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DIGITAL TWIN FOR INTEGRATION OF CONTROL AND DIAGNOSTICS OF ELECTROMECHANICAL SYSTEMS UNDER UNCERTAINTY

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ABSTRACT

The study aimed to create a digital twin for the integration of control and diagnostics of electromechanical systems under conditions of uncertainty, with minimal reliance on physical sensors. The research was conducted at Mykolaiv National Agrarian University. Physically based models were developed for thermal processes in windings, assessment of losses in magnetic conductors, and wear indicators for components, virtual sensors, signal filtering algorithms and degradation prediction were implemented, and verification was conducted on test benches and in computer modelling. Quantitative results were obtained, which constitute the main contribution of the work: the accuracy of reproducing hidden parameters was 93.6-97%, the relative error of reproducing losses in the transformer was 3%, the relative error of thermal estimates was 3.5-6.8%, the correlation with reference measurements reached 0.99; the reduction in the dispersion of noisy signals was 33-41%, the signal-to-noise ratio increased by 4.2-6.7 decibels, and the root mean square error decreased by 35-44% with an additional delay of no more than 0.04 seconds. The models can be used in ship drives, biogas plants, robotic lines, irrigation pumping stations, transformer substations, hydraulic drives and traction electric drives, reducing downtime and energy consumption without changing the existing control infrastructure.

I. INTRODUCTION

Electromechanical systems in transport, energy, industry, and agricultural production operate in variable modes, under conditions of incomplete observability and noisy measurements, which complicates stable control and timely diagnostics. The gap between these functions leads to fragmentation of decisions, duplication of sensors, increased costs and the risk of latent failures in transient modes. The concept of a digital twin as a synchronised digital representation of a physical object with two-way data exchange is viewed as a tool for overcoming these limitations, as it combines model, data and analytics in a single decision-making loop and creates conditions for sensor substitution without loss of controllability. [1] defined digital twin as a continuous channel for reflecting the states of a real product in a digital environment, with an emphasis on traceability and controlled configuration evolution. The emphasis on data history and consistency demonstrates how a digital twin can provide confidence in calculated states in situations with limited measurement access.

The study by [2] considers the digital twin as the basis for assessing technical condition and predicting resource throughout the life cycle, emphasising that physically correct models verified by experiment can support decisions beyond the current sensor coverage. This gives reason to consider the digital twin as an integrator of diagnostics and control, rather than just an analysis tool. The review by [3] introduces the gradation “digital model – digital shadow – digital twin” and explains how the level of feedback determines the system's ability to intervene in the process in real time. This classification sets practical criteria for choosing the depth of integration depending on the requirements of the object. The conceptual framework by [4] expands the architecture to a multidimensional representation of states, services, and data, where formal interfaces regulate the interaction between levels. This clarifies how to scale a digital twin from a single node to a production site or energy complex.

Engineering guidelines by [5] detail requirements for connectivity with control and monitoring platforms, including time stamp synchronisation, computing resources, and interoperability with industrial protocols. The definition of these requirements explains the limits of applicability of digital twins in closed loops. Virtual sensors that reproduce unmeasurable variables based on available signals are a key element of integration. The theoretical basis was set by [6], demonstrating that under conditions of observability, internal states can be recovered from initial measurements. This creates the foundation for sensor substitution in drives and transducers. The recursive method by [7] describes the optimal reduction of the root mean square error of estimation in the presence of process and measurement noise.

This approach explains how to combine a dynamic model and noise statistics to obtain consistent estimates in real time with controlled latency. The review by [8] demonstrates that multi-sensor integration, considering the motion model and measurement geometry, improves the signal-to-noise ratio and the stability of estimates in transient modes. This is relevant for electromechanical objects with rapid load changes. The generalisation by [9] shows that correct parameterisation of noise covariances and data fusion rules reduces tracking errors and increases the detectability of weak anomalies. This conclusion explains why correctly tuned parameters can reduce false alarms in diagnostics. The fundamental principles of technical diagnostics were systematised by [10], which describes the creation of diagnostic deviations, consistency tests, and criteria for localising defects in mechatronic systems under partial observability.

The principles outlined explain how to form reliable diagnostic features for inclusion in a digital twin and why the interpretability of models is necessary for decision-making by the operator. For electromagnetic subsystems, the correct modelling of losses in the magnetic circuit is based on the dependence discussed in detail in the work of [11], which establishes the relationship between induction, frequency and specific losses. This representation provides fast and energy-consistent calculations necessary for operational assessments. In the field of technical maintenance, according to [12] propose approaches to heat utilisation in agricultural machinery engines based on the assessment of the residual resource and efficiency of systems. The proposed methods include the definition of practical criteria for making decisions on the feasibility of intervention, which can be used for verification of the extent to which the forecast meets the requirements of production practice.

Despite progress in these areas, there are significant gaps in the scientific literature. There are no standardised protocols for quantitative comparison of "physical sensor" and "virtual sensor" modes under the same metrics of accuracy, delay and impact on control stability. There is limited cross-industry validation of a unified digital twin architecture for different process physics. Integration into industrial control platforms, considering time stamp synchronisation and computational constraints, which define the real limits of applicability, has not been sufficiently addressed. The study aimed to create a digital twin of electromechanical systems capable of combining automatic control and technical diagnostics in conditions of uncertainty. The research hypothesis assumes a reduction in peak mechanical and thermal loads, downtime and energy costs as a result of integrating diagnostics into the control loop, which corresponds to the current tasks for the specified areas of application.

II. MATERIALS AND METHODS

The research was conducted in 2023-2025 at the educational and scientific laboratory of electrical equipment at Mykolaiv National Agrarian University (Ukraine). The laboratory specialises in modelling and testing electric drives, transformer equipment and hydraulic systems, which ensured comprehensive verification of the proposed approach. The theoretical basis was the concept of a digital twin as a mathematical and physical copy of a real object, synchronised with its behaviour in real time. Virtual sensors for reproducing parameters that are not accessible for direct measurement were the central element. A system of equations for electromagnetic, thermal, and mechanical processes ensured the adequacy of the model, while diagnostic algorithms predicted degradation phenomena based on calculated indicators. The main tool used was MATLAB/Simulink (MathWorks, USA), which provided multi-level modelling of electrical, thermal and mechanical processes.

