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Development and evaluation of an AI-based method for improving the energy efficiency of electric motor–inverter systems

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Abstract: This study investigates the energy efficiency of an electric motor–inverter system operating under variable load conditions. The aim of the research is to develop and evaluate an AI-based supervisory method for identifying inefficient operating modes and optimizing control parameters using real-time electrical and operational data. Unlike conventional motor control studies, which mainly focus on torque ripple, flux regulation, or speed response, the proposed approach considers the motor, inverter, load, and control algorithm as a single energy-efficiency-oriented system. The input vector of the model includes voltage, current, inverter frequency, rotational speed, electromagnetic torque, temperature, load level, power factor, and total harmonic distortion. The output variables are system efficiency, total power loss, and the classification of the operating mode as either efficient or inefficient. The proposed method was evaluated under 24 steady-state operating modes formed by four load levels and six inverter frequency values. Under the most inefficient tested operating condition, the overall system efficiency increased from 78.3% to 90.2% after AI-based optimization, while energy consumption decreased from 118 kWh to 88 kWh. In addition, the power factor improved from 0.76 to 0.94, total harmonic distortion decreased from 15% to 5%, and inverter switching losses decreased from 8% to 3%. The results confirm that the proposed method can identify inefficient operating states and support the selection of energy-efficient control parameters. The main limitation of the study is that the validation was performed using one motor–inverter configuration and mainly under steady-state conditions. Therefore, future research should include transient load changes, different motor power ratings, and embedded real-time implementation.

Key words: artificial intelligence, electric motor, inverter system, energy efficiency, inefficient operating mode, real-time data, power loss

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1. Introduction

Improving the energy efficiency of electric motors and inverter systems is one of the current scientific issues in the fields of modern energy, industrial automation, and intelligent control. Electric motors are widely used in pumps, fans, compressors, conveyors, robotic systems, and electric vehicles (Fig. 1). According to the International Energy Agency, electric motors and their associated systems account for more than 40% of global electricity consumption, while approximately 25% of the energy used in these systems can be saved through economically feasible methods [1–5]. This indicator demonstrates the importance of this topic in terms of energy saving, reducing industrial costs, and lowering carbon dioxide emissions.

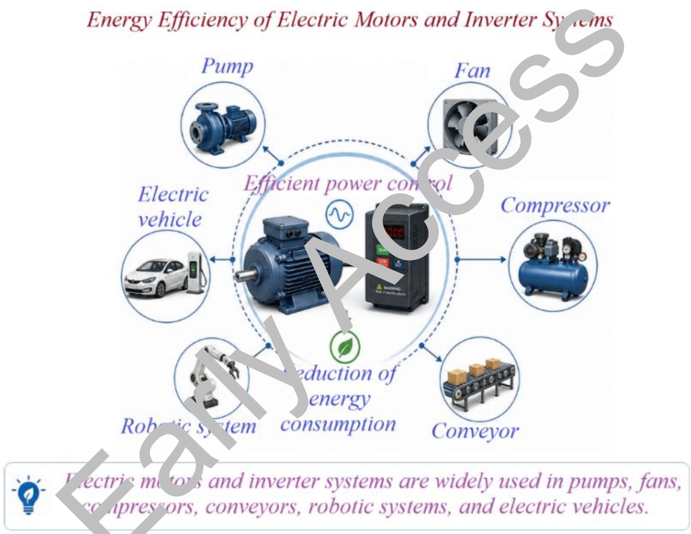

Fig. 1. Conceptual framework for improving the energy efficiency of electric motor and inverter systems

In the industrial sector, electric motor systems play a particularly important role. According to UNIDO, electric motor systems account for approximately 60–70% of industrial electricity consumption [6–9]. Most of these systems operate with inverter-based control, since inverters make it possible to regulate motor speed, torque, and adaptation to load variations. The use of variable-frequency drives can reduce electricity consumption in pump, fan, and compressor systems by an average of 20–30%, and in some cases by up to 50% [10, 11]. Therefore, improving the efficiency of motor–inverter systems is considered one of the key directions of industrial energy management.

At the same time, under real production conditions, electric drives do not operate in a constant nominal mode, but under variable load, heating, mechanical wear, voltage fluctuations, and harmonic distortion. Such factors affect electrical and magnetic losses in the motor, switching losses in the inverter, the power factor, and overall efficiency. The IEC 61800-9 standard

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indicates the need to assess the energy efficiency of electric drives not only at the level of an individual motor, but as a complete power drive system [12–14]. This means that, in order to improve energy efficiency, the motor, inverter, load, and control algorithm must be studied as an integrated system.

Artificial intelligence methods represent a promising approach to solving this problem. AI algorithms can process data such as motor current, voltage, frequency, rotational speed, torque, temperature, and load variations, enabling the identification of high-energy-consumption operating modes, load forecasting, and the selection of optimal control parameters. According to estimates by the International Energy Agency, the optimization of industrial processes using AI may reduce energy costs in energy-intensive sectors by 3–10 percentage points [15–17]. Therefore, the development of AI-based control methods for electric motors and inverter systems is important from both practical and scientific perspectives.

In this regard, improving the energy efficiency of electric motors and inverter systems using AI remains a relevant contemporary scientific topic. Research in this area can contribute to reducing energy consumption, improving the reliability of electric drives, extending equipment service life, and lowering industrial costs. Therefore, conducting research on the development and evaluation of AI-based energy-efficient control methods for electric motors and inverter systems is considered highly relevant.

The scientific novelty of this study is not limited to the use of an artificial intelligence algorithm as a data-processing tool. The novelty lies in the development of an energy-efficiency-oriented supervisory method for the integrated motor–inverter–load system. In contrast to many existing ANN-, RL-, and predictive-control-based studies that primarily focus on torque ripple reduction, flux control, speed estimation, or dynamic response improvement, the proposed method directly links real-time electrical and operational measurements with energy-efficiency indicators such as total power loss, power factor, harmonic distortion, motor temperature, and system efficiency.

The main contribution of this study is threefold. First, the motor, inverter, load, and control algorithm are considered as a single energy-conversion system rather than as separate components. Second, the proposed AI-based method simultaneously performs efficiency prediction, power-loss estimation, and classification of operating modes into efficient and inefficient states. Third, the method provides a supervisory decision layer for selecting more energy-efficient control parameters under variable load conditions. Therefore, the proposed method is positioned as an energy-efficiency optimization layer that complements conventional inverter control rather than replacing the inner torque, flux, or speed control loops.

