and a New Commutation Duration Approach for Electrical Vehicle. *International Journal of Circuit Theory and Applications*, Vol. 53, No. 2, 2025, pp. 1135-1150. https://doi.org/10.1002/cta.4407

[23] Kouhi, Y., Müller, J., Leonow, S., Mönnigmann, M. Estimating load points of a motor-pump system using pressure and inverter drive data. *arXiv preprint arXiv:2010.04090*, 2020. https://doi.org/10.48550/arXiv.2010.04090

[24] Dilys, J., Stankevič, V., Łuksza, K. Implementation of Extended Kalman Filter with Optimized Execution Time for Sensorless Control of a PMSM Using ARM Cortex-M3 Microcontroller. *Energies*, Vol. 14, No. 12, 2021, art. 3491. https://doi.org/10.3390/en14123491

[25] Farhan, A., Abdelrahem, M., Shaltout, A., Kennel, R., Saleh, A. Encoderless current predictive control of synchronous reluctance motor by extended Kalman filter based state estimation. In: *PCIM Europe digital days 2020; International Exhibition and Conference for Power Electronics, Intelligent Motion, Renewable Energy and Energy Management*, VDE, 2020. https://ieeexplore.ieee.org/abstract/document/9178174

[26] Chen, L., Jiang, B., Liu, Y., Chen, J. Application of adaptive EKF in real-time orbit determination. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, Vol. 43, No. 4, 2021. https://doi.org/10.1007/s40430-021-02867-z

[27] Abdullabekov, I., Sapaev, Kh. An energy efficient control system for water lifting units of the ramadan pumping station based on frequency controlled electric drives. *AIP Conf. Proc.*, Vol. 2552, 2023, art. 040023 . https://doi.org/10.1063/5.0130676

[28] Shashi Menon, E., Pramila, S. Menon, working guide to pumps and pumping stations. Gulf Professional Publishing, 2010. ISBN 978-1-85617-828-0. https://books.google.de/books?hl=uk&lr=&id=2Vm2-r-sEeQC&oi=fnd&pg=PP1&dq=%5B28%5D%09Shashi+Menon,+E.,+Pramila,+S.+Menon,+

working+guide+to+pumps+and+pumping+stations.+Gulf+Professional+Publishing,+2010.+ISBN+978-1-85617-828-0&ots=2oEwJPOETx&sig=lkISqmMcCo5XnoEcskLml_qF5Sk&redir_esc=y#v=onepage&q&f=false (Accessed Date: 21 Apr 2026)

[29] Sapaev, K., Umarov, S., Abdullabekov, I., Khamudkhanova, N., Nazarov, M. Scheme of effective regulation of pumping station productivity. *AIP Conference Proceedings*, Vol. 2402, 2021, art. 060016. https://doi.org/10.1063/5.0071557

[30] Aamiovuori, L., Kärkkäinen, H., Niemelä, M., Pyrhonen, J., Alalibo, B., Cao, W. Modelling a vector controlled induction motor in Simulink. In *2018 X International Conference on Electrical Power Drive Systems (ICEPDS)* IEEE. 2018. (pp. 1-8). https://doi.org/10.1109/ICEPDS.2018.8571659

[31] Hizhnyakov, Y.N., Yuzhakov, A.A., Storozhev, S.A. An Adaptive Fuzzy Excitation Controller of a Brushless Synchronous Generator. *Russian Electrical Engineering*, Vol. 93, No. 11, 2022, pp. 723-727. https://doi.org/10.3103/S1068371222110062

[32] Assimakis, N., Alexandridis, G., Papaioannou, T. Temperature prediction using kalman filters in connection. *WSEAS Transactions on Circuits and Systems*, Vol. 24, 2025, pp. 195‑200. https://doi.org/10.37394/23201.2025.24.22