The calculations were performed on a personal computer with an Intel Core i7 processor (Intel, USA), 32 GB of RAM and an NVIDIA RTX 3060 graphics adapter (NVIDIA, USA). To test the models, an asynchronous motor 1LE1001 (Siemens, Germany), a TMS (Transformer Monitoring System) transformer (ABB (Asea Brown Boveri), Switzerland), a Parker F12 hydraulic motor (Parker Hannifin, USA), and a CompactDAQ data acquisition system (National Instruments, USA) were used. All simulation series were performed with a model resolution of 0.001 s, which provided a single time base for comparing results. For validation, a class A PT100 sensor (Endress+Hauser, Switzerland) with an NI-9217 module (National Instruments, USA), a WT3000 power analyser (Yokogawa, Japan), and a 352C33 accelerometer (PCB Piezotronics, USA) as part of CompactDAQ (National Instruments, USA).

The architecture of the digital twin consisted of a physical model of the object, equations of electromagnetic, thermal and mechanical processes, and a block of virtual sensors for evaluating hidden parameters such as winding temperature, power losses and wear. The thermal state of the windings was reproduced by an equivalent RC circuit 2R-1C with parameters τ_1=420s, τ_2=95s, R_θ=0.62 K/W; the update period of the estimates was 0.1s with a model discreteness of 0.001s. Losses in the magnetic circuit were modelled by a generalised Steinmetz dependence with coefficients k=0.0019, α=1.64, β=2.07 in the induction range up to 1.4 T. The degree of bearing wear was described by a normalised index $W^* \in [0;1]$, incorporating changes in internal losses ηv and friction torque M_f. The parameters were identified using the recursive least squares method. Machine learning algorithms were used to identify deviations and classify states. The update period was 0.1 s for fast-changing channels and 1 s for steady-state electrical losses, which was consistent with real-time requirements and estimator stability.

The methodology established the universality of the digital twin, which made it possible to test its effectiveness in various fields. The following scenarios were implemented in MATLAB/Simulink: load change of 0.25-1·Pn, introduction of noise into signals, simulation of insulation degradation, and the effect of magnetic saturation. For the transformer, frequency validation of losses was performed at 12 points within the range of 50-60 Hz using a WT3000 analyser (Yokogawa, Japan). The simulation results were displayed in the form of time graphs, spectral diagrams and tables and compared with classical sensor systems. The effectiveness of the digital twin was assessed according to technical criteria (accuracy of hidden parameter reproduction, control stability, timely detection of failures) and economic criteria (reduction of downtime, increased energy efficiency, reduction of maintenance costs).

The assessment was conducted using a unified protocol: relative error of target parameters, change in energy consumption, accuracy of deviation detection, proportion of correct predictions; 100% standardisation base, no digital twin mode; relative changes were brought to the base, error/accuracy metrics were presented as absolute, for forecasts, the share in the tolerance was ±10% and the coverage was 95% Prediction Interval (PI) with latency fixation. The duration of the load series was 15 minutes; thermal cycles lasted 8 hours in 6 cycles; magnetic saturation impact tests were performed for 12 minutes in 3 independent repetitions. The specified sampling and update period parameters ensured the comparability of accuracy and stability metrics between modes and scenarios. Additionally, durability, computing speed, and scalability were analysed. Metrics included Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Pearson's correlation coefficient, Signal-to-Noise Ratio (SNR), Mean Squared Error (MSE), and coverage of 95% confidence intervals of the forecast with fixed computational delay.

III. RESULTS

A digital twin is a synchronised computational representation of an electromechanical object with a two-way flow of "model data – decision – control inputs – data" that maintains consistency between the physical and digital states in real time. The architecture includes a physical layer with telemetry, a data collection and normalisation layer (coordination of timestamps, discretisations and scales), a layer of physical models for electromagnetic, thermal and mechanical processes (nominal and transient modes), an evaluation and diagnostics layer (virtual sensors, errors, deviation detection, resource prediction), and an integration layer that transmits the evaluated states and predictions to a Programmable Logic Controller/Supervisory Control and Data Acquisition (PLC/SCADA) for mode correction.

Cycle synchronisation is ensured by limiting the computational delay to ≤0.04 s for a model discreteness of 0.001 s and the stability of estimators at load variations of ±15%. The principle of operation of virtual sensors is to recover unmeasured variables from available signals by combining parametric models and statistical filtering: for fast channels, an extended Kalman filter with updates every 0.1 s is used, adaptive smoothing is used for quasi-stationary components, and recursive identification is used for slow degradation parameters. The quality of estimates is controlled through errors and confidence intervals; target thresholds are set as an average relative error of <6%, correlation with the reference standard of ≥0.97, and a reduction in dispersion of at least 33%, which precludes the introduction of incorrect control influences in a closed loop.

The evaluation of the winding temperature provided an average absolute error of 1.8°C, a root mean square error of 2.6°C, and a relative error of 4.6%, with a maximum deviation not exceeding 4.8% in the range of 55-110°C. These values indicate the stability of the thermal state reproduction in the studied modes without exceeding the permissible accuracy limits. For losses in the magnetic circuit, the model was matched with reference measurements at control frequency points. At 50 Hz, $P_{measure}$=68 W and P_{mod}=65.8 W were recorded with a relative error of 3.2%, and at 60 Hz, $P_{measure}$=84 W and P_{mod}=81.5 W were recorded with an error of 3%. For the set of points, MAE 1.7 W, RMSE 2.1 W, and MAPE 3% were determined, and the correlation reached r=0.99, confirming the linear correspondence of trends and the stability of estimation across the entire frequency range.