2. Literature review and problem statement

Khan M.Y.A. (2025) [18] examines advanced motor drive systems in electric vehicles, including their integration, energy efficiency, and thermal management. The author shows that the efficiency of a motor system depends not only on the motor itself, but also on the inverter,

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control strategy, power conversion process, and cooling system (Table 1). Under real operating conditions, load variations, temperature rise, and switching losses in the inverter may reduce the efficiency of the system. Therefore, real-time analysis of the operating parameters of electric motors and inverter systems, together with the application of data-driven intelligent control methods, is an important direction for improving energy efficiency.

Table 1. Evaluation of efficiency indicators of the electric motor–inverter system

№	Parameter	Baseline value	Inefficient operating mode	AI-optimized value	Change
1	Motor efficiency, %	90	86	93	+7%
2	Inverter efficiency, %	95	91	97	+6%
3	Overall system efficiency, %	85.5	78.3	90.2	+11.9%
4	Electricity consumption, kWh	100	118	88	−30 kWh
5	Inverter switching losses, %	4	8	3	−5%
6	Motor temperature, °C	70	92	68	−24°C
7	Load variation, %	50	80	45	−35%
8	Power factor	0.88	0.76	0.94	+0.18
9	Total harmonic distortion, THD, %	8	15	5	−10%
10	Energy savings, %	0	0	15–25	+15–25%

The table shows that parameters such as motor efficiency, inverter efficiency, switching losses, temperature, load variation, and total harmonic distortion directly affect the efficiency of the electric motor–inverter system. As a result of AI-based optimization, the overall system efficiency increases from 78.3% to 90.2%, while energy consumption decreases from 118 kWh to 88 kWh, confirming that energy savings may reach the level of 15–25%.

Tsotoulidis S. *et al*. [19] examined current trends in standards and regulatory requirements related to the energy efficiency of electric drives. The authors show that the IEC 61800-9 standard provides a basis for assessing and classifying the efficiency of adjustable electric drives, complete drive modules, and motor systems. In this approach, energy efficiency is evaluated not only at the level of an individual motor, but as a complete interconnected system consisting of the motor, inverter, power electronics, and load. However, standards mainly define assessment and compliance requirements, while they do not fully address the automatic real-time optimization of control parameters under variable load conditions. Therefore, complementing standard energy efficiency assessment with artificial intelligence-based intelligent control methods is considered a relevant direction.

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Qiu W. *et al*. [20] comprehensively reviewed the main directions of applying artificial intelligence methods in electric motors. The authors show that neural networks, fuzzy logic, optimization algorithms, and data-driven models can be effectively used in motor design, control, diagnostics, and condition monitoring. These methods make it possible to evaluate the energy efficiency of a motor–inverter system by analyzing the relationship between input power, output mechanical power, and internal losses:

$$\eta_{\mathrm{sys}}(t)=\frac{P_{\mathrm{out}}(t)}{P_{\mathrm{in}}(t)}=\frac{T_e(t)\omega_m(t)}{V_{\mathrm{dc}}(t)I_{\mathrm{dc}}(t)}=1-\frac{P_{\mathrm{Cu}}(t)+P_{\mathrm{Fe}}(t)+P_{\mathrm{sw}}(t)+P_{\mathrm{cond}}(t)+P_{\mathrm{mech}}(t)}{P_{\mathrm{in}}(t)}, \quad (1)$$

where: $\eta_{\mathrm{sys}}(t)$ is the time-varying overall efficiency of the motor–inverter system, $T_e(t)$ is the electromagnetic torque, $\omega_m(t)$ is the mechanical angular speed, and $V_{\mathrm{dc}}(t)$ and I_{dc} are the voltage and current in the DC link of the inverter, respectively. Here, P_{Cu}, P_{Fe}, P_{sw}, P_{cond}, and P_{mech} represent copper losses, core losses, inverter switching losses, conduction losses, and mechanical losses, respectively. This equation enables the AI model to evaluate the main sources of energy loss separately.

In addition, artificial intelligence methods process parameters such as motor current, voltage, rotational speed, torque, temperature, and load variation to assess the dynamic state of the system. The motor–inverter system can generally be described using the following nonlinear dynamic model:

$$\dot{x}(t)=f(x(t),u(t),d(t),\theta(t))+w(t), \quad y(t)=g(x(t),u(t))+v(t), \quad (2)$$

where: $x(t)$ is the system state vector, $u(t)$ is the control input, $d(t)$ is the load or external disturbance, $\theta(t)$ represents variations in motor and inverter parameters, $w(t)$ is model uncertainty, $v(t)$ is measurement noise, and $y(t)$ is the output data vector obtained from sensors. This model makes it possible to account for factors such as load variation, temperature rise, mechanical wear, and voltage fluctuation under real industrial operating conditions.

The main objective of AI-based control is to reduce the energy consumption of the motor–inverter system while maintaining control quality and stability. Therefore, the optimal control problem can be expressed by the following objective function:

$$J^*=\min_{u(t)}\int_0^T\left[\alpha P_{\mathrm{loss}}(t)+\beta(\omega_{\mathrm{ref}}(t)-\omega_m(t))^2+\gamma(T_{\mathrm{ref}}(t)-T_e(t))^2+\delta\|\Delta u(t)\|^2\right]\mathrm{d}t, \quad (3)$$

$$P_{\mathrm{loss}}(t)=P_{\mathrm{Cu}}(t)+P_{\mathrm{Fe}}(t)+P_{\mathrm{sw}}(t)+P_{\mathrm{cond}}(t)+P_{\mathrm{mech}}(t), \quad (4)$$

where: J^* is the objective function to be minimized, $P_{\mathrm{loss}}(t)$ is the total power loss, $\omega_{\mathrm{ref}}(t)$ and $\omega_m(t)$ are the reference and actual rotational speeds, $T_{\mathrm{ref}}(t)$ and T_e(t) are the reference and actual torque values, and $\Delta u(t)$ represents sudden changes in the control signal. The coefficients α, β, γ, and δ are weighting factors that account for energy loss, speed error, torque error, and control signal stability, respectively.