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APPENDIX

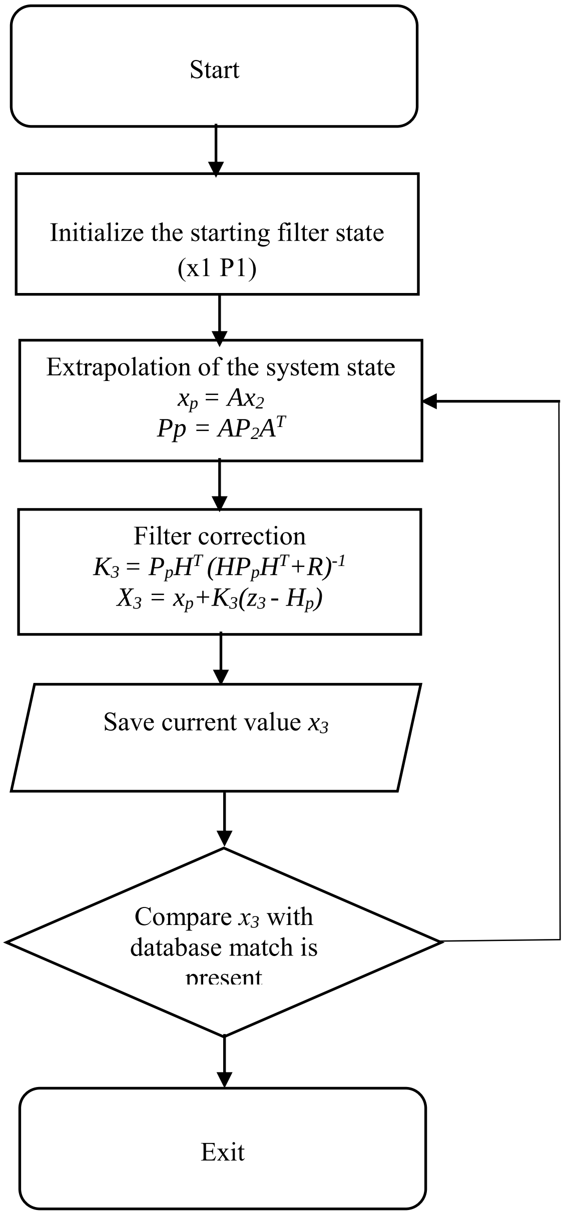


Fig. 1: The extended Kalman filter algorithm

Source: prepared by the author

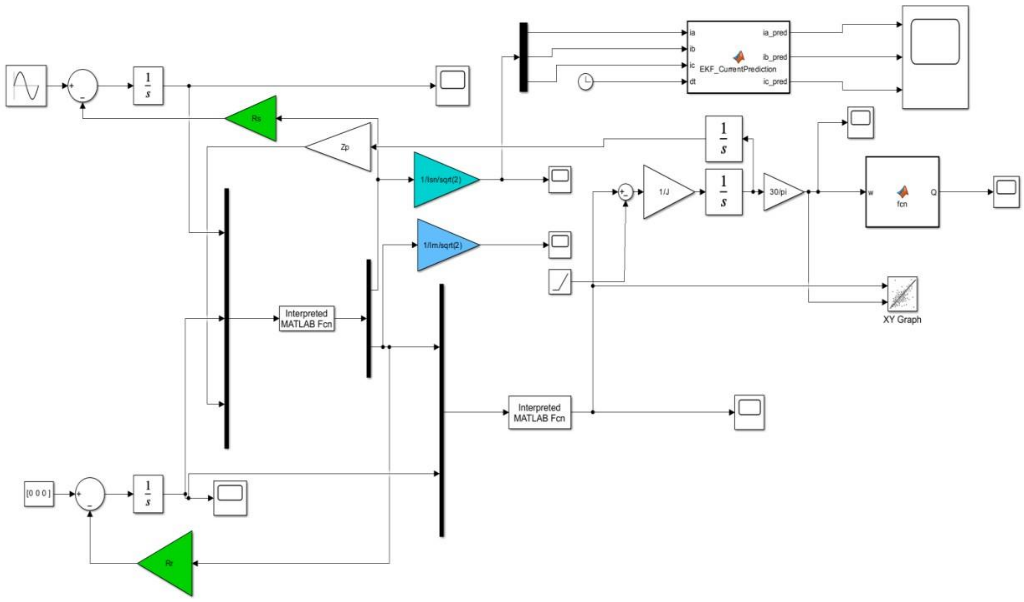