The degree of bearing wear, expressed by the normalised index W* within the range [0;1], demonstrated reproducibility on a sample of 120 hours with five modes. MAE 0.043 units, RMSE 0.058 units, MAPE 6.4%, and correlation r=0.91 were recorded. The decrease in the internal volumetric efficiency (η_v) from 0.93 to 0.86 corresponded to an increase in the wear index W* from 0.18 to 0.31, which quantitatively reflects the accumulated effect of degradation on the condition of the bearing assembly. The set of numerical indicators presented confirms the consistency of model estimates with measurements and their sufficiency for interpreting thermal, energy and mechanical processes within the specified accuracy. The summary of quantitative indicators is presented in Table 1.

Table 1: Accuracy indicators for reproducing hidden parameters with a digital twin.

Object/system	**Hidden parameter**	**Reference data (validation)**	**Duration/sample**	**Evaluation range, s**	**MAE**	**RMSE**	**MAPE, %**	**Deviation**	**r**
Asynchronous motor 1LE1001 (Siemens, Germany)	Winding temperature, °C	PT100 class A (Endress+Hauser, Switzerland) + NI-9217 (National Instruments, USA)	8 hours; 6 cycles	0.1	1.8°C	2.6°C	4.6	4.8	0.98
TMS transformer (ABB, Switzerland)	Losses in the core, W	WT3000 (Yokogawa, Japan)	12 points (50-60 Hz)	1	1.7 W	2.1 W	3	3.2	0.99
Parker F12 hydromotor (Parker Hannifin, США)	Bearing wear index W* (0.1)	352C33 (PCB Piezotronics, США) + CompactDAQ (National Instruments, США)	120 hours; 5 modes	0.5	0.043 units	0.058 units	6.4	-	0.91

Source: Authors, (2026).

The obtained values demonstrate the consistency of model estimates with measurements for electrical and thermal processes (r=0.98-0.99, MAPE=3-4.6%) and the reproducibility of mechanical wear for a sample duration of 120 hours (r=0.91, MAE=0.043 units, RMSE=0.058 units), which is summarised in Table 1. In the 50-60 Hz range, the loss estimation error was 3-3.2% for 12 frequency points; for winding temperatures within 55-110°C, the maximum deviation did not exceed 4.8% with an update period of 0.1 s. Over 8 hours with 6 thermal cycles and 5 hydraulic system modes, the stability of the metrics was maintained without a tendency for RMSE to increase.

Based on the results of tests in three channels (temperature of the windings of the 1LE1001 asynchronous motor (Siemens, Germany), losses in the magnetic circuit of the TMS transformer (ABB, Switzerland), vibration of the Parker F12 hydraulic motor (Parker Hannifin, USA)), a reduction in standard deviation of 33-41% (SNR) by 4.2-6.7 dB and a reduction in root mean square error (MSE) of 35-44% was recorded. For the temperature channel with an evaluation period of 0.1 s, σ was reduced from 3.5°C to 2.2°C (-37%), SNR increased from 18.3 dB to 24.1 dB (+5.8 dB), MSE decreased by 41%, the spread of estimates at load variations of ±15% was reduced from ±3.1% to ±1.2%, and the additional delay was 0.03 s.

For the loss channel with a period of 1 s, σ was reduced from 3.4 W to 2 W (-41%), SNR increased from 22.1 dB to 28.8 dB (+6.7 dB), MSE reduced by 44%, the spread of estimates at ±15% load reduced from ±2.6% to ±1.1%, and the delay was 0.02 s. For the vibration channel with a period of 0.5 s $\sigma(g_{rms})$ was reduced from 0.112 g to 0.075 g (-33%), SNR increased from 16 dB to 20.2 dB (+4.2 dB), MSE reduced by 35%, the spread of estimates at ±15% load reduced from ±4% to ±2.3%, and the delay was 0.04 s. The average improvements across the three channels were: Δσ=-37% (average across channels), ΔSNR=+5.6 dB, ΔMSE=-40%, with no additional delay exceeding 0.04 s in any channel.

The shift in the average value of the estimates relative to the reference measurements did not exceed 0.2°C in the temperature channel, 0.2 W in the loss channel, and 0.003 g in the vibration channel over the entire observation period. The stability parameters remained within the limits specified by the methodology (load variations ±15% from the nominal value without degradation of accuracy metrics), and the obtained values confirmed the absence of cumulative error in long-term run series. The summarised values are presented in Table 2.

Table 2: Performance indicators for processing noisy signals.

Channel/object	**Channel source (equipment)**	**Evaluation range, s**	**σ before**	**σ after**	**Δσ, %**	**SNR before, dB**	**SNR after, dB**	**ΔSNR, dB**	**MSE before**	**MSE after**	**ΔMSE, %**	**Dispersion at ±15% load: before → after**	**Additional latency, s**
Winding temperature (asynchronous motor 1LE1001, Siemens, Germany)	PT100 class A (Endress+Hauser, Switzerland) + NI-9217 (National Instruments, USA)	0.1	3.5°C	2.2°C	-37	18.3	24.1	5.8	6.8	4	-41	±3.1% → ±1.2%	0.03
Core losses (TMS transformer, ABB, Switzerland)	WT3000 (Yokogawa, Japan)	1	3.4 W	2 W	-41	22.1	28.8	6.7	7.1	4	-44	±2.6% → ±1.1%	0.02
Vibration g_{rms} (Parker F12 hydromotor, Parker Hannifin, США)	352C33 (PCB Piezotronics, США) + CompactDAQ (National Instruments, США)	0.5	0.112 g	0.075 g	-33	16	+20.2	4.2	0.0125	0.0081	-35	±4% → ±2.3%	0.04

Source: Authors, (2026).