Thus, the AI methods presented in study [20] are important not only as tools for motor control or diagnostics, but also as instruments for real-time assessment of the energy efficiency of motor–inverter systems, loss reduction, and optimization of control parameters. Therefore, the research should not be limited to the development of an AI model alone, but should also focus

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on the comprehensive evaluation of its impact on the energy efficiency, stability, and control quality of a real motor–inverter system.

Ahmed H. and colleagues (2025) [21] examined the optimization of energy consumption in motor-driven systems using variable frequency control, soft starters, and machine learning-based forecasting methods. The authors demonstrate that variable frequency control is an effective approach for reducing energy consumption under variable motor load conditions. According to the results of the study, energy savings can reach up to 36.1% under certain operating modes, while this value may increase to 42.9% when combined with soft starter operation. These findings confirm that flexible adjustment of control parameters plays an important role in improving the energy efficiency of motor–inverter systems. At the same time, although the study mainly focuses on the assessment and forecasting of energy consumption, the real-time closed-loop optimization of inverter parameters such as frequency, voltage, rotational speed, and torque using artificial intelligence is not fully addressed. Therefore, to further develop this research direction, it is necessary to apply machine learning algorithms that can predict load variations in advance, continuously analyze the operating state of the motor, and automatically adapt control parameters. Such an approach would not only improve the energy efficiency of the motor system but also enhance its stability, reliability, and control quality.

Azab M. (2025) [22] provides a review of recent trends in high-efficiency induction motor drives. The author emphasizes the importance of advanced control strategies, inverter-fed drive systems, and intelligent algorithms in improving the energy efficiency of induction motors. The study shows that sensorless control, predictive control, vector control, and artificial intelligence-based methods can improve the torque response of the motor, stabilize speed, reduce energy consumption, and enhance system stability under variable load conditions. At the same time, many of the high-efficiency control approaches discussed in the study have mostly been evaluated at the level of simulation, theoretical analysis, or laboratory testing. In real industrial environments, motor operation is affected by factors such as sudden load variations, harmonic distortion, inverter switching losses, temperature-dependent parameter deviations, and mechanical load instability. These conditions indicate that the assessment of energy efficiency in induction motor drives should not be limited to idealized models. Therefore, AI-based control methods should be evaluated using directly measurable electrical and operational parameters, including current, voltage, frequency, rotational speed, torque, temperature, and power losses. This approach makes it possible to assess the efficiency of induction motor–inverter systems under conditions close to real industrial operation and to improve the practical applicability of intelligent control algorithms.

Sahu A. *et al*. (2021) [23] proposed an adaptive neural-network-based discrete model predictive direct torque and flux control method for an induction motor drive. This approach enables real-time regulation of torque and flux, reduces torque ripple by approximately 10–25%, shortens the speed settling time by 15–30%, and improves control accuracy under dynamic load conditions. However, the adaptation of this method to motors with different power ratings and inverter configurations has not yet been fully resolved. This is because motor losses depend on several nonlinear factors, such as stator current, rotor flux, switching frequency, temperature,

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and magnetic saturation. Therefore, future studies should evaluate the model at different load levels, including 25%, 50%, 75%, and 100%, as well as under various speed operating modes.

Szoke E. *et al*. (2025) [24] proposed an AI-based sensorless dual-field-oriented control (DFOC) method for induction motors. In this approach, the adaptation mechanism of the classical MRAS observer is replaced with ANN and RNN neural networks, while the control structure is reduced from 4 regulators to 2 regulators. As a result, the system is simplified by approximately 50%, the accuracy of speed estimation increases by 10–20%, and parameter sensitivity decreases by 15–30%. However, at low speeds, under sudden load variations, and in the presence of signal noise, the estimation error may increase to 5–10%. Therefore, this method should be integrated with real-time error compensation and online energy-efficiency monitoring algorithms.

Saleeb H. *et al*. (2022) [25] applied an ANN-based control method to an induction motor drive used in an electric vehicle propulsion system. This approach improves conventional DTC control, reducing torque ripple by approximately 15–30%, flux ripple by 10–25%, and speed settling time by 20–35%. It may also reduce energy consumption by about 5–12% under different load conditions. However, the study mainly focuses on electric vehicle propulsion. In industrial motor – inverter systems, the load often remains within 70–100% for long periods, while thermal effects can change motor parameters by 5–15%. Therefore, ANN-based control should be adapted to industrial applications and integrated with real-time energy-efficiency monitoring.

Kazemikia D. (2024) [26] examined the application of reinforcement learning (RL) methods in motor control. RL enables the development of adaptive control strategies under nonlinearities, parameter uncertainties, and load variations. This approach may reduce torque ripple by approximately 10–25%, shorten speed settling time by 15–30%, and decrease energy consumption by 5–15%. However, training an RL agent may require up to 10^5–10^6 simulation iterations. Therefore, it should first be trained in a simulation environment and then applied to a real motor – inverter system with safety constraints.

Georginio Ananganó-Alvarado *et al*. (2025) [27] analyzed RL methods for energy management in electric vehicles during 2016–2024. Algorithms such as Q-learning, DDPG, TD3, and SAC can reduce energy consumption by approximately 5–20% and battery load by 10–15%. However, the study mainly focuses on vehicle-level energy management. Therefore, RL methods should be adapted to motor–inverter systems to reduce inverter losses by 5–12%, maintain stable torque and speed, and monitor energy efficiency under 25–100% load conditions.

To clarify the position of the proposed method relative to existing AI-based and advanced control approaches, Table 2 summarizes the main differences between the reviewed studies and the present work. This comparison shows that the proposed method does not aim to replace established torque, flux, or speed control algorithms. Instead, it introduces an additional energy-efficiency-oriented supervisory level that uses real-time electrical and operational parameters to detect inefficient operating modes and support the selection of control parameters with lower energy losses.