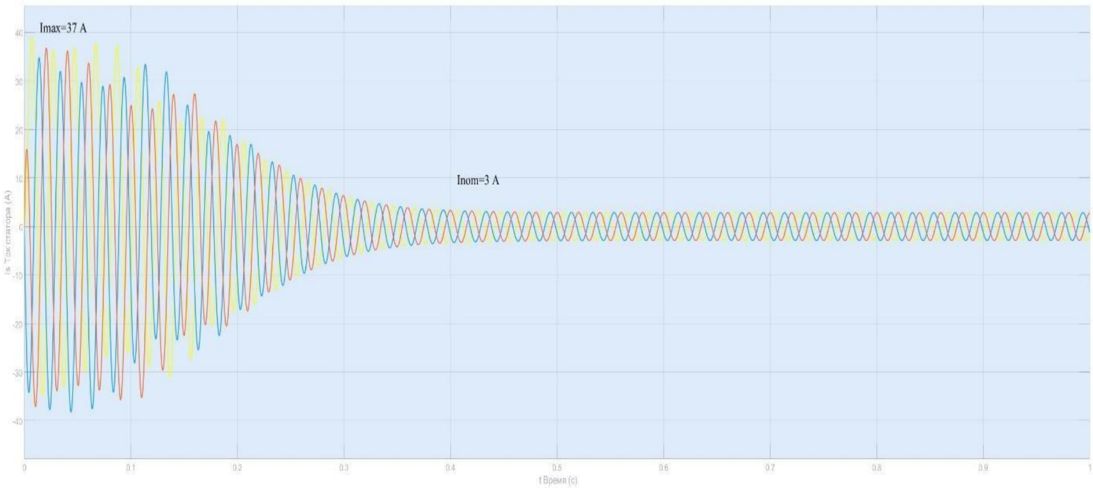
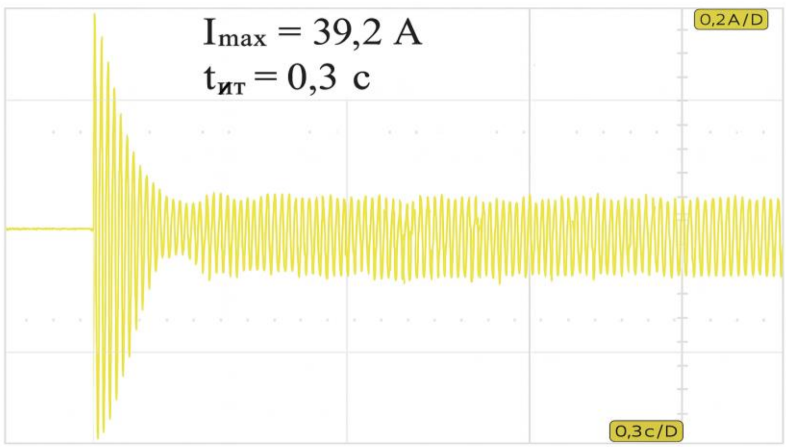


Fig. 2: Mathematical model of the asynchronous motor with a short-circuited rotor of the GFm32160B pump
Source: prepared by the author