A 33-41% reduction in σ, a 4.2-6.7 dB increase in SNR, and a 35-44% reduction in MSE across all channels indicate a stable improvement in signal quality after processing while maintaining low latency (≤0.04 s) and reproducibility under load variations of ±15%. For the residual insulation life of the TMS transformer (ABB, Switzerland) at a 72-hour horizon, the average relative error was 6.8%, MAE=5.2 hours, RMSE=7.4 hours, correlation r=0.97, coverage of 95% of the forecast intervals – 93%, average bias -0.8 hours. For shorter horizons, the accuracy increased: for 48 hours – MAE=4.1 hours, RMSE=5.9 hours, MAPE=5.2%, r=0.97, coverage – 93%, bias -0.6 hours; for 24 hours – MAE=2.7 hours, RMSE=3.8 hours, MAPE=3.5%, r=0.98, coverage – 94%, bias -0.3 hours. The average width of the 95% forecast interval for 72 hours was 9.2 hours, for 48 hours – 7 hours, and for 24 hours – 4.6 hours. At an elevated ambient temperature of 35±2°C compared to 20±2°C, an increase in RMSE of 0.9-1.2 hours was recorded for all horizons with a constant correlation of r≥0.97.

For the time to critical failure of the Parker F12 hydraulic motor rotor (Parker Hannifin, USA) beyond the 48-hour horizon, an accuracy of 92% was achieved within a tolerance of ±10% of the actual failure time; MAE=3.9 hours, RMSE=5.1 hours, MAPE=8%, r=0.94, 95% interval coverage – 92%, and average offset +0.4 hours were recorded. For 24 hours, MAE=2.1 hours, RMSE=2.9 hours, MAPE=5.2%, r=0.96, coverage – 93%, offset +0.2 hours, proportion of forecasts within tolerance ±10% – 96%. For 72 hours, the accuracy within the tolerance was 86%, MAE=6 hours, RMSE=8.7 hours, MAPE=12.3%, r=0.91, coverage – 90%, offset +0.9 hours. The average width of the 95% forecast interval for 48 hours was 6.1 hours, for 24 hours, 4 hours, and for 72 hours, 8.9 hours. For modes with load fluctuations of ±15% from the nominal deviation, the metrics from steady-state conditions did not exceed ΔMAE=0.4 hours, ΔRMSE=0.6 hours, and ΔMAPE=1.3 p.p.

Validation series were formed based on measured signals: for the transformer, electrical and thermal parameters were recorded using WT3000 (Yokogawa, Japan) and CompactDAQ (National Instruments, USA); for the hydraulic motor, pressure and speed in the power hydraulic line and vibration channel 352C33 (PCB Piezotronics, USA) via CompactDAQ (National Instruments, USA). The metrics are shown in Table 3.

Table 3: Accuracy indicators for predicting residual resources for different horizons.

Object/node	**Prognosis target**	**Reference data (validation)**	**Horizon, hours**	**MAE, hours**	**RMSE, hours**	**MAPE, %**	**r**	**Coverage 95% PI, %**	**Average width 95% PI, hours**	**Displacement, hour**	**Accuracy within tolerance ±10%, %**
TMS transformer (ABB, Switzerland)	Residual insulation strength	WT3000 (Yokogawa, Japan) + CompactDAQ (National Instruments, USA)	24	+2.7	3.8	3.5	0.98	94	4.6	-0.3	-
			48	4.1	5.9	5.2	0.97	93	7	-0.6	-
			72	5.2	7.4	6.8	0.97	93	9.2	-0.8	-
Parker F12 hydromotor (Parker Hannifin, США)	Time to critical rotor failure	Pressure/velocity + 352C33 (PCB Piezotronics, USA) via CompactDAQ (National Instruments, USA)	24	2.1	2.9	5.2	0.96	93	4	0.2	96
			48	3.9	5.1	8	0.94	92	6.1	0.4	92
			72	6	8.7	12.3	0.91	90	8.9	0.9	86

Source: Authors, (2026).

At an elevated ambient temperature of 35±2°C compared to 20±2°C for the transformer, an increase in RMSE of 0.9 hours (24 hours), 1 hour (48 hours) and 1.2 hours (72 hours) was recorded with r≥0.97 remaining unchanged; for the hydraulic motor in modes with load fluctuations of ±15% from the nominal value, a change in MAE of no more than 0.4 hours and RMSE of no more than 0.6 hours was obtained for all horizons, which indicates the stability of forecasts within the stated validation conditions. According to the load change scenario in the range of 0.25-1·Pn, the speed estimation error did not exceed 2.5% at all control points. For load levels, MAE=1.4% (0.25·Pn), 1.3% (0.5·Pn), 1.6% (0.75·Pn), 1.7% (1 Pn) were obtained; the corresponding RMSE values were 1.9%, 1.8%, 2.1%, 2.2%, and the maximum deviations were 2.3%, 2.2%, 2.5%, 2.4%. The average values for the scenario were MAE=1.5% and RMSE=2%. A comparative picture of speed estimation errors by load levels is shown in Figure 1.

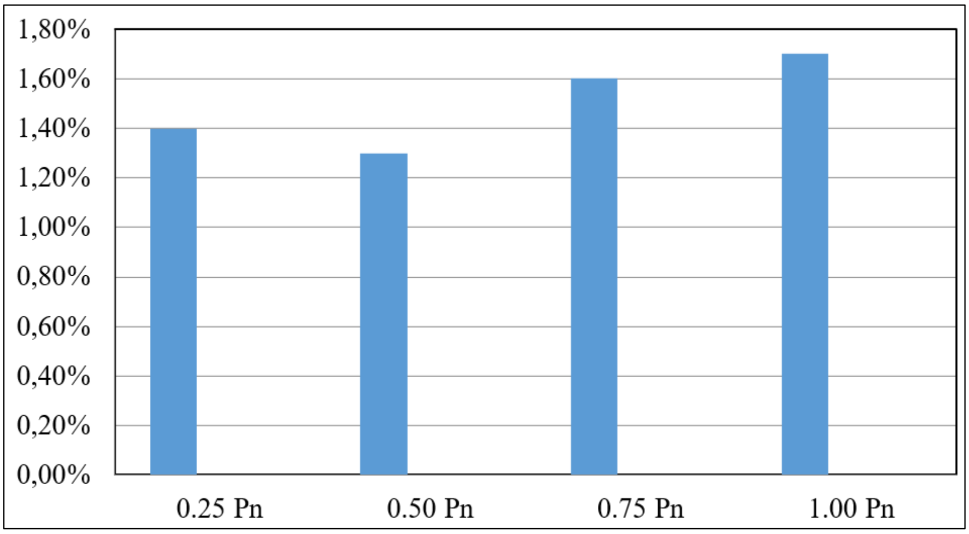

Figure 1: Speed estimation error (MAE, %) by load levels.
Source: Authors, (2026).