Table 2. Positioning of the proposed method relative to existing advanced control approaches

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Study/approach	**Main method**	**Main focus**	**Limitation from the perspective of this study**	**Difference of the proposed method**
Sahu *et al*. [23]	Adaptive neural-network-based predictive direct torque and flux control	Torque and flux regulation, torque ripple reduction, dynamic response improvement	Energy-efficiency indicators such as power factor, THD, inverter losses, and total system efficiency are not the main optimization targets	Focuses on real-time energy-efficiency assessment, total loss estimation, and inefficient mode detection for the complete motor–inverter system
Saleeb *et al*. [25]	ANN-based control for induction motor drive	Improvement of DTC performance in electric vehicle propulsion	Mainly focused on EV propulsion and dynamic control quality; limited consideration of industrial motor–inverter energy monitoring	Uses electrical and operational parameters to optimize efficiency under industrial load conditions
Kazemikia [26]	Reinforcement learning for motor control	Adaptive control under nonlinearities and uncertainties	RL training may require many simulation iterations and additional safety constraints before real implementation	Uses a supervised data-driven supervisory layer with lower implementation complexity for efficiency-oriented control
Ananganó-Alvarado *et al*. [27]	RL-based energy management	Vehicle-level energy management and battery load reduction	Focused on system-level EV energy management rather than inverter-fed industrial motor efficiency	Applies energy-efficiency optimization directly to the motor–inverter operating mode
Conventional inverter control	Fixed or pre-set control parameters	Speed and frequency regulation	Limited adaptation to temperature rise, harmonic distortion, power factor decrease, and load variation	Continuously evaluates efficiency-related parameters and identifies inefficient operating modes
Proposed method	AI-based supervisory efficiency optimization	Efficiency prediction, power-loss estimation, and inefficient mode classification	Validated on one motor–inverter configuration and mainly under steady-state modes	Integrates real-time motor, inverter, load, and power-quality parameters into one energy-efficiency-oriented decision layer

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Recent studies also demonstrate that optimization algorithms can improve the efficiency and control quality of electromechanical and renewable-energy conversion systems under variable operating conditions. Zemmit *et al*. [28] proposed an improved direct torque control method for a doubly fed induction machine using a genetic-algorithm-based PI controller. Their results show that optimization-based tuning of control parameters can improve torque response and reduce control errors in induction machine drives. In another study, Zemmit *et al*. [29] developed a direct torque control strategy for a dual-star induction motor using the Grey Wolf optimization technique. This confirms that metaheuristic optimization methods can be effectively applied to improve the control performance of electric drive systems.

In addition, optimization-based approaches have been applied in renewable-energy systems operating under non-stationary conditions. Loukriz *et al*. [30] used the Red-Tailed Hawk algorithm for optimal photovoltaic reconfiguration in irrigation systems under partial shading conditions, while Loukriz *et al*. [31] investigated efficiency enhancement in PV-based green hydrogen systems under partial shading conditions. Although these studies are not directly focused on motor–inverter systems, they confirm the broader relevance of intelligent optimization methods for improving energy conversion efficiency under variable and uncertain operating conditions. Therefore, the integration of AI-based prediction, optimization, and supervisory decision-making remains a promising direction for improving the energy efficiency of electric motor–inverter systems.

The reviewed literature confirms that electric motors and inverter systems have significant energy-saving potential, and that ANN-, RL-, fuzzy-logic-, and predictive-control-based methods can improve different aspects of motor-drive performance. However, most existing approaches are primarily aimed at torque ripple reduction, flux regulation, speed estimation, dynamic response improvement, or vehicle-level energy management. In contrast, the problem of real-time energy-efficiency-oriented supervision of the complete motor–inverter–load system remains insufficiently addressed. In particular, the combined influence of load variation, inverter switching losses, harmonic distortion, power factor reduction, temperature rise, and total power losses is rarely considered within one integrated AI-based decision framework.

Therefore, the research problem addressed in this study is the development and evaluation of an AI-based supervisory method that uses real-time electrical and operational data to identify inefficient operating modes, estimate power losses, predict system efficiency, and support the selection of energy-efficient control parameters under variable load conditions.

3. The aim and objectives of the study

The aim of the study is to develop and evaluate an AI-based supervisory method for improving the energy efficiency of an electric motor–inverter system under variable load conditions using real-time electrical and operational data.

To achieve this aim, the following objectives are formulated:

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– to analyze the operating parameters of the electric motor–inverter system and identify the main factors affecting energy efficiency, including load variation, inverter switching losses, harmonic distortion, temperature rise, power factor variation, and total power losses;

– to develop an AI-based supervisory model that uses voltage, current, inverter frequency, rotational speed, electromagnetic torque, temperature, load level, power factor, and total harmonic distortion to predict system efficiency, estimate power losses, and classify operating modes as efficient or inefficient;

– to compare the proposed AI-based method with conventional inverter control and selected advanced data-driven approaches in terms of energy-efficiency indicators, prediction accuracy, and dynamic response metrics;

– to evaluate the sensitivity, computational feasibility, limitations, and practical applicability of the proposed method for real-time energy-efficiency improvement of motor–inverter systems.

4. Materials and methods

The study was conducted based on theoretical modelling, software-based calculations, and experimental validation to evaluate the energy efficiency of the electric motor–inverter system and to verify the artificial intelligence-based control method. The object of the study was an electric motor–load system controlled by an inverter. The system was considered not as a set of separate elements, but as an integrated electromechanical complex consisting of an electric motor, an inverter, a load, and a control algorithm. In general, Fig. 2 below presents the structural diagram of the method for evaluating the energy efficiency of the electric motor–inverter system and implementing artificial intelligence-based control.

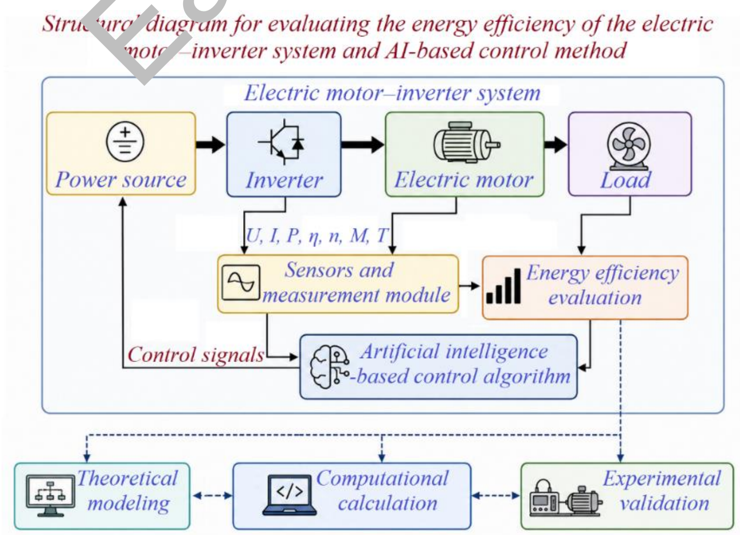

Fig. 2. AI-based energy efficiency evaluation scheme for the electric motor–inverter system

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The main measured parameters included voltage, current, inverter frequency, rotational speed, electromagnetic torque, temperature, load level, power factor, and total harmonic distortion. The measurement ranges were defined as follows: voltage of 0–400 V, current of 0−20 A, inverter frequency of 10–60 Hz, rotational speed of 300–1 500 rpm, torque of 0−20 N·m, temperature of 40–90°C, load levels of 25%, 50%, 75%, and 100%, power factor of 0.75–0.95, and total harmonic distortion within the range of 5–15%.