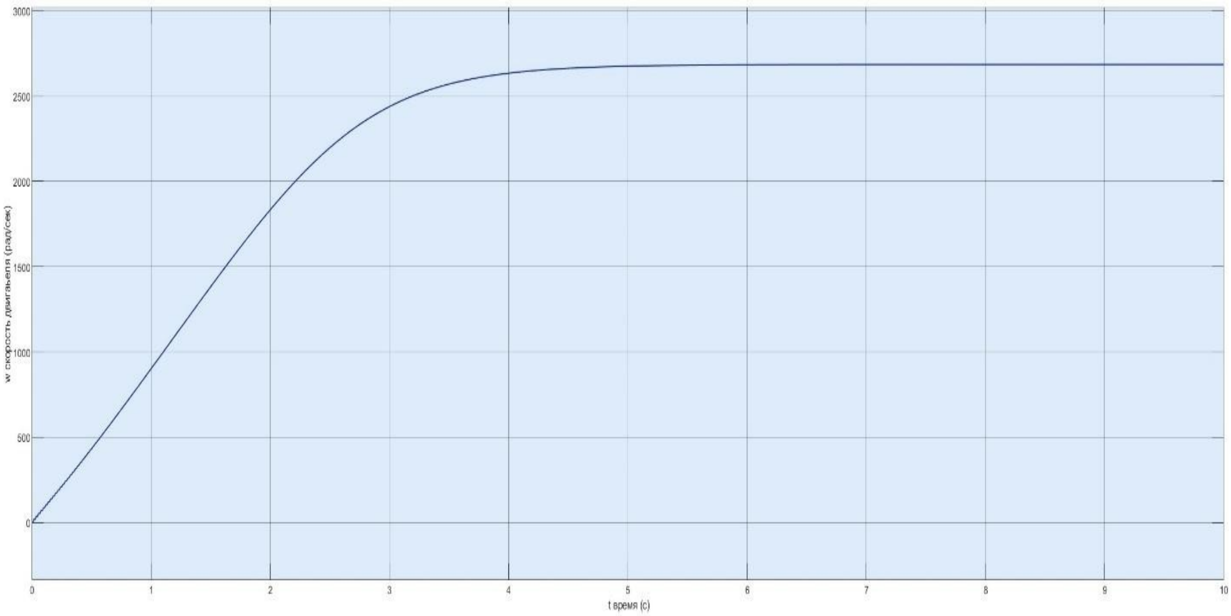


a



b

Fig. 3: Measurement results of the stator current of the GFm32-160B pump's electric drive:
a) mathematical model; b) experimental findings
Source: prepared by the author