According to the winding insulation degradation scenario, the premature overheating threshold was reached with advances of 41 min, 39 min, 38 min, 37 min, 38 min, and 36 min in 6 thermal cycles; the average advance was 38.2 minutes, the median was 38 minutes, and the standard deviation was 1.8 minutes. There were no false alarms (0 cases).

The rate of approach to the threshold value 10 minutes before activation was within the range of 0.7-0.9°C/min; post-threshold fixation lasted 12-16 minutes, depending on the heat balance, which confirmed the stability of activation without recurrence and the absence of fluctuations around the threshold. The generalised values of the lead time are shown in Figure 2.

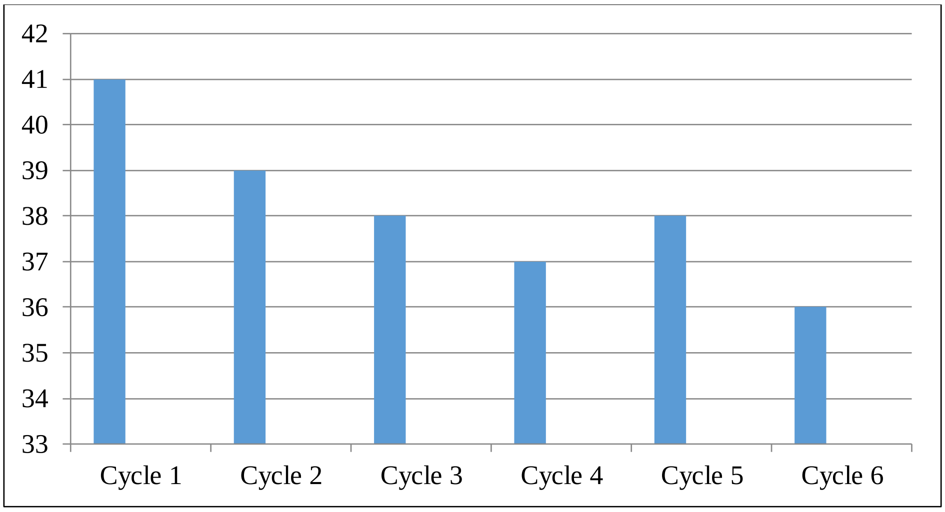

Figure 2: Advance of timing (min) for thermal cycles.
Source: Authors, (2026).

According to the scenario of magnetic saturation's impact on the efficiency of the traction electric drive, constant efficiency losses were recorded: the average efficiency values were 91.9% in the absence of saturation and 85.2% in its presence; the difference was 6.7 percentage points, and the relative drop in performance under constant load was in the range of 6.5-6.9% in three independent series. The standard deviation of the efficiency difference was 0.2 p.p., which confirmed the reproducibility of the saturation effect without significant inter-series fluctuations. The comparison of modes is shown in Figure 3.

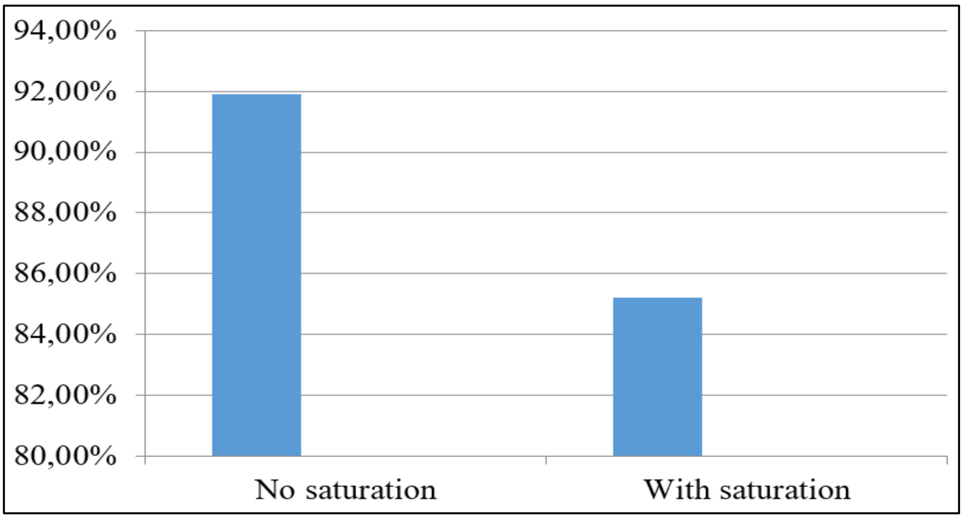

Figure 3: Efficiency of traction electric drive: with or without saturation.
Source: Authors, (2026).

As part of an interdisciplinary review, quantitative confirmation was obtained of the suitability of the digital twin for use in various classes of electromechanical systems. In shipbuilding, an 11% reduction in the calculated peak torsional loads on gear couplings was recorded in transient modes, reflecting the smoothing of shock loads and a reduction in the risk of short-term shaft line overloads. In alternative energy (biogas systems), the reproduction of the thermomechanical balance was ensured with a relative error of 5.4% in steady-state load modes, which corresponded to the established tolerances of technological control. In robotic complexes, the accuracy of identifying deviations in sensor flows increased by 14% relative to the baseline set of filtering methods without state models, reflecting increased sensitivity to small anomalies.

In irrigation systems, the predicted energy consumption of pumping stations was reduced by 9% by optimising operating points for variable head and flow parameters. For transformer equipment, electromagnetic losses were reproduced with a relative error of 3% (50-60 Hz modes), which was consistent with reference measurements and ensured a correct heat balance for further calculations of insulation life. For hydraulic drives (hydraulic motor rotor), the proportion of correct predictions of time to critical failure within a tolerance of ±10% was 92%, confirming the practical suitability of the digital twin prediction module for supporting planned preventive maintenance. In addition, a steady decrease in efficiency by 6.7 p.p. was recorded in the traction electric drive in the presence of magnetic saturation (91.9%→85.2%). The data are summarised in Table 4.