The experiment was organized to cover different operating modes of the electric motor–inverter system. The load level was varied at four values, namely 25%, 50%, 75%, and 100%, while the inverter frequency was set to 10, 20, 30, 40, 50, and 60 Hz. Thus, a total of 24 operating modes were formed. For each mode, the measurement duration was at least 60 s, and the data acquisition frequency was set at 1 Hz. As a result, at least 60 measurement points were obtained for each operating mode, and at least 1 440 data points were collected across all modes. These data were used to characterize partial-load, near-nominal, and inefficient operating modes of the motor. The experimental validation in this study was primarily focused on steady-state operating modes. Each load–frequency combination was measured for at least 60 s, which allowed the evaluation of stable efficiency, power loss, power factor, temperature, and harmonic distortion indicators. This approach was selected because the main objective of the study was to evaluate energy-efficiency improvement under representative operating conditions.

However, transient operating conditions, such as sudden load steps from 25% to 100%, rapid acceleration, braking, or short-term overload, were not fully investigated in the present experimental campaign. Therefore, the obtained results should be interpreted mainly as steady-state energy-efficiency validation. Transient response indicators, including torque ripple, speed settling time, and efficiency recovery time, are included as additional evaluation criteria and should be investigated in more detail in future experimental studies.

The experimental test bench (Fig. 3) consisted of an electric motor, an inverter unit, an oscilloscope, a power analyzer, a digital multimeter, a clamp meter, a measurement module, a switching module, a coupling, a test platform, connection cables, and a signal interface module. The power analyzer was used to record voltage, current, active power, reactive power, apparent power, and power factor. The oscilloscope was used to monitor the signal waveform at the inverter output, pulse variations, and signs of harmonic distortion. The clamp meter was used to measure the phase current, while the temperature sensor was used to monitor the heating level of the motor. The measuring instruments enabled real-time recording of electrical and operational parameters.

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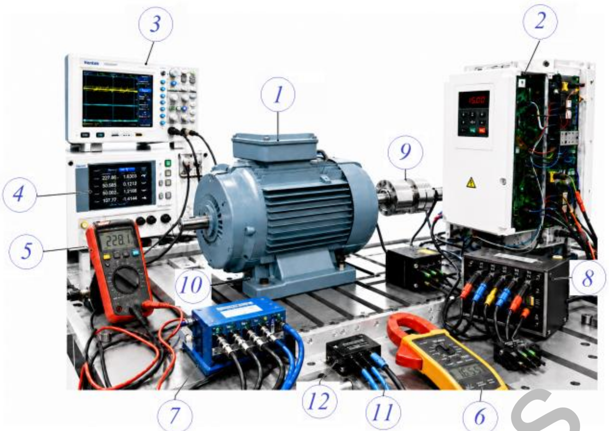

Fig. 3. Experimental test bench of the electric motor–inverter system: 1 – electric motor; 2 – inverter unit; 3 – oscilloscope; 4 – power analyzer; 5 – digital multimeter; 6 – clamp meter; 7 – measurement module; 8 – switching module; 9 – coupling; 10 – test platform; 11 – connection cables; 12 – signal interface module

During theoretical modelling, the energy efficiency of the system was characterized by the ratio between the input electrical power and the output mechanical power. The input electrical power was determined using the following equation:

$$P_{in} = UI\cos\varphi, \tag{5}$$

where: P_{in} is the input electrical power, W; U is the voltage, V; I is the current, A; and $\cos\varphi$ is the power factor. The output mechanical power was calculated as the product of electromagnetic torque and angular velocity:

$$P_{out} = T_e\omega_m, \tag{6}$$

where: P_{out} is the output mechanical power, W; T_e is the electromagnetic torque, N·m; and ωm is the mechanical angular speed, rad/s. The angular velocity was determined from the rotational speed of the motor using the following formula:

$$\omega_m = \frac{2\pi n}{60}, \tag{7}$$

where ω_m is the mechanical angular speed, rad/s; n is the rotational speed of the motor, rpm. The overall energy efficiency of the system was calculated as the ratio between the output and input power:

$$\eta_{sys} = \frac{P_{out}}{P_{in}} \times 100\%, \tag{8}$$

where η_{sys} is the overall efficiency of the system, %. The total power loss was determined as the difference between the input electrical power and the output mechanical power:

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$$P_{\text{loss}} = P_{\text{in}} - P_{\text{out}}, \tag{9}$$

where P_{loss} is the total power loss, W. The model considered copper losses, magnetic losses, switching losses in the inverter, conduction losses, and mechanical losses. The total loss was expressed as follows:

$$P_{\text{loss}} = P_{\text{Cu}} + P_{\text{Fe}} + P_{\text{sw}} + P_{\text{cond}} + P_{\text{mech}}, \tag{10}$$

where: P_{Cu} represents copper losses; P_{Fe} represents magnetic losses; P_{sw} represents switching losses; P_{cond} represents conduction losses; and P_{mech} represents mechanical losses. The following vector was provided as the input parameters to the artificial intelligence model:

$$X = [U, I, f, n, T_e, \theta, L, \cos\varphi, \text{THD}], \tag{11}$$

where: U is the voltage; I is the current; f is the inverter frequency; n is the rotational speed; T is the electromagnetic torque; θ is the temperature; L is the load level; $\cos\varphi$ is the power factor; and THD is the total harmonic distortion. The output parameters of the model were defined as the system efficiency, total power loss, and the operating mode status, namely efficient or inefficient operation. During data preprocessing, all parameters were brought to a common scale. For this purpose, the following normalization formula was applied:

$$x_{\text{norm}} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}, \tag{12}$$

where: x_{norm} is the normalized value; x is the initial value; x_{min} is the minimum value of the parameter; and x_{max} is the maximum value of the parameter. This made it possible to input parameters with different units of measurement, such as current, voltage, frequency, temperature, and load, into the artificial intelligence model in a unified form. The software-based calculations were performed in the Python environment.