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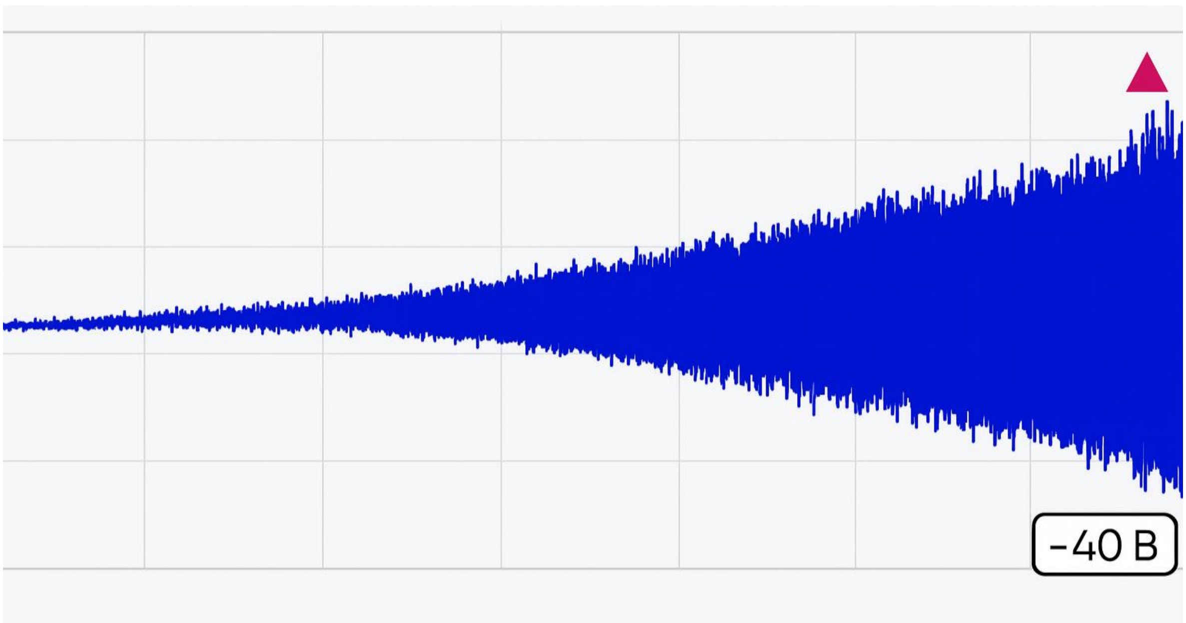
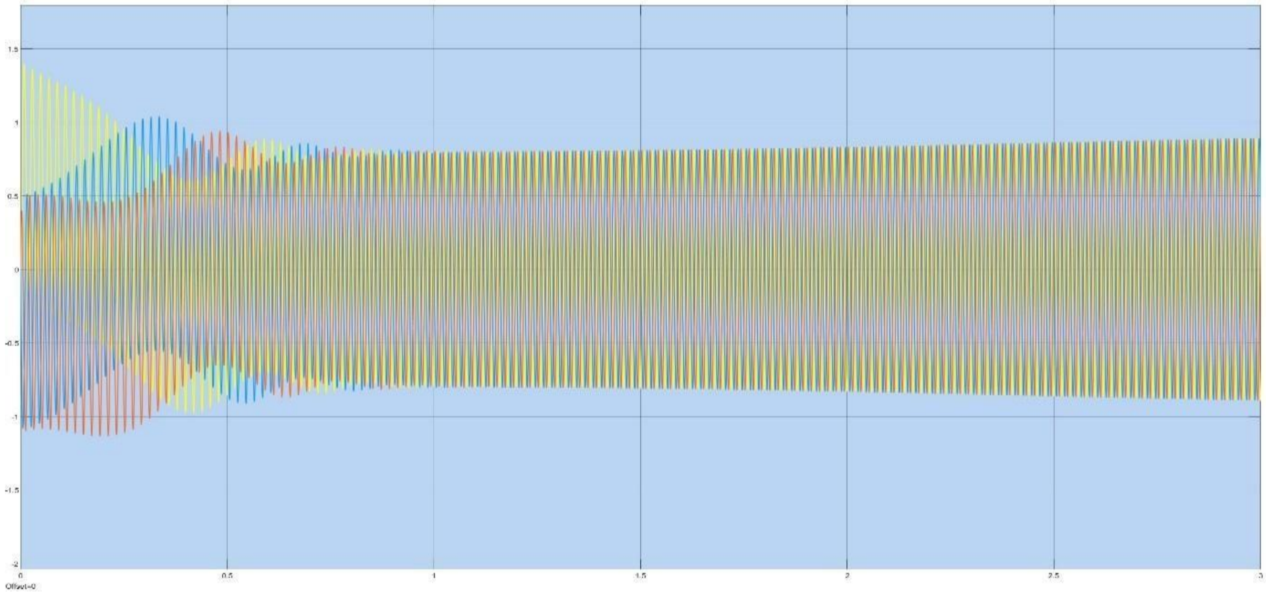


b

Fig. 4: Measurement results of the angular velocity of the GFm32-160B pump electric drive:
a) mathematical model; b) experimental findings

Source: prepared by the author



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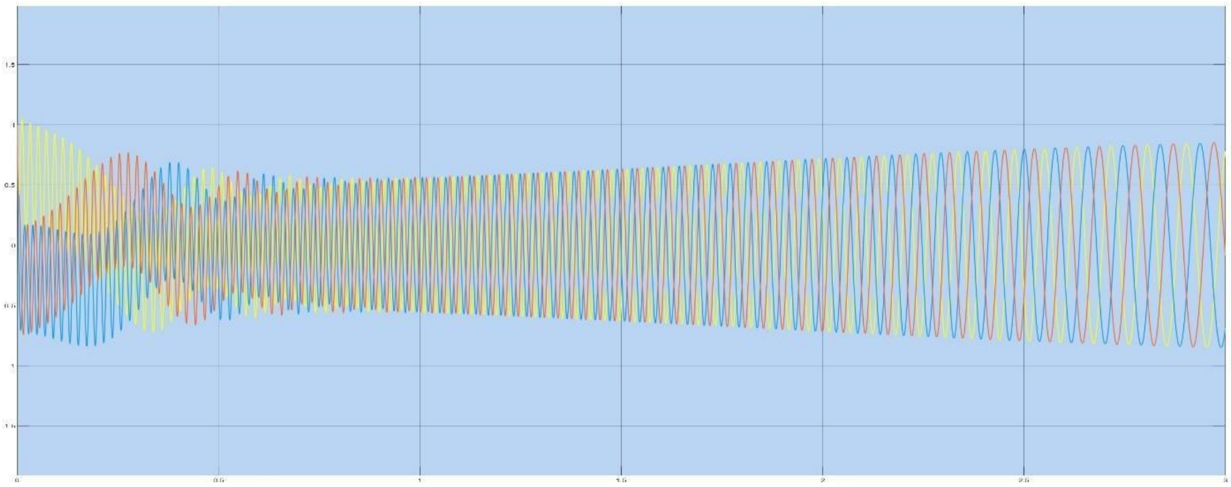

b

Fig. 5: Results of measurements of the magnetic flux linkages of the GFm32-160B pump motor:
a) stator; b) rotor

Source: prepared by the author

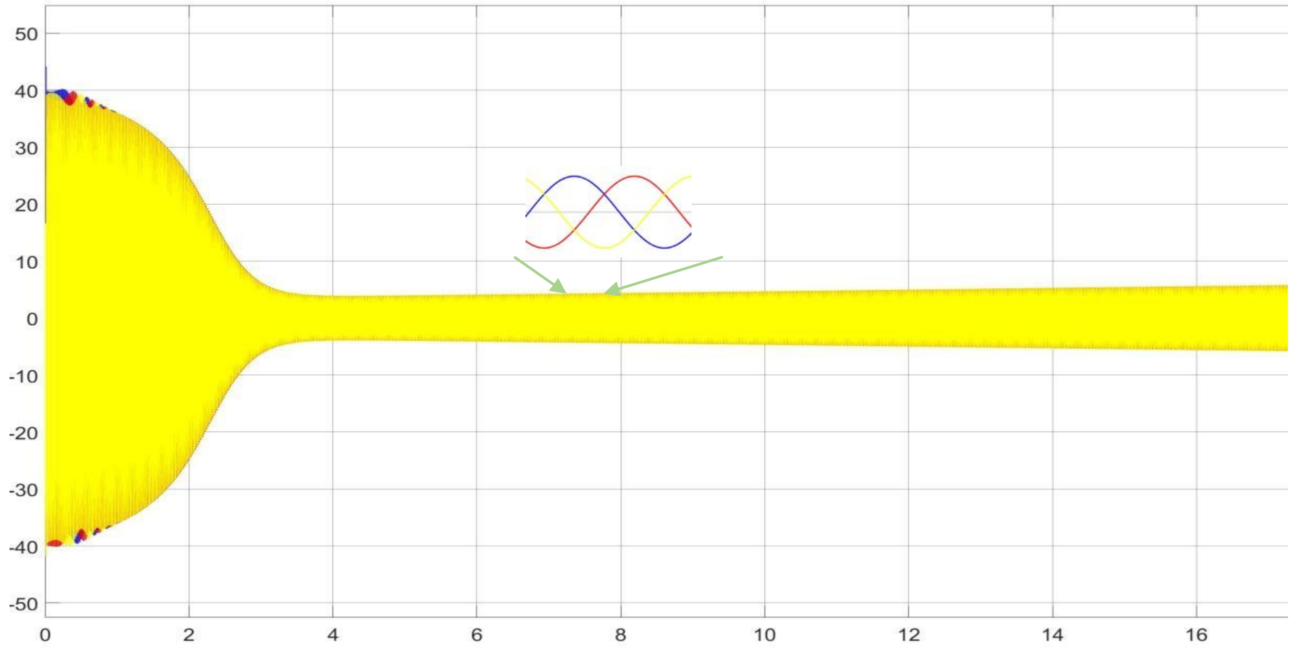

Fig. 6: Stator current of an asynchronous motor
Source: prepared by the author

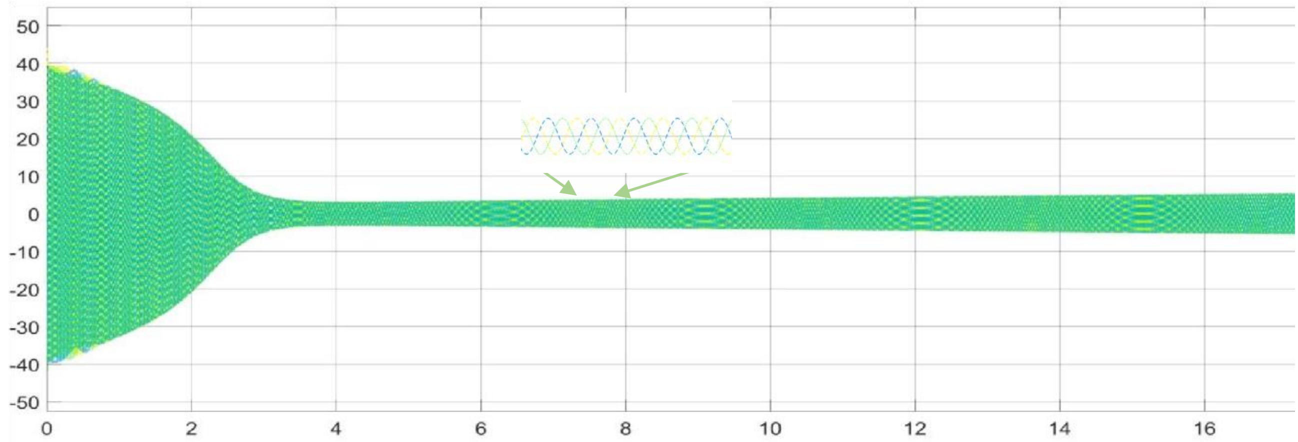

Fig. 7: Stator current of an asynchronous motor predicted by the application of RKF
Source: prepared by the author

Table 1. Table of comparative errors

Maximum stator current of the mathematical model [A]	Maximum stator current of the experimental model [A]	Relative error	Absolute error
37	39	5%	2
Nominal stator current of the mathematical model [A]	Nominal stator current of the experimental model [A]	Relative error	Absolute error
3	3	0 %	0
Nominal shaft rotation frequency of the motor mathematical model [rpm]	Nominal shaft rotation frequency of the motor experimental model [rpm]	Relative error	Absolute error
2800	2850	1.7%	50

Source: prepared by the author

Table 2. Comparative table of the mathematical and experimental models of the GFm32-160B pump's electric drive

Model	Maximum current (A)	Nominal stator current (A)	Stator angular velocity (rad/s)	Transition process time (s)
Mathematical model	37	3	2800	0.3-0.4
Experimental model	39	3	2850	0.3-0.4

Source: prepared by the author