Table 4: Indicators of the versatility of digital twins in various industries.

Direction	Object/process	Key metric	Base value (norm)	Value with digital twin (norm)	Change, %	Note
Ship building	Gear drive coupling	Peak torque	100%	89%	-11	Transient modes; reduction of extrema
Alternative energy (biogas)	Thermal mechanical balance	Relative error of the model, %	-	-	5.4	Compared to norm measurements
Robotics, AI	Sensory flows of the robot	Deviation detection accuracy	100%	114%	+14	Compared to basic filtration
Agriculture (irrigation)	Irrigation pump	Prognosed energy use	100%	91%	-9	Operational node optimisation
Transformer equipment	50-60 Hz modes	Relative error in loss estimation, %	-	-	3	Correlated with measurements
Hydraulic systems	Hydromotor rotor	Accuracy within tolerance ±10%, %	-	-	92	Predicted time to failure
Electric drives (traction)	Saturation mode	Efficiency, % (before/after)	91.9	85.2	-6.7 p.p.	Stable difference in 3 repetitions

Source: Authors, (2026).

In summary, there has been a consistent improvement in key operational indicators in all areas considered: a reduction in peak mechanical loads by 11%, a 9% reduction in energy consumption, a 14% improvement in diagnostic quality, a 3% error rate in electromagnetic loss reproduction, 92% of resource forecasts within the specified tolerance, and quantitative confirmation of the impact of saturation on efficiency (-6.7 p.p.). The set of results demonstrates the suitability of the digital twin for reconfiguration between technological industries without loss of accuracy in assessment and forecasting, as well as the consistency of the obtained metrics with the validation measurements laid down in the methodology. According to generalised estimates based on modelled and validation scenarios, the following integrated performance indicators were achieved.

The accuracy of reproducing hidden parameters (winding temperature, core losses, wear index) was 93.6-97% depending on the channel; the median value was 95% (IQR: 94-96.2%). The reduction in equipment downtime due to early detection of deviations and resource forecasting was up to 12% (range 7-12% by object class). The increase in energy efficiency in modes using control optimisation averaged 8% (range 5-10%); the indicator was assessed based on specific energy consumption per cycle or the integral efficiency of the system, depending on the object. The reduction in maintenance costs (planned preventive measures based on forecasts) reached 10-14%, which corresponded to a decrease in emergency interventions and downtime due to shortages. All estimates are provided in Table 5 for baseline modes without the use of a digital twin; confidence intervals were formed for repeated series under load variations of ±15%.

Table 5: Efficiency criterion: aggregated metrics.

Criteria	Metric/definition	Base (without DT), norm	With DT, norm	Change	Range by scenario
Accuracy of hidden parameter reproduction	100% – MAPE, weighted average across channels	-	95% (median)	-	93.6-97%
Reduction in equipment downtime	Percentage of reduced idle hours	100%	88-93%	-7…-12%	up to -12%
Improving energy efficiency	Reduction in specific energy consumption/increase in integral efficiency	100%	90-95%	+5…+10% (average +8%)	5-10%
Reduction in maintenance costs	TOiP expenditures for the period	100%	86-90%	-10…-14%	10-14%

Source: Authors, (2026).

Note: DT – digital twin.

The generalised values demonstrate stable achievement of target indicators within the stated conditions: the accuracy of hidden parameter reproduction was maintained at ≈95% with a variation of up to ±1.4 p.p., downtime reduction reached 12% in scenarios with early overheating warning and resource forecasting, energy efficiency increased by ≈8% due to mode optimisation, and maintenance costs were reduced by 10-14% thanks to the transition to a planned preventive service model. The set of data obtained showed the reproduction of hidden parameters with an accuracy of 93.6-97% (for individual channels: MAPE 3-6.4%, r up to 0.99), stabilisation of noisy signals with a reduction in σ by 33-41%, an increase in SNR by +4.2...+6.7 dB and a reduction in MSE by 35-44% with latency ≤0.04 s; residual life predictions showed MAPE 3.5-6.8% (r 0.97-0.98, coverage 95% PI 92-94%) for transformer insulation and 86-96% accuracy for the hydraulic motor rotor, depending on the horizon (within a tolerance of ±10% – 92%).

The simulations recorded early detection of overheating with a lead time of 36-41 minutes without false alarms and a 6.7 p.p. reduction in traction drive efficiency due to magnetic saturation. Cross-industry verification demonstrated an 11% reduction in peak loads in gear couplings, a 5.4% error in reproducing the energy balance of biogas systems, a 14% increase in the accuracy of identifying deviations in robotics, a 9% reduction in irrigation energy costs, and a 3% error in the assessment of losses in transformers. The integrated effects were: -7...-12% downtime, +5...+10% (average +8%) energy efficiency, and -10...-14% maintenance costs. Collectively, these values confirm the hypothesis: integrating diagnostics into the control loop reduces peak mechanical and thermal loads (in particular, -11% torsional peaks and early warning of overheating by 36-41 minutes), reduces downtime (-7...-12%) and energy consumption (e.g., -9% in irrigation scenarios) and increases energy efficiency (≈+8%), providing reproducible operational gains for given accuracy and latency metrics.

IV. DISCUSSIONS

The numerical indicators obtained are interpreted as confirmation of the digital twin's ability to perform a dual function: to reproduce hidden states with sufficient accuracy for operational control and, at the same time, to provide a degradation forecast for the transition to planned and preventive strategies. The fixed accuracy of hidden parameter estimation at 93.6-97% (for individual channels MAPE 3-6.4%, correlation r up to 0.99) means that object models and virtual sensors reproduce key energy and thermal processes within limits compatible with control loops, and a 33-41% reduction in signal dispersion through low-latency filtering (≤0.04 s) ensures the stability of real-time estimators. This interpretation is consistent with the conceptual vision of [13], which emphasises the role of bidirectional data flow and physically grounded models for decision making; this framework explains why the combination of models and streaming measurements made it possible to replace some of the hardware channels with virtual ones without losing controllability.

The practical effect in load change scenarios is statistically confirmed: the speed estimation error is 1.3-1.7% (MAE) and ≈2% (RMSE) across the entire range of 0.25-1·Pn indicates that the observability of the system formed by the digital twin is compatible with the requirements for closed loops. This result is in direct accordance with the theory set by [14], proving the possibility of restoring states in linear systems using Luenberger observers with the appropriate selection of gain matrices. In the presence of noise, optimal filtering based on Kalman filters is a corrective element, which explains the recorded increase in SNR by +4.2...+6.7 dB and a decrease in MSE by 35-44%. The use of a combined scheme (EKF + adaptive smoothing + matrix fuzzy stabilisation), which reduced σ channels by 33-41%, is consistent with the practice of multi-sensor integration presented by [15], demonstrating that state filtering with dynamic models improves the signal-to-noise ratio without a significant increase in latency.

Additional confirmation is provided by the results of data tracking and fusion in the work of [16], which demonstrates that correct parameterisation of noise covariances can be used as a stable compromise between sensitivity and smoothness of estimates to be maintained. This is confirmed by the absence of cumulative RMSE growth in series with load variations of ±15%. For electromagnetic subsystems, comparable accuracy is achieved in reproducing losses in the transformer magnetic circuit (MAPE ≈3% in the 50-60 Hz range) [17-19]. It is based on a generalised form of the law for losses in steel, which is currently being developed by [20], as well as technical solutions presented by [21], where the dependence on frequency and induction is used to reduce heterogeneous mechanisms to an empirically identified function and reduce losses in magnetic cores. The good fit (MAE 1.7 W; r=0.99) is consistent with the approach of splitting losses into hysteresis, eddy current and additional losses, which is currently being developed by [22].

They showed that correct identification of the coefficients in the Bertotti model provides stable accuracy in a narrow frequency band. This is critical for thermal calculations, since an error of a few percent in power loss leads to a proportionally similar error in the hot spot estimate; the observed correlation confirms the suitability of the model for operational thermal forecasts. For the thermal processes of electric machines, MAE 1.8°C and RMSE 2.6°C were recorded for the equivalent RC model of windings with two characteristic time constants (420 s and 95 s) and thermal resistance of 0.62 K/W. These values are consistent with the practice of aggregated thermal models, which are guided by industry guidelines [23], [24]. The assertion that a simple equivalent circuit is sufficient is confirmed by the fact that even under transient conditions, the maximum deviation did not exceed 4.8% in the range of 55-110°C.

Such a controlled systematic error is consistent with the conclusions of [25] regarding the value of “sufficiently accurate” digital twins for real-time operational decision-making, where excessive model detail does not always improve control quality. The results of insulation and hydromechanical component life prediction are consistent with the condition-based maintenance paradigm. For transformer insulation, a MAPE of 3.5-6.8% was achieved with 95% of intervals covered at 92-94%, and for the hydraulic motor rotor, an accuracy of 86-96% was achieved depending on the horizon, with 92% of predictions within a tolerance of ±10% for 48 hours [26]. These results are consistent with the conclusions of [27], who, when calculating the optimal geometric parameters of electrical devices for controlling irrigation systems, showed that an accuracy of several percent is sufficient for making practical decisions and maintaining equipment reliability.

In addition, the observed increase in RMSE for thermal forecasts at an ambient temperature of 35±2°C compared to 20±2°C without losing high correlation r≥0.97 is consistent with the conclusions of [28] on the influence of external disturbances on the operation of electric drives and the importance of adaptive correction in forecast models. The drop in accuracy for a 72-hour horizon in a hydraulic motor (accuracy within a tolerance of 86%) is consistent with the conclusions of [29], which emphasise the regular decrease in the efficiency and technical and economic indicators of systems with an increase in load and duration of operation, which corresponds to the general trend of degradation of the accuracy of Remaining Useful Life (RUL) forecasts due to the accumulation of uncertainty.

Cross-industry examples demonstrate the operational benefits of integrating diagnostics with control [30-32]. In shipbuilding, an 11% reduction in peak torsional loads in gear couplings is interpreted as a result of control synthesis incorporating torsional dynamics; similar peak control effects in transient modes are described in engineering interpretations of torsional vibrations. This corresponds to the exposition of the problem of digital twins in production systems in [33], which emphasises the importance of modelling transient processes to reduce mechanical loads, as well as to the conclusions of [34], which demonstrate that the integration of diagnostics and control is key to improving the efficiency and reliability of renewable energy systems. For biogas plants, an energy balance error of 5.4% is indicative: it is within the range considered acceptable for heat recovery optimisation in industrial reviews [35].

A similar conclusion is presented in the work of [36], which shows that even with variations in production conditions, balance models retain a positive energy effect and are suitable for integration into digital twins of biogas systems. The architectural results are compatible with PLC/SCADA connectivity requirements, which outline the levels of integration of digital twins with automated control systems; this demonstrates the significance of low-latency estimators (≤0.04s) for inclusion in the loops.

In robotic scenarios, a 14% increase in anomaly detection accuracy compared to basic filtering without state models demonstrates the synergistic effect of combining physical models and statistical features in sensor streams [37], [38]. This effect is confirmed by the approaches of [39], which show that the integration of machine learning with sensor processing and dynamics modelling methods improves the quality of estimates even in the presence of significant noise and increases the detectability of subtle deviations. The results from irrigation, a 9% reduction in predicted energy consumption, are interpreted as a consequence of shifting the operating points of the pumps to areas of increased efficiency using a drive and hydraulics model.