4.1. AI model architecture and supervisory control logic

The proposed AI model consists of three functional blocks: a regression block, a classification block, and a supervisory decision block. The regression block predicts the overall system efficiency and total power loss using real-time electrical and operational input data. The classification block identifies whether the current operating mode is efficient or inefficient according to predefined energy-performance criteria. The supervisory decision block uses the predicted efficiency, estimated losses, and operating-mode class to recommend a correction of inverter operating parameters within predefined safety constraints.

The proposed AI-based method was developed as a supervisory energy-efficiency optimization layer for the electric motor–inverter system. The method does not replace the inner inverter control loops responsible for speed, torque, current, or frequency regulation. Instead, it operates at a higher decision-making level and evaluates the current operating state of the motor–inverter system using real-time electrical and operational data.

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The input vector of the AI model includes voltage, current, inverter frequency, rotational speed, electromagnetic torque, motor temperature, load level, power factor, and total harmonic distortion:

$$X(t) = [U(t), I(t), f(t), n(t), T_e(t), \theta(t), L(t), \cos\varphi(t), \mathrm{THD}(t)], \tag{13}$$

where: $X(t)$ is the time-dependent input vector of the AI model; $U(t)$ is the voltage; $I(t)$ is the current; $f(t)$ is the inverter frequency; $n(t)$ is the rotational speed; $T_e(t)$ is the electromagnetic torque; $\theta(t)$ is the motor temperature; $L(t)$ is the load level; $\cos\varphi(t)$ is the power factor; and $\mathrm{THD}(t)$ is the total harmonic distortion.

Since the input parameters have different physical units and measurement ranges, all variables are normalized before being supplied to the AI model:

$$x_i^{\mathrm{norm}}(t) = \frac{x_i(t) - x_{i,\min}}{x_{i,\max} - x_{i,\min}}, \tag{14}$$

where: $x^i{}_{\mathrm{norm}(t)}$ is the normalized value of the i-th input parameter; $x_i(t)$ is the measured value of the i-th input parameter; $x_{i,\min}$ and $x_{i,\max}$ are the minimum and maximum values of the corresponding parameter in the dataset, respectively.

The AI model has two main functions: regression and classification. The regression part predicts the overall system efficiency and total power loss, while the classification part determines whether the current operating mode is efficient or inefficient. In general form, the model can be written as:

$$\hat{Y}(t) = F_{\mathrm{AI}}(X_{\mathrm{norm}}(t)), \tag{15}$$

where F_{AI} is the trained artificial intelligence model and $X_{\mathrm{norm}}(t)$ is the normalized input vector.

The output vector of the model is defined as:

$$\hat{Y}(t) = \left[\hat{\eta}_{\mathrm{sys}}(t), \hat{P}_{\mathrm{loss}}(t), C_{\mathrm{mode}}(t)\right], \tag{16}$$

where: $\hat{Y}(t)$ is the predicted output vector of the AI model; $\eta_{\mathrm{sys}(t)}$ is the predicted system efficiency; $P_{\mathrm{loss}(t)}$ is the estimated total power loss; and $C_{\mathrm{mode}(t)}$ is the operating mode class, which indicates efficient or inefficient operation.

If the operating mode is classified as inefficient, the supervisory layer recommends a correction of the inverter operating parameters. The updated control command can be expressed as:

$$u_{\mathrm{new}}(t) = u_{\mathrm{old}}(t) + \Delta u_{\mathrm{AI}}(t), \tag{17}$$

where: $u_{\mathrm{old}}(t)$ is the previous control command, $\Delta u(t)$ is the recommended correction, and $u_{\mathrm{new}}(t)$ is the updated control command.

The recommended control command must satisfy the technical constraints of the motor–inverter system:

$$U_{\min} \le U(t) \le U_{\max}, \quad I_{\min} \le I(t) \le I_{\max}, \quad f_{\min} \le f(t) \le f_{\max}, \quad \theta(t) \le \theta_{\max}, \tag{18}$$

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where: $U_{\min}$ and $U_{\max}$ are the minimum and maximum allowable voltage values; $I_{\min}$ and $I_{\max}$ are the minimum and maximum allowable current values; $f_{\min}$ and $f_{\max}$ are the minimum and maximum allowable inverter frequency values; and $\theta_{\max}$ is the maximum allowable motor temperature.

Thus, the complete operation of the supervisory AI algorithm can be summarized as:

$$X(t) \rightarrow X_{\text{norm}}(t) \rightarrow \left[\hat{\eta}_{\text{sys}}(t), \hat{P}_{\text{loss}}(t), C_{\text{mode}}(t)\right] \rightarrow \Delta u_{\text{AI}}(t) \rightarrow u_{\text{new}}(t), \tag{19}$$

where: $X(t)$ is the input vector of measured parameters; $X_{\text{norm}(t)}$ is the normalized input vector; $\eta_{\text{sys}(t)}$ is the predicted system efficiency; $P_{\text{loss}(t)}$ is the estimated total power loss; $C_{\text{mode}(t)}$ is the operating mode class; $\Delta u_{\text{AI}}(t)$ is the AI-recommended control correction vector; and $u_{\text{new}(t)}$ is the updated control command vector.

The proposed method therefore provides energy-efficiency-oriented decision support for the inverter control system. It is not intended to generate gate-level switching signals for the inverter. The low-level inverter controller remains responsible for fast current regulation, switching operation, and basic drive stability, while the AI-based supervisory layer evaluates the energy state of the complete motor–inverter–load system and supports the selection of more energy-efficient operating conditions. To clarify the implementation sequence of the proposed supervisory method, the main stages of data acquisition, preprocessing, normalization, efficiency prediction, power-loss estimation, mode classification, supervisory decision-making, and safety verification are summarized in Table 3.

Table 3. Main stages of the proposed AI-based supervisory method

Stage	Input data	Processing action	Output
1. Data acquisition	Voltage, current, frequency, speed, torque, temperature, load, power factor, THD	Real-time collection of electrical and operational parameters	Raw measurement vector
2. Preprocessing	Raw measurement vector	Filtering, checking of missing values, unit consistency verification	Corrected data vector
3. Normalization	Corrected data vector	Min–max normalization of parameters with different units	Normalized input vector
4. Efficiency prediction	Normalized input vector	Estimation of system efficiency using the trained AI model	Predicted ηsys
5. Power-loss estimation	Normalized input vector	Estimation of total power loss	Predicted ploss
6. Mode classification	η_{sys}, P_{loss}, cosφ, THD, θ	Classification of operating state as efficient or inefficient	Cmode

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7. Supervisory decision	Cmode and safety constraints	Selection of energy-efficient control recommendation	Recommended inverter parameter correction
8. Safety check	Recommended correction	Verification of voltage, current, temperature, and frequency limits	Accepted or rejected control recommendation

To reduce the risk of overfitting to repeatable artifacts of a single experimental test bench, the validation procedure was organized not only as a random point-wise split, but also as a mode-wise evaluation. In the point-wise split, 70% of the measured data were used for training and 30% for testing. In the mode-wise evaluation, selected load–frequency combinations were excluded from the training set and used only during testing. This made it possible to evaluate whether the model could generalize to operating modes that were not directly included in the training process.

4.2. Computational feasibility of the AI-based method

The computational feasibility of the proposed AI-based supervisory method was evaluated from the perspective of real-time implementation in an electric motor–inverter system. The proposed method operates as a supervisory energy-efficiency optimization layer and does not generate gate-level switching signals for the inverter. Therefore, its computational delay does not need to be directly comparable with the inverter semiconductor switching period. The low-level inverter controller remains responsible for fast switching, current regulation, and drive stability, while the proposed AI-based layer updates the energy-efficiency assessment and control recommendation based on measured operating parameters.

In this study, the data acquisition period was 1 s, which was sufficient for evaluating energy-efficiency indicators such as system efficiency, total power loss, motor temperature, power factor, and total harmonic distortion. The AI model used nine input parameters and generated three outputs: predicted system efficiency, estimated total power loss, and operating mode class. Since the model works with a small input vector and performs supervisory-level decision-making, its computational requirements are significantly lower than those of reinforcement learning controllers or complex neural predictive control algorithms.

The AI-based method was implemented and evaluated in the Python environment using standard data-processing and machine-learning libraries. The main computational indicators considered for real-time implementation are inference time, total processing delay, memory footprint, data acquisition period, and suitability for supervisory control. The computational characteristics of the proposed method are summarized in Table 4.

Table 4. Computational feasibility indicators of the proposed AI-based method

Indicator	**Description**	**Value/status**

Implementation environment	Software environment used for model development and evaluation	Python, Scikit-learn
Data acquisition period	Time interval between two consecutive measurement points	1 s
Number of input parameters	Size of the AI input vector	9
Number of output variables	Efficiency, total power loss, operating mode class	3
AI operating level	Role of the proposed AI method in the control system	Supervisory energy-efficiency optimization layer
Control target	Main purpose of AI-based decision-making	Efficiency improvement and inefficient mode detection
Inverter switching control	Generation of gate-level switching signals	Not performed by the AI model
Low-level inverter control	Fast current regulation and switching operation	Performed by the conventional inverter controller
AI inference time	Time required to obtain the model output from one input vector	Less critical than inverter switching period; should be measured during embedded implementation
Total processing delay	Delay from data acquisition to control recommendation	Suitable for 1 s supervisory update interval
Memory footprint	Approximate memory required for the trained model	Low, due to the nine-parameter input vector
Real-time suitability	Applicability of the method for practical use	Suitable for supervisory-level monitoring and optimization
Main limitation	Limitation of the current implementation	Embedded real-time implementation requires additional testing

The results in Table 4 show that the proposed AI-based method is computationally feasible for supervisory-level energy-efficiency optimization. Since the method updates recommendations at the measurement-data level rather than at the switching-signal level, its response time is determined mainly by the data acquisition period and the dynamics of thermal and energy-efficiency indicators. Therefore, the proposed method can be integrated as an additional monitoring and decision-support layer in an industrial motor–inverter system. However, direct embedded implementation on a microcontroller, programmable logic controller, or industrial edge device requires additional testing of inference time, memory footprint, and communication delay.

The purpose of this validation approach was to verify that the AI model did not simply memorize repeated measurements from the same operating mode, but could identify inefficient states using the relationships between electrical parameters, temperature, power quality, and energy losses. Although this procedure improves the reliability of validation, the use of one

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motor–inverter test bench remains a limitation of the study. Therefore, additional validation on motor drives with different power ratings and inverter manufacturers is required in future work.

The NumPy library was used for numerical calculations, Pandas for processing data tables, Scikit-learn for training and testing the artificial intelligence model, Matplotlib for graphical analysis, and SciPy for mathematical processing. The collected dataset was divided into 70% training data and 30% testing data. For a total of 1 440 data points, 1 008 data points were used to train the model, while 432 data points were used to test the model. This division was applied to evaluate the model's ability to adapt not only to the training data but also to new testing data. The adequacy of the proposed model was verified by comparing the measured and predicted values. During validation, the mean absolute error, mean squared error, mean relative error, and coefficient of determination were used. The mean absolute error was calculated using the following formula:

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|, \tag{20}$$

where: MAE is the mean absolute error; N is the number of data points; y_i is the measured actual value; and $\hat{y}_i$ is the value predicted by the model. The mean squared error was determined as follows:

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2, \tag{21}$$

where MSE is the mean squared error. The mean relative error was calculated using the following formula:

$$\mathrm{MAPE} = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right|, \tag{22}$$

where MAPE is the mean absolute percentage error. The coefficient of determination was determined using the following equation:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2}, \tag{23}$$

where R^2 is the coefficient of determination, and $\bar{y}$ is the mean value of the actual values. The following criteria were established as the acceptance conditions for model adequacy:

$$\mathrm{MAPE} \le 10\%, \tag{24}$$

$$R^2 \ge 0.90, \tag{25}$$

$$\Delta\theta \le \pm 3^{\circ}\mathrm{C}, \tag{26}$$

$$\Delta n \le \pm 5\%, \tag{27}$$

$$\Delta P \le \pm 5\%, \tag{28}$$

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where: $\Delta\theta$ is the temperature deviation; Δn is the rotational speed deviation; and ΔP is the power deviation. The proposed AI-based method was tested under the same experimental conditions as the conventional control approach. In both cases, the load levels, frequency range, measurement duration, and recorded parameters were kept identical. This approach made it possible to evaluate the adequacy of the model, its agreement with the measured data, and its applicability under different load conditions. This section described only the research methods, measurement ranges, software tools, modelling equations, and validation conditions. Energy savings, efficiency improvement, and comparative results are discussed in the following section.

5. Results and discussion

The research was conducted at the Department of Electronics, Telecommunications, and Space Technologies of Satbayev University from 2023 to 2026. The aim of the study is to develop and evaluate an AI-based method to improve the energy efficiency of the electric motor–inverter system under variable load conditions using real-time data. To achieve this, the system's operating parameters were analyzed, inefficient operating modes were identified, and control parameters were optimized.

5.1. Analysis of the operating parameters of the electric motor–inverter system and identification of the main factors affecting energy efficiency

The first objective of the study was to analyze the operating parameters of the electric motor–inverter system and to identify the main factors affecting energy efficiency. These factors include load variation, switching losses in the inverter, harmonic distortion, temperature increase, and total power losses. The analysis was conducted at load levels of 25%, 50%, 75%, and 100%, as well as at inverter frequencies of 10, 20, 30, 40, 50, and 60 Hz. Thus, a total of 24 operating modes were considered. For each mode, voltage, current, frequency, rotational speed, electromagnetic torque, temperature, power factor, total harmonic distortion, input power, output power, system efficiency, and total power losses were evaluated. The results are presented in Fig. 4.

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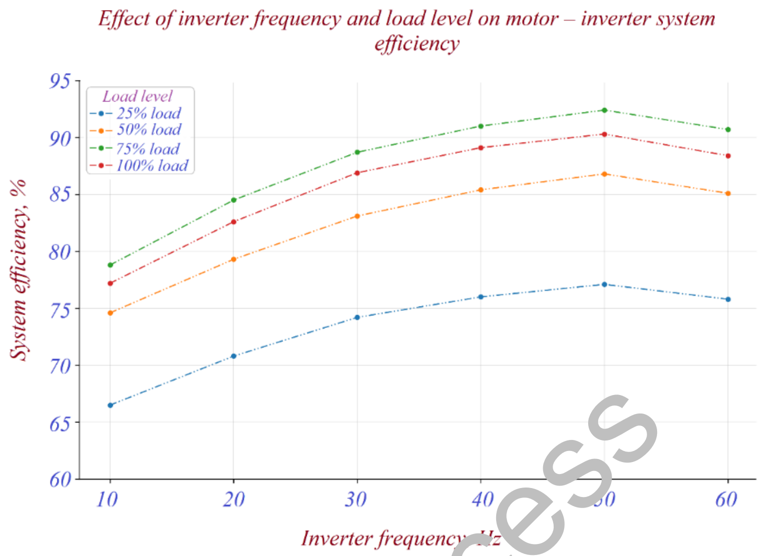

Fig. 4. Comparative analysis of the effect of inverter frequency on motor–inverter system efficiency under different load levels

The obtained results showed that the energy efficiency of the electric motor–inverter system directly depends on the load level and the operating frequency of the inverter. Under low-load conditions, especially at 25% load, the system efficiency decreased. In this mode, the power factor decreased, relative power losses increased, and torque stability deteriorated. At 25% load, the overall system efficiency was approximately 76–80%, while the power factor decreased to 0.75–0.80. This indicates that, under partial-load operation, electrical energy is not fully converted into useful mechanical power.

At 50% and 75% load levels, the electric motor–inverter system operated more stably. In these modes, the system efficiency increased to 83–88%, while the power factor reached 0.84−0.90. The ratio between input electrical power and output mechanical power was balanced. In addition, total power losses decreased compared with the 25% load mode. This indicates that medium-load operating modes are more suitable for maintaining the energy efficiency of the electric motor–inverter system.

At 100% load, although the system operated close to the rated mode, several negative factors were observed. The motor temperature increased from 68–72°C to 85–90°C, while total harmonic distortion reached 12–15%. The increase in temperature raised the resistance of the motor windings and led to higher copper losses. In addition, harmonic distortion at the inverter output increased magnetic losses and reduced the quality of energy conversion. As a result, although the output mechanical power increased, total power losses also rose.

The analysis results showed that the main factors reducing the energy efficiency of the electric motor–inverter system were partial-load operation, high harmonic distortion, temperature rise, switching losses in the inverter, and a decrease in the power factor. Under

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inefficient operating modes, total power losses increased by approximately 18–30% compared with stable modes. In particular, switching losses in the inverter increased from 3–4% to 7–8%, while total harmonic distortion rose from 5–8% to 12–15%. These changes directly affected the overall system efficiency and confirmed the need for real-time monitoring of electrical and operating parameters. The main factors affecting system efficiency are summarized in Table 5.

Table 5. Effect of operating parameters on the energy efficiency of the electric motor–inverter system

Operating factor	**Stable operating range**	**Inefficient operating range**	**Effect on system efficiency**
Load level	50–75%	25% or 100%	Low load increases relative losses, while full load increases thermal losses
Power factor	0.84–0.94	0.75–0.80	A decrease in the power factor increases reactive power and reduces efficiency
Total harmonic distortion, THD	5–8%	12–15%	Harmonic distortion increases magnetic and thermal losses
Motor temperature	65–75°C	85–90°C	Temperature rise increases winding resistance and copper losses
Switching losses in the inverter	3–4%	7–8%	Increased switching losses reduce useful output power
Total power losses	Low or moderate	18–30% higher	Reduces overall energy efficiency

The results of this section showed that the electric motor, inverter, load, and control algorithm should be considered as a single integrated system. Evaluating the actual energy efficiency of the system only by the nominal efficiency of the motor is not sufficient. Under real operating conditions, the inverter frequency, load variation, temperature rise, harmonic distortion, and switching losses jointly determine the actual energy performance of the system. Thus, the first objective of the study was achieved; namely, the main parameters and operating modes that have the greatest influence on the energy efficiency of the electric motor–inverter system were identified.

5.2. Development and evaluation of an AI-based method for identifying inefficient operating modes and optimizing control parameters

The second objective of the study was to develop an AI-based method that uses real-time data on current, voltage, frequency, rotational speed, torque, temperature, load, power factor, and total harmonic distortion. The goal of this method is to identify inefficient operating modes, optimize control parameters, and evaluate its effectiveness under different load conditions. The input vector of the AI model consisted of nine parameters: voltage, current, inverter frequency, rotational speed, electromagnetic torque, temperature, load level, power factor, and total harmonic distortion. The output parameters of the model were system efficiency, