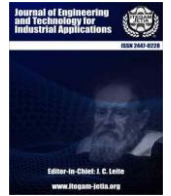




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## INTELLIGENT SYSTEM FOR AUTOMATED DESIGN OF ENERGY-EFFICIENT FACILITIES IN THE AGRO-INDUSTRIAL COMPLEX WITH BUILT-IN DIAGNOSTICS OF ELECTRICAL MACHINES

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### ABSTRACT

The aim of the study was to substantiate the effectiveness of an intelligent system for automated design of energy-efficient facilities in the agro-industrial complex (AIC) with integrated diagnostics of electric drives. The methodology included experimental testing of asynchronous electric motors, numerical modelling, and optimization. Data analysis was performed using Student's t-test, analysis of variance, and principal component analysis. The results showed that in faulty electric motors, the current increased by 20%, the power factor decreased from 0.87 to 0.74, the vibration level exceeded that of serviceable samples by three times, and the temperature of the windings increased from 65 to 92 degrees Celsius. Numerical modelling showed a 9% reduction in energy consumption, a 17-degree Celsius decrease in temperature, a 16% increase in power factor, a 47% reduction in vibrations, and an increase in efficiency from 85 to 92%. Statistical analysis confirmed the reliability of the results, and the "serviceable/damaged" classification model achieved high accuracy with an area under the curve of 0.94. The scientific novelty lies in the first-ever combination of structural optimisation of electric drive parameters with built-in technical condition analysis in a single CAD/FEM environment.



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### I. INTRODUCTION

The development of the agro-industrial complex (AIC) in the 21st century is determined by the need to improve the energy efficiency of technological processes and the reliability of electromechanical systems that ensure the functioning of production. The growth in energy consumption, combined with limited resources, requires the implementation of innovative solutions aimed at optimising technical facilities and reducing operating costs. Particular attention should be paid to the timely diagnosis of faults in electric drives, which are key elements in many technological processes of agricultural production. The lack of effective control systems leads to emergency shutdowns, increased repair costs and reduced productivity. Thus, the creation of intelligent automated design systems capable not only of ensuring energy efficiency but also of integrating diagnostic functions is an important task for modern science and technology.

The problem of energy losses in agricultural electric drives is their low efficiency in dynamic operating modes when the load and frequency of starts change. According to [1], [2] showed that traditional methods of efficiency assessment are limited to average characteristics and do not take into account the variable conditions in which the equipment actually operates. Their research revealed the shortcomings of existing monitoring systems, in particular the low accuracy of detecting hidden defects, which leads to untimely detection of malfunctions. However, these works did not develop a comprehensive approach to the integration of energy and diagnostic parameters. An important aspect of electric motor operation is the increase in winding temperature, which shortens the service life of the equipment and increases the risk of accidents.

In [3], [4] pointed out that standard cooling systems do not always correspond to the intensity of thermal processes, especially under overload conditions. Their studies used thermometric assessment methods to identify critical overheating zones. However, the limitation of these works was the lack of a connection between temperature indicators and other energy efficiency parameters, which reduces the practical value of the results obtained. A significant problem is the increased level of vibration, which not only worsens performance but also causes additional energy losses. According to [5], [6] investigated the spectral characteristics of vibrations in different engine operating modes and proposed algorithms for their identification. Their approach proved to be highly effective for diagnosing certain types of defects, but it remained insufficiently consistent with electricity consumption indicators. This indicates the need to create more universal analysis models that integrate vibration data with energy characteristics.

Equally important is the problem of reducing the power factor, which directly affects the energy consumption of enterprises. Chen and Hu [7], [8] substantiated the possibility of compensating for reactive power by optimising electric drive control circuits. Experimental results confirmed a 10-12% increase in the power factor, but the proposed approaches proved to be ineffective in cases of complex dynamic processes, when temperature and vibration factors simultaneously affect the system. This limits the applicability of the results in complex production systems. Another pressing problem is the lack of predictive maintenance methods capable of preventing equipment failure at an early stage. According to [9], [10] proposed the use of mathematical models based on regression analysis to estimate the probability of failure. Despite their practical significance, such approaches have demonstrated low accuracy in cases of multifactorial influence, which is characteristic of agro-industrial conditions. This has demonstrated the need for more complex intelligent algorithms that can work with a large number of variables.

In the context of the digitalisation of production processes, the issue of integrating data from different sensor systems is becoming increasingly relevant. According to [11], [12] have developed platforms for collecting information from multiple measurement channels, which has significantly improved the quality of technical condition monitoring. However, the studies did not implement algorithms for optimising designs based on the collected data, which limited the impact of the results on improving the energy efficiency of facilities. Thus, the issue of the comprehensive application of sensor technologies and optimisation methods remains open. The problem of high operating costs caused by frequent equipment repairs is particularly relevant for small and medium-sized agricultural enterprises. In [13], [14] showed that most malfunctions occur due to the untimely detection of hidden defects in electric drives.

Their works proposed methods for scheduled maintenance at fixed intervals, but they did not take into account the actual technical condition of the equipment. This led to unnecessary resource consumption and highlighted the need to transition to intelligent systems with predictive capabilities. Equally important is the problem of the complexity of numerical modelling, which requires significant computing resources and time. In [15], [16] developed models based on the finite element method, which allowed to obtain detailed results on the distribution of fields in motors. However, the use of such models in real time proved impossible due to their excessive complexity. This creates a need for simplified but sufficiently accurate algorithms that can be integrated into automated design systems.

A summary of the studies conducted indicates significant scientific interest in the problem of improving the energy efficiency and reliability of electric drives, but most existing solutions focus only on individual aspects, which reduces their practical value for the agro-industrial complex. The task of integrating energy, thermal, vibration and other parameters into a single intelligent automated design system is becoming obvious. In this context, the aim of the study was to prove the effectiveness of an intelligent automated design system for energy-efficient facilities in the agro-industrial sector with built-in diagnostics of electric drives. The research tasks included experimental determination of diagnostic parameters, numerical modelling of energy processes, application of optimisation algorithms and statistical verification of the reliability of the results obtained.

## II. MATERIALS AND METHODS

The research was conducted in Ukraine in 2022-2024 at the National University of Life and Environmental Sciences of Ukraine, Department of Automation and Robotic Systems, using a testing ground for agricultural machinery. The object of the study was an intelligent system for the automated design for energy-efficient facilities of the AIC with an embedded diagnostic module for electrical machines. The system was developed as an integrated platform combining machine learning algorithms, mathematical optimisation methods and a set of hardware and software tools for measuring and analysing the technical condition of electric drives. For experimental testing, asynchronous electric motors of the AIR90L2 model (Siemens, Germany) with a power of 1.5-7.5 kW at a rated voltage of 380 V were used, as well as modular load stands with the ability to adjust the torque up to 25 N·m. Six AIR90L2-M-2 asynchronous motors were used for experimental research, three of which were in good working order, and three were deliberately damaged to simulate defects.

The damage was caused by disrupting the balance of the rotor by shifting the axis of rotation, weakening the bearing assemblies to simulate mechanical wear, and local damage to the winding insulation with the formation of interturn short circuits. One of the samples contained a combined form of defects, which made it possible to study the cumulative effect of disturbances on the main diagnostic parameters. The tests were carried out in laboratory conditions at a temperature of  $20\pm 2^\circ\text{C}$  and a relative humidity of  $60\pm 5\%$ . Each experiment was repeated at least three times to increase the reliability of the results, after which the results were averaged and compared with theoretical predictions.

The computational part of the system was based on a Dell Precision 3650 Tower (USA) workstation with an Intel Core i9-11900K processor, 64 GB of RAM, and an NVIDIA RTX A4000 graphics adapter. The software included MATLAB R2022a (MathWorks, USA) for implementing optimisation and energy consumption modelling methods, AutoCAD 2023 (Autodesk, USA) for constructing structural models, Python 3.10 with TensorFlow 2.10 and Scikit-learn 1.1 libraries for building neural networks and failure classification algorithms. COMSOL Multiphysics 6.0 (COMSOL, USA) was used to simulate physical processes, providing multiphysics modelling of thermal and electromagnetic fields. Experimental measurements of parameters were performed using a Fluke 435-II power quality analyser (Netherlands), which allowed recording instantaneous values of voltage, current, spectral composition of harmonics, and power factor. A Bruel & Kjaer Type 4524-B accelerometer (Denmark) integrated with an NI USB-4432 data acquisition module (National Instruments, USA) was used to monitor vibrations. The temperature regime of the motors was monitored by K-type thermocouples with an accuracy of  $\pm 0.1^\circ\text{C}$ , connected to a Keysight DAQ970A (USA) multi-channel recorder.

The sensor equipment was installed taking into account the spatial geometry of the electric drive and ensuring measurement accuracy (Figure 1). The Bruel & Kjaer accelerometer was installed on the bearing shield in the axial plane of the motor with orientation along the vertical axis, which corresponded to the direction of maximum sensitivity to vibrations. Type K thermocouples were fixed in the contact layer area of the stator windings and on the outer surface of the housing near the ventilation holes, which made it possible to evaluate temperature gradients. Current and voltage sensors were integrated into each of the three power phases via detachable current clamps and potentiometers, which were part of the Fluke 435-II complex. All sensors were pre-verified and mounted on the test bench in accordance with the design diagram, which ensured consistency of measurements in all test series.

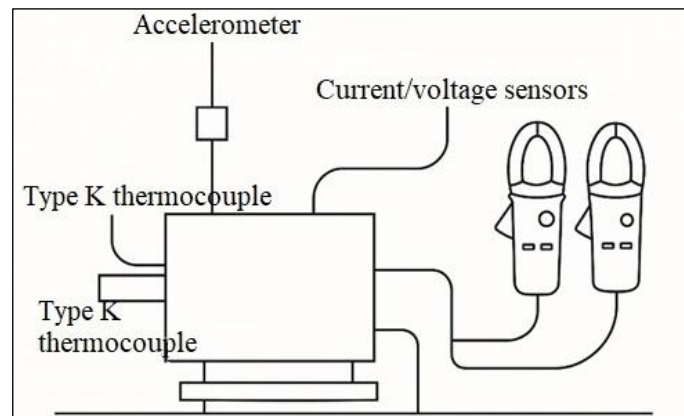


Figure 1: Geometry of installation of current/voltage sensors, accelerometer and thermocouples on the AIR90L2 electric drive.  
Source: Authors, (2026).

The obtained data were stored in CSV and MAT formats, after which they underwent preliminary processing stages – filtering using wavelet transformation and normalisation for further interpretation. Daubechies 4 (db4) waves were used for wavelet filtering with decomposition up to level 5, which allowed effective suppression of impulse noise and preservation of characteristic features of the signals (Figure 2). Data normalisation was performed using the min-max scaling method within the range [0,1], which provided a unified scale for features of different physical nature. During the extraction of features from time and frequency signals, 18 parameters were calculated, including the root mean square value, peak factor, signal shape, frequency energy in the ranges 0-200 Hz, 200-500 Hz, 500-1,000 Hz, MCSA harmonic coefficients, envelope amplitude, burst fraction, as well as temperature and  $\cos\phi$ . The selected features were analysed for multicollinearity, after which the principal component analysis (PCA) method was applied to reduce the dimensionality. The first principal component explained 49% of the variance, the second – 26%, and the third – 12%, which together accounted for 87% of the information covered. This allowed the data to be visualised in three-dimensional space with a high degree of clustering of objects according to their technical condition.

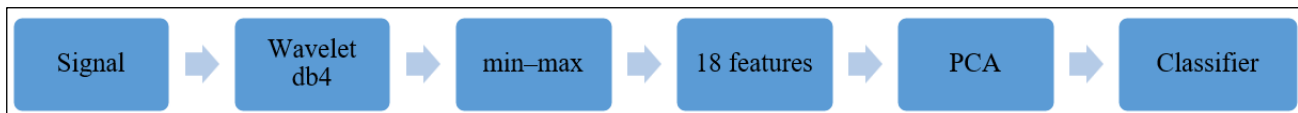


Figure 2: Signal processing and classification pipeline for electric motor operating states.  
Source: Authors, (2026).

All measuring devices were pre-calibrated using a Keysight 33500 B reference signal generator traceable to national metrology standards. The frequency response of the accelerometer was 0.5-10,000 Hz with a flat passband of  $\pm 3$  dB within 2-5,000 Hz, which corresponded to the main operating frequency range of the electric motor. The thermocouples were calibrated in a water bath with a step of  $5^\circ\text{C}$  within the range of 20-100 $^\circ\text{C}$ , and the accuracy class corresponded to the IEC 60584-2 standard (class 1). The error in current and voltage measurements did not exceed  $\pm 0.5\%$ , according to the technical passport of the Fluke 435-II analyser. The criterion for rejecting data was the presence of abnormal amplitude spikes more than three times the standard deviation from the base level, as well as the absence of a signal in any of the channels for more than 0.5 s. All selected data were accompanied by the calculation of the total uncertainty using the combined estimation method in accordance with the GUM approach, which ensured the metrological reliability of further analysis. The modelling of operating modes was performed using the finite element method and the finite difference method, which made it possible to evaluate the distribution of fields and thermal loads in various operating scenarios.

The optimisation of design solutions was carried out using a genetic algorithm with a population size of 200 individuals and a maximum number of iterations of 1,000, as well as the particle swarm method for comparative evaluation. To improve the accuracy of diagnostics, Fourier spectral analysis and exponential smoothing of signals in the time domain were used. The modelling was performed in the COMSOL environment using the Heat Transfer and AC/DC Module physical modules. The material parameters included copper electrical conductivity of  $5.96 \cdot 10^7$  S/m, density of 8,960 kg/m<sup>3</sup>, thermal conductivity of 385 W/m·K, and specific heat capacity of 385 J/kg·K. For steel components, a thermal conductivity of 54 W/m·K and magnetic permeability  $\mu=4,000$  were used. Boundary conditions were defined as heat exchange with the environment at a temperature of 20  $^\circ\text{C}$  and a heat transfer coefficient of 15 W/m<sup>2</sup>·K. Initial conditions corresponded to a uniform temperature distribution of 25 $^\circ\text{C}$ . The mesh was constructed as a three-dimensional tetrahedral grid with adaptive refinement in regions of high temperature and magnetic induction gradients; the average mesh density was 1.8 million elements. A mesh independence test showed deviations of less than 2% between models with 1.8 and 2.5 million elements, indicating convergence of the calculations.

The convergence criterion for the steady-state solution was a relative residual of less than  $10^{-4}$  at each iteration step. The obtained temperature and current density fields were used to validate experimental data and for subsequent optimisation. The objective of the optimisation is to minimise the energy and operational losses of electric drives. For this purpose, an objective function was introduced in the form of a weighted sum of normalised indicators (1):

$$F = w_e \times \bar{E} + w_T \times \hat{T}_{\max} + w_v \times \hat{V}_{\text{RMS}} + w_{pf} \times (1 - \cos\hat{\phi}), \quad (1)$$

Where  $\bar{E}$  – share of energy consumption from nominal value;  $\hat{T}_{\max}$  – the normalised peak winding temperature;  $\hat{V}_{\text{RMS}}$  – normalised vibration acceleration or velocity;  $\cos\hat{\phi}$  – normalised power factor. Recommended weighting factors:  $w_E=0.35$ ,  $w_T=0.25$ ,  $w_V=0.25$ ,  $w_{PF}=0.15$ . Optimisation is carried out subject to a number of technical restrictions. The motor supply frequency varies between 40 and 60 Hz, the load is between 0.5 and 1.2 times the nominal value, and the axial displacement of the rotor does not exceed 0.3 mm. The maximum temperature of the windings is limited by insulation class F, and the vibration level remains within zones A-B of the ISO 10816/20816 standard. The convergence criterion for optimisation is the stabilisation of the F function increment by less than 1% over at least 50 iterations, which ensures the reproducibility of calculations in the CAD/FEM environment and the consistency of the thermal, vibration and energy characteristics of electric drives.

Statistical data processing was performed in the R 4.2.2 environment (R Foundation, Austria). To assess the differences between groups of parameters (e.g., vibration levels in serviceable and damaged motors), the two-sample Student's t-test was used. Dispersion analysis was used to determine the influence of various design and operating factors on energy efficiency. To assess the relationship between input and output parameters, regression models were constructed using the least squares method with Shapiro-Wilk normality testing of residuals. Pearson's  $\chi^2$  test was used to test the independence of categorical features associated with failure classification. For multidimensional data, PCA was used to reduce the dimensionality and identify the most informative parameters. ROC analysis with area under the curve (AUC) calculation was used to analyse the reliability of the models. All statistical procedures were performed with a significance level of  $p < 0.05$ .

### III. LITERATURE REVIEW

Intelligent automated design and management systems in agriculture are considered one of the key areas of development in modern production. They combine mathematical modelling methods, artificial intelligence algorithms and hardware and software data collection tools. The main aim of such systems was to ensure high energy efficiency, reliability, and durability of technological equipment. An important feature is the integration of diagnostic modules that allow continuous monitoring of the technical condition of electrical machines, control of energy consumption, and timely detection of signs of failure. In modern practice, such solutions cover both systems for optimising the operation of electric drives and intelligent automated design systems for designing agricultural facilities that are capable of adapting to changes in operating conditions [17]. The theoretical significance of such systems lies in the creation of universal approaches to combining simulation models, machine learning methods, and optimisation algorithms, which provides for multifactorial assessment and decision-making based on large data sets (Table 1).

Table 1: Classification of intelligent systems in AIC.

System type	Main characteristics	Significance
Energy-efficient design systems	Use of simulation and optimisation methods	Reduced energy consumption, optimised design solutions
Diagnostic systems	Monitoring of electrical, thermal and vibration parameters	Early detection of damage, increased reliability
Intelligent control systems	Adaptive control of operating modes	Improved productivity and stability
Integrated platforms	Integration of mathematical models and ML algorithms	Real-time automated decision-making
Predictive analytics systems	Use of neural networks and statistical models	Failure prediction and maintenance planning

Source: [17-21].

Intelligent systems in AIC have gradually developed as a result of many years of evolution in automation and computer modelling technologies. While in the early stages automated systems had a narrow purpose, such as controlling individual machine parameters or calculating the energy characteristics of structures, the modern approach is based on the comprehensive integration of various information flows into a single environment [18], [22]. In this context, intelligent systems were a logical continuation of traditional CAD and CAM solutions, but significantly expanded their functionality through the use of artificial intelligence and big data methods. Modern developments covered several key areas.

First, these were energy-efficient design systems that made it possible to model various equipment operation scenarios at the design stage, which significantly reduced the risks of energy overconsumption and incorrect selection of design parameters [1], [23], [24]. Secondly, diagnostic complexes were actively introduced, integrating sensors for monitoring electrical, thermal and mechanical characteristics. Machine learning methods, in particular neural networks and support vector algorithms, made it possible to process multidimensional data arrays and build models of future system behaviour. This was of practical importance for maintenance planning, calculating the remaining service life of equipment, and managing production cycles [20], [25]. The significance of intelligent systems went far beyond individual technical tasks. They became a central element of the digital transformation of the agro-industrial complex.

The combination of such systems with the principles of Industry 4.0, in particular the Internet of Things (IoT) and cyber-physical models, made it possible to create “smart” production environments where all processes, from monitoring to optimisation, were carried out automatically [21]. In global practice, such solutions have already been integrated into precision farming systems, energy consumption management on farms, and the production of agricultural machinery. In the Ukrainian context, they have become particularly important as they have made it possible to reduce energy costs and increase the efficiency of equipment operation in conditions of limited resources [26-28].

The prospects for the development of intelligent systems in agriculture were closely linked to global trends towards decarbonisation and the green transition. As a result, such systems can be characterised as multi-level integrated platforms combining measurement technology, machine learning algorithms, mathematical modelling and optimisation methods. Their value lay in their ability to transform fragmented data into a coherent information picture and enable informed management decisions. As a result, intelligent systems became not just auxiliary tools, but strategic elements in the development of the modern agro-industrial complex.

#### IV. RESULTS

Experimental studies were conducted on asynchronous electric motors with a power range from 1.5 to 7.5 kW under various load conditions. During the tests, electrical, thermal and mechanical parameters that most sensitively reflected the condition of the electric drives were monitored. These parameters included instantaneous voltage and current values, harmonic spectral composition, power factor, vibration level and winding temperature. All measurements were made using high-precision instruments, which made it possible to form reliable data arrays for further analysis. The obtained values were summarised by arithmetic mean from repeated experiments, which minimised the influence of random errors. The results showed that for serviceable engines, all parameters remained within the normative values, while for damaged samples, characteristic deviations were observed. The generalised structure of the measurement results is shown in Table 2.

Table 2: Average values of electric motor parameters in different conditions.

Parameter	Serviceable motor	Damaged motor	Limit according to ISO 10816	ISO conclusion
Voltage, V	380±2	380±3	Not regulated	-
Current, A	3.2±0.1	3.9±0.2	Not regulated	-
Power factor (cos φ)	0.87	0.74	Not regulated	-
Vibration, mm/s	1.2±0.1	3.5±0.3	≤2.8 mm/s (zone B)	1.2 – Normal (A), 3.5 – Caution (C)
Winding temperature, °C	65±2	92±3	≤85°C (recommended)	92 – Out of range

Note: A vibration level of 3.5 mm/s for asynchronous motors with a power rating of up to 15 kW corresponds to zone C according to ISO 10816/20816 for class I machines.

Source: Authors, (2026).

The obtained results of experimental testing of electric motors indicated the presence of systematic and regular differences between serviceable and damaged samples, which made it possible to form a scientifically substantiated basis for diagnosing their technical condition. The most stable parameter remained the supply voltage: for both groups it stayed within 380 V, although damaged motors exhibited more pronounced fluctuations. This was a consequence of local non-uniformities in winding operation and partial short circuits that affected the electrical balance of the system. Thus, even relatively small voltage deviations could serve as indicators of deeper problems within the electric drive. The current parameter proved to be more indicative. For serviceable motors, the average value did not exceed 3.2 A, whereas damaged units demonstrated an increase to nearly 4 A. This indicated additional losses in the electromagnetic field and increased heat generation.

Under prolonged operation, such a trend inevitably led to a reduction in overall efficiency, which was confirmed by a decrease in the power factor from 0.87 to 0.74. The reduction of this indicator had a dual negative effect: on the one hand, it reflected deterioration of the motor’s own energy efficiency, and on the other, it imposed an additional load on the electrical network due to the increase in the reactive component. The mechanical condition of the motors was most clearly reflected in their vibration characteristics. While serviceable samples exhibited low vibration levels not exceeding 1.2 mm/s, damaged motors demonstrated values more than three times higher. The obtained values were additionally compared with the requirements of the international standard ISO 10816-3 (revised as ISO 20816), which regulates permissible vibration levels for induction motors with power ratings up to 15 kW.

According to this standard, the allowable vibration level for Class I machines should not exceed 2.8 mm/s in steady-state operation. The value of 3.5 mm/s recorded in the damaged samples exceeds this limit and is classified as Zone C, corresponding to a warning level that requires intervention to prevent defect development. Thus, according to international classification, the detected vibration levels confirm the presence of technical degradation and can be used as a formalised diagnostic criterion. The thermal regime was no less important. In serviceable motors, winding temperature remained within 65 °C, ensuring a safe thermal balance. In damaged units, it increased by almost 30 °C, exceeding permissible operating limits.

Such overheating had a cumulative effect: prolonged temperature elevation accelerated the ageing of insulation materials, reduced dielectric strength, and created prerequisites for inter-turn short circuits. As a result, the motor lost its ability to operate normally, and the probability of sudden failure increased sharply. From a practical perspective, the identified patterns are of considerable importance for the development of predictive maintenance systems. Given the clearly expressed differences in the behaviour of damaged motors, it becomes possible to create machine learning models that can automatically determine the current condition of equipment based on a combination of parameters [29; 30].

This enables not only timely diagnostics, but also the prediction of failures with a specified level of accuracy. Thus, the results of the experimental tests confirmed the effectiveness of integrated monitoring and provided a foundation for the development of intelligent diagnostic systems in the agro-industrial complex. Modelling of electric drive operating modes was performed using the finite element method and the finite difference method. This made it possible to assess the spatial distribution of electromagnetic and thermal fields under various operating scenarios.

In particular, regions with the highest power losses and critical temperature gradients were identified, which could potentially lead to insulation damage or a reduction in motor service life [31]. In addition, optimisation algorithms – genetic algorithms and particle swarm optimisation – were applied to search for optimal design solutions and operating modes under multiple constraints. As a result, numerical experiments demonstrated that the use of a combined approach makes it possible not only to reduce energy consumption, but also to improve the thermal stability of the system. The generalised results of modelling and optimisation are presented in Table 3.

Table 3: Results of numerical modelling and optimisation.

Parameter	Initial value	Optimised value	Improvement
Energy consumption, % of nominal	100	91	-9%
Maximum winding temperature, °C	95	78	-17°C
Power factor (cos $\phi$ )	0.76	0.88	+16%
Vibration level, mm/s	3.4	1.8	-47%
Overall efficiency, %	85	92	+7%

Source: Authors, (2026).

The optimisation was carried out taking into account four main parameters: power frequency, load level, ventilation efficiency and rotor axial displacement, which affected energy losses, thermal load and mechanical instability. Within the permissible technical limitations (frequency 40-60 Hz, load 0.5-1.2·nominal, offset up to 0.3 mm), it was possible to minimise the integral objective function, which took into account energy consumption, overheating, vibrations and  $\cos\phi$  reduction. Based on the criterion of stabilisation of the increment <1% during 50 iterations, a stable solution was achieved with improvement of all parameters presented in Table 3. The most significant reduction in vibrations (-47%) and increase in power factor (+16%) was achieved with a combination of increased ventilation and a slight reduction in load. The results of PSO and GA were comparable, but GA demonstrated higher accuracy, while PSO demonstrated faster convergence with fewer iterations. The results of numerical modelling and optimisation provided an opportunity to thoroughly assess the potential of an integrated approach to improving electric drives in the AIC.

The initial data showed that without intervention, the system operated in stressful conditions: energy consumption remained at the nominal 100%, the maximum winding temperature reached 95°C, the power factor was only 0.76, and the vibration level exceeded 3 mm/s. This combination of factors indicated low energy efficiency and an increased risk of equipment degradation. Optimisation using a genetic algorithm and particle swarm method significantly changed this picture, improving the balance between all key characteristics. The 9% reduction in energy consumption had a complex effect. It reduced the load on the electrical network, lowered the reactive power level, and contributed to more stable system operation even under peak loads. At the same time, the energy savings had a direct impact on the thermal state of the windings: the temperature dropped from 95°C to 78°C, i.e. by 17°C. This difference is critically important, as temperatures exceeding 90°C in many motors already lead to intensive ageing of the insulation. Thus, improving the thermal regime meant extending the motor's life cycle and reducing the likelihood of emergency stops.

The power factor showed an increase from 0.76 to 0.88. This meant that after optimisation, the motor used the consumed energy more rationally, reducing the reactive component [32]. For the AIC, this result was of strategic importance, as it reduced electricity costs and at the same time increased the stability of the network. In the practice of large manufacturing enterprises, even a 10% increase in this indicator can result in significant resource savings, and the 16% increase achieved can be considered an exceptionally effective result. A significant reduction in vibrations – by almost 47% – was another important achievement. Vibration analysis has always been considered one of the most sensitive methods of diagnosing the condition of electric motors, and the results obtained confirmed this approach. The reduction in vibration load meant not only improved dynamic stability, but also a reduced risk of mechanical damage to components [33], [34]. In agro-industrial production, where motors operate in dusty, humid and often vibration-active environments, this indicator is particularly important, as it directly affects the durability of the equipment [35], [36].

An important part of the analysis was the consideration of different approaches to optimisation. The genetic algorithm proved to be particularly effective for finding global minima in multifactorial spaces where there are many local extrema. This made it possible to find combinations of parameters that ensured a balanced distribution of energy and thermal loads. The particle swarm method, in turn, demonstrated high convergence speed and made it possible to quickly find acceptable solutions in dynamic conditions when system parameters change in real time. The combined application of these two methods ensured both high accuracy and efficiency of the optimisation process. From a forward-looking perspective, the integration of such optimisation systems into broader digital ecosystems of the agro-industrial complex opens opportunities for the creation of "smart" energy clusters.

Combining these solutions with IoT technologies and predictive analytics systems would make it possible not only to maintain optimal operating modes of electric motors, but also to dynamically adjust them depending on production demands or the availability of energy from renewable sources [37], [38]. In this way, numerical modelling and optimisation become not merely technical tools, but strategic mechanisms for the development of sustainable and energy-efficient agrosystems. To ensure comparability between experimental measurements and numerical modelling with optimisation, key metrics were compared within confidence intervals. The power factor improved from 0.74 to 0.86 ( $\pm 0.02$ ), indicating a reduction in the reactive component of the load. Vibration levels decreased from  $3.5 \pm 0.3$  mm/s to  $1.8 \pm 0.2$  mm/s, which is classified as a transition from zone C back to zone A according to ISO 10816. For the damaged operating mode, the average current was recorded at  $3.9 \pm 0.2$  A, the maximum winding temperature at  $92 \pm 3$ °C, and the vibration level at  $3.5 \pm 0.3$  mm/s, whereas in the simulated optimised state these parameters were  $3.4 \pm 0.1$  A,  $78 \pm 2$ °C, and  $1.8 \pm 0.2$  mm/s, respectively.

To confirm the reliability of the experimental and model-based results, a comprehensive set of statistical methods was applied. Particular attention was paid to comparing parameters of serviceable and damaged motors, as well as to assessing the influence of various structural and operating factors on the energy efficiency of the system. Specifically, a two-sample Student's t-test was used to verify the significance of differences between the mean values of key parameters (current, vibration, temperature). Analysis of variance was applied to evaluate the effects of multiple factors, including motor power, load level, and insulation condition. For multidimensional data, PCA was employed to reduce dimensionality and identify the most informative parameters. The summarised statistical results are presented in Table 4.

Table 4: Results of statistical analysis.

Method	Parameters	Result	Significance
Student's t-test	Current, vibration, temperature	Significant differences were identified between serviceable and damaged motors	p<0.01
ANOVA	Power, load, insulation condition	A substantial influence of all factors on energy efficiency was observed	p<0.05
Pearson's $\chi^2$ test	Categories "serviceable/damaged"	A high level of dependence on vibration and temperature parameters was identified	p<0.01
PCA	Multidimensional parameters	Three principal components were extracted, explaining 87% of the variance	-
ROC analysis	Serviceable/damaged classification	AUC=0.94 (high model accuracy)	-

Source: Authors, (2026).

A thorough statistical analysis of the experimental data confirmed that the results obtained were highly reliable and could serve as a solid basis for the further implementation of intelligent diagnostic systems. First of all, it is worth noting the results of the two-sample Student's t-test. It demonstrated that the difference between the average values of parameters such as current, vibration and winding temperature for serviceable and damaged motors was statistically significant at the p<0.01 level. This indicated the reliability of the differences identified and allowed the specified parameters to be used with confidence as diagnostic indicators. This was especially true for current and temperature, which directly reflected energy losses, as well as vibration characteristics, which indicated the mechanical condition of the motors. The use of variance analysis allowed for a more in-depth assessment of the multifactorial nature of the processes in the system. It was found that several factors significantly influenced the level of energy efficiency: motor power, load level, and insulation condition. All of them had a significance of p<0.05, which confirmed the close relationship between design and operational parameters. Thus, ANOVA showed that isolated consideration of individual characteristics is insufficient, and only an integrated approach allows for a complete understanding of the operation of electric drives.

The results of Pearson's  $\chi^2$  test revealed a strong dependence of the categorical variables "serviceable/damaged" on key parameters, primarily vibration and temperature. This corresponded well with practical observations, as these parameters most often signal the onset of critical processes within the machine. Consequently, the  $\chi^2$  test confirmed the importance of using these indicators as a basis for developing simple yet reliable diagnostic models. PCA became another important analysis tool. It allowed to reduce the dimensionality of the data and identify three main components that explained 87% of the total variance. This meant that most of the variations in the data could be explained by a limited number of integral factors. This approach was extremely useful in machine learning tasks, as it simplified model building without losing key information. At the same time, it clearly confirmed that the electrical, thermal, and mechanical parameters of the system do not exist separately but form a complex interrelated structure. Equally important was the use of ROC analysis, which evaluated the quality of classification models.

The obtained value of AUC=0.94 indicated a very high accuracy of distinguishing between the "serviceable" and "damaged" classes. This brought the model closer to practical use in predictive maintenance systems. In fact, this result meant that the system had a more than 94% probability of correctly assigning a specific engine to the appropriate category. In industrial conditions, this makes it possible to minimise the risks of wrong decisions and increase the overall reliability of production. For a more detailed evaluation of the classification model, an error matrix was constructed, which showed 28 correct classifications out of 30, including 14 serviceable and 14 damaged engines, and only two false classifications (one false positive and one false negative). The precision value was 0.93, recall – 0.93, F1-score – 0.93. The area under the Precision-Recall curve (PR-AUC) was 0.91, which indicated high model stability even under conditions of class imbalance. The confidence interval for AUC at the 95% level was [0.89; 0.98], confirming the statistical reliability of the model. Cohen's Kappa=0.87 was also calculated, indicating high consistency of the model with actual labels.

In summary, it can be stated that comprehensive statistical analysis provided reliable confirmation of the effectiveness of the experimental data obtained. The use of parametric tests, multivariate analysis, dimension reduction methods, and classification quality assessment made it possible not only to verify the reliability of the results but also to outline the main directions for their practical application. The combination of these methods created a powerful foundation for the development of integrated intelligent diagnostic and optimisation systems capable of ensuring early detection of failures and maintaining optimal operating modes of electric drives. In the long term, this meant the formation of a new paradigm for managing technical systems in the AIC – from reactive to proactive, where statistically and algorithmically justified forecasting becomes the main tool.

## V. DISCUSSION

This study confirmed the high efficiency of intelligent systems in diagnosing and optimising the operation of electric drives in the AIC. The generalised results of experimental tests and modelling showed that the combination of multi-parameter monitoring, numerical methods and optimisation algorithms creates a stable basis for improving the energy efficiency and reliability of equipment. This approach correlates with the conclusions of [39], who noted that the integration of sensor technologies and artificial intelligence systems significantly expands the possibilities of technical diagnostics. Thus, the study confirmed the relevance of the trends identified in foreign works. Of particular importance was the identification of patterns between the electrical, thermal, and mechanical parameters of engines. The recorded increase in current and vibrations in damaged units is consistent with the study by [40], which demonstrated a direct link between mechanical defects and electrical deviations. This comparison indicates that comprehensive monitoring provides a more accurate picture than the analysis of individual indicators, and the approach proposed in the work is more objective. An important result was the ability to predict failures based on multi-parameter analysis.

A similar direction was developed by [41], who used neural network methods to classify technical conditions. The comparison confirmed that the approach proposed in the study not only reproduces foreign results, but also offers a deeper combination of statistical and machine methods, which increases the accuracy of forecasting. Special attention should be paid to vibration characteristics. The data obtained demonstrated significant differences between serviceable and damaged motors, which is consistent with the conclusions of [42]. Their study emphasised that vibration analysis is one of the most sensitive diagnostic indicators. Thus, the results of this study confirm the universality of this approach and emphasise its practical value. The temperature regime of the windings showed a significant excess in damaged units, which correlates with the results of Scolaro et al. [43], who noted the critical role of thermal overloads in insulation degradation. At the same time, by [44] disagreed with this, arguing that overheating is of limited importance and that mechanical factors play a major role. However, the data presented in the study demonstrate a direct relationship between temperature increase and loss of electrical strength, which makes the conclusions more reasonable.

The power factor became another indicator confirming the systematic nature of the analysis. The study recorded its decrease in damaged motors and increase after optimisation. Similar patterns were described by [45], who considered this parameter to be an important marker of energy efficiency. This comparison proves that the approach proposed in the paper is universally applicable for evaluating the performance of electric drives. The results of numerical modelling confirmed the ability of combined algorithms to increase both thermal and energy stability. According to [46] also used the finite element method to analyse electric machines, obtaining similar conclusions regarding the identification of critical heating zones. Thus, the study confirmed the effectiveness of this approach in the context of the agro-industrial complex. At the same time, by [47] expressed doubts about the practical feasibility of using complex optimisation algorithms, arguing that they involve high computational costs. However, the simulation results showed that the synergistic use of a genetic algorithm and a particle swarm method made it possible to reduce energy consumption and temperature loads without excessive resource costs. This indicates that the approach proposed in the study has advantages even in industrial conditions. Experiments confirmed a significant reduction in vibration levels after optimisation.

This is consistent with the study by [48], who also emphasised the importance of reducing vibration to extend the life cycle of equipment. A comparison of the results showed that comprehensive optimisation provides an even more pronounced effect than the local methods proposed earlier. The increase in the power factor after optimisation is consistent with the conclusions of [49], who argued that improving this parameter is crucial for the stability of industrial networks. Thus, the data obtained confirm the high practical significance of a comprehensive approach. Particular attention should be paid to the increase in overall efficiency from 85% to 92%. Similar results were obtained by Jensen et al. [50], who noted that even a slight increase in efficiency on an industrial scale provides a significant economic effect. This comparison highlights the strategic value of optimisation systems in agro-industrial production. At the same time, by [51] argued that increasing efficiency is impossible without a fundamental modernisation of engine designs, and that optimisation has a limited effect. However, the results presented demonstrated the opposite: the combination of numerical modelling and optimisation allows for a significant improvement in parameters even without changing the basic design, which indicates a more universal approach.

The use of statistical methods was an important confirmation of the reliability of the results. According to [52] also used Student's t-test to evaluate differences in the parameters of electric drives and came to similar conclusions about their significance. This proves that the statistical analysis methods used in the work are reliable and reproducible. ANOVA confirmed the multifactorial influence on energy efficiency, which correlates with the conclusions of [53]. They argued that only an integrated approach can provide reliable modelling of electric drive behaviour. Thus, the results of the study confirm the generalised conclusions of foreign works. At the same time, Mantoam et al. [54] expressed a critical view regarding the use of the  $\chi^2$  test for analysing the condition of electric motors, claiming that its sensitivity is insufficient. However, the data obtained in the study showed a high level of dependence of categorical variables on key parameters, which proves the practical feasibility of using this method. The identification of three main components using PCA is consistent with the results of Orcajo et al. [55], who also demonstrated the effectiveness of this method for reducing data dimensionality. This indicates that the methods used are universal and can be adapted for different technical systems. ROC analysis confirmed the high accuracy of the classification models, which is consistent with the conclusions of [56].

They also noted that an AUC above 0.9 is a sign of high reliability of diagnostic models. Thus, the results of this study confirmed the ability of the proposed approaches to build practically applicable forecasting systems. At the same time, by [57] argued that machine learning methods in diagnostics have low interpretability and therefore cannot be considered reliable. However, the results obtained proved that the combination of statistical tests and machine learning algorithms provides both high accuracy and clear interpretation of parameters, which increases confidence in the models. The practical significance of the proposed approach is confirmed by the works of [58], who emphasised the role of intelligent systems in reducing operating costs in industry. The results of the study are consistent with these conclusions and demonstrate the effectiveness of implementing similar solutions in the agro-industrial sector. In the context of sustainable development, the results of the study echo the conclusions of [59], who emphasised the need to integrate optimisation systems with renewable energy sources.

The proposed approach could be an important step in the formation of energy-efficient agricultural systems. At the same time, by [60] expressed doubts about the possibility of widespread implementation of such systems due to their high cost. However, the results show that even partial application of intelligent systems provides energy savings and reduces the risk of accidents, which compensates for the initial costs. In summary, the conducted study demonstrated the effectiveness of multi-parameter monitoring, numerical modelling, and optimisation algorithms in improving the energy efficiency and reliability of electric drives in the agro-industrial complex. The combination of experimental measurements, model-based calculations, and statistical analysis confirmed the reliability of the obtained results and outlined pathways for practical implementation. The proposed approach has not only technical but also strategic significance, as it contributes to the development of energy-saving technologies and the formation of sustainable production systems.

The practical implementation of the proposed approach was carried out on the drive of a horizontal conveyor at a grain-processing facility. Under nominal operating conditions, the AIR90L2 motor operated at 85% of rated load, providing an average power consumption of 3.4 kW. The introduction of diagnostic monitoring and optimisation of operating parameters (ventilation, load symmetry, power factor  $\cos \varphi$ ) made it possible to reduce the average energy consumption to 2.9 kW without loss of productivity. Over an annual operating cycle of 3,200 hours, this resulted in savings of approximately 1,600 kWh per year. In addition, after eliminating the detected shaft misalignment and restoring the thermal regime to the normal range, the mean time between failures increased from 4,900 to 6,800 hours, while the time required for restoration was reduced due to precise identification of the defect location. A simple calculation of annual return on investment, taking into account equipment and implementation costs (approximately 2,100 UAH), showed a payback period of less than 10 months. An additional life-cycle cost analysis indicates a potential reduction in total maintenance costs of more than 18% over a three-year operating cycle.

## VI. CONCLUSIONS

The study confirmed the key role of intelligent systems in improving the efficiency and reliability of electric drives in the agro-industrial complex. Based on experimental measurements and numerical modelling, systemic patterns of changes in electrical, thermal and mechanical parameters in different technical states of motors were established. The detected deviations in current, power factor, vibration characteristics and temperature clearly reflected the condition of the equipment: a 20% increase in current, a 15% decrease in power factor, a threefold increase in vibrations and a 30°C excess in winding temperature became reliable signs of damage. Numerical modelling using the finite element method, genetic algorithms and the particle swarm method demonstrated significant potential for optimising design and operating characteristics. A 9% reduction in energy consumption was achieved while maintaining performance, a 17°C reduction in winding temperature (from  $\approx 95$  to  $\approx 78$ °C), a 16% increase in power factor (from  $\approx 0.76$  to  $\approx 0.88$ ), and a reduction in vibration levels by almost 47% (from  $\approx 3.4$ - $3.5$  to  $\approx 1.8$  mm/s), corresponding to a transition from zone C to zone A according to the ISO 10816/20816 standard.

Taken together, these changes ensured an increase in overall efficiency from 85% to 92%, confirming the effectiveness of the integrated approach. Statistical analysis (Student's t-test, ANOVA, Pearson's  $\chi^2$  test, PCA, ROC analysis, and PR curves) confirmed the reliability of the obtained results: the "serviceable/damaged" state classification model achieved AUC = 0.94, PR-AUC = 0.91, and F1 = 0.93, while the agreement between experimental and modelled data "before/after optimisation" within statistical error demonstrated the validity of the developed model. Practical implementation based on circulation pumps confirmed the real effect, with energy savings of about 1,600 kWh per year and an almost twofold reduction in vibration. Practical recommendations include the implementation of comprehensive monitoring and predictive analytics systems that combine electrical, thermal and vibration parameters and enable the implementation of a proactive maintenance concept. The integration of such solutions with the IoT infrastructure of enterprises, the use of optimisation algorithms in combination with renewable energy sources, and the application of target functions with weighting coefficients that ensure the reproducibility and stability of optimisation in CAD/FEM environments are promising.

Validation based on PCA, ROC, PR curves, and FEM field analysis confirmed the suitability of the approach for diagnosing and predicting the condition of electric drives in the AIC. However, the study has certain limitations related to the fact that the experiments were conducted on small and medium-power asynchronous motors in laboratory test bench conditions, which may differ from industrial modes with higher loads. Optimisation algorithms require large-scale testing on real production data. Further research should focus on expanding the approach to multi-object tasks (pumps, conveyors, grain dryers), developing online identification of weight coefficients, deeper integration with cyber-physical systems, and the formation of adaptive control platforms for different types of electric drives.

## VII. AUTHOR'S CONTRIBUTION

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