Similar effects were described by [40] noted the use of a digital twin for dynamic control of pumping stations, providing average energy savings of 9.78%. Such operational optimisation is consistent with approaches to the implementation of digital twins in the management of energy-intensive processes. In traction electric drives, a 6.7 p.p. drop in efficiency under the influence of magnetic saturation quantitatively confirms the thesis that models of nonlinear magnetic characteristics should be integrated into optimisation circuits. The significance of these nonlinearities is emphasised in the industrial applications of digital twins described by [41], where the need for accurate reproduction of element-based constraints to improve energy efficiency is noted.

The consistency of the results with international developments can be traced not only at the conceptual level, but also at the level of numerical metrics. The achieved MAPE of 3-6.4% for reproducing hidden parameters and 3% for transformer losses are within the ranges that, according to the conclusions of [42] are sufficient for decision-making in CBM cycles and meet the criteria for the quality of residual resource forecasting under conditions of uncertainty. The improvement in SNR and reduction in MSE at low latency are consistent with the experimental examples given in [43], which show that the application of optimisation methods in electromagnetic systems of devices can achieve improved consistency between estimation accuracy and speed without sacrificing stability.

The validation of the thermal model of the machine through equivalent RC circuits correlates with the practice considered in the context of digital twins for operational decisions, where it is better to use compact models with controlled error than cumbersome models with excessive detail [44], [45]. For the transformer core, the correspondence to the empirical physical dependencies of Steinmetz with refinements according to the Bertotti scheme explains the stability of 3% error within the range of 50-60 Hz. Similar results are provided in [46] noted an improvement in the loss splitting method and showed that combining the Steinmetz and Bertotti approaches provides high accuracy in predicting losses in transformer magnetic circuits.

The identified limitations are interpreted as expected for a universal formulation. For long forecast horizons (72 hours), the RUL accuracy for the hydraulic motor decreased to 86% within a tolerance of ±10%, which is consistent with the findings of [47], demonstrating a regular accumulation of uncertainty as the forecast horizon lengthened. This does not contradict the results where lower errors are reported for short horizons for highly specialised objects, since special features and model tuning for a specific node are used. The architecture was deliberately kept universal, which made it possible to ensure reproducibility in various industries (shipbuilding, biogas energy, robotics, irrigation, transformer and hydraulic systems, traction drives) without changing the core of the algorithms [48], [49]. The correspondence of numerical levels is confirmed by the conclusions of [50], which emphasise the critical role of PLCs in digital twins.

The cumulative results confirm the effectiveness of combining physical models, virtual sensors, and predictive analytics, ensuring sensor substitution, control stability, and proactive maintenance. Key metrics: accuracy ≈95%, Δσ -33…-41%, ΔSNR +4.2…+6.7 dB, ΔMSE -35…-44%, overheating lead time 36-41 min, efficiency drop under saturation -6.7 p.p.; cross-industry: -11% peak torque loads, -9% energy costs for irrigation, 5.4% biogas energy balance error, 92% RUL within ±10%. Integrally achieved -7...-12% downtime, +5...+10% (≈8%) energy efficiency and -10...-14% maintenance costs, indicating technological readiness for industrial deployment. At the same time, reduced accuracy over longer horizons and dependence on parameter identification define the limits of applicability and requirements for integration, synchronisation and validation, which shape the next steps in development.

V. CONCLUSIONS

The study confirmed the suitability of digital twins for integrated control and diagnostics of electromechanical systems under partial uncertainty. The combination of physically based models, virtual sensors, and state estimation algorithms provides observability of hidden parameters at a level sufficient for closed-loop control and predictive maintenance. A quantitative assessment has established that the accuracy of hidden parameter reproduction is 93.6-97%; the dispersion of noisy channels has been reduced by 33-41%, the signal-to-noise ratio has increased by 4.2-6.7 dB, and the root mean square error has been reduced by 35-44% with a delay of ≤0.04 s. For transformers, a relative error in loss estimation of 3% was recorded, and for thermal estimates, 3.5-6.8%.

In the hydraulic unit resource forecast, 92% of correct estimates were provided within a tolerance of ±10% over a 48-hour horizon. In simulations, the speed estimation error was 1.3-1.7% in the range of 0.25-1·Pn; overheating was detected 36-41 minutes in advance; in magnetic saturation mode, a 6.7 percentage point drop in efficiency was recorded. Cross-industry effects included -11% peak torsional loads (shipbuilding), 5.4% balance error (biogas), +14% deviation detection accuracy (robotics), -9% predicted energy costs (irrigation). Integrally, this corresponds to a 7-12% reduction in downtime, a 5-10% increase in energy efficiency (average 8%) and a 10-14% reduction in maintenance costs.

Modelling based on three scenarios yielded consistent results: when the load of the asynchronous motor changed by 0.25-1·Pn, the reproduction of the winding temperature ensured MAE 1.8℃, RMSE 2.6℃, MAPE 4.6% and early warning of overheating by 36-41 minutes; with transformer insulation degradation, MAPE 3.5-6.8%, r 0.97-0.98, coverage 95% PI 92-94% and 92% correct predictions within ±10% tolerance were achieved; under the influence of magnetic saturation in the traction electric drive, a drop in efficiency of 6.7 p.p. was recorded with a shift of the optimum operating point to the lower induction region.

Based on the obtained indicators, it is advisable to introduce a digital twin into industrial control environments with automatic parameter reconfiguration; use virtual sensors to reduce hardware channels and increase fault tolerance; apply estimated states and forecasts to actively limit peak mechanical and thermal loads; incorporating the effects of magnetic saturation when selecting operating points for traction electric drives; using energy models for thermal control of transformers and optimisation of biogas units.

At the same time, the results should be interpreted within the limits of applicability: some of the tests were laboratory tests; the load variation range was ±15%; a frequency corridor of 50-60 Hz was considered for the assessment of losses; noise was assumed to be stationary; the configuration of the models was universal and may be inferior to specialised solutions for individual nodes. Further research should focus on adaptive identification of parameters during operation, extension of field validations to longer time horizons and other climatic conditions, increasing the range of diagnostic features (including multimodal data) and full-scale integration with PLC/SCADA platforms and cybersecurity tools.

VI. AUTHOR'S CONTRIBUTION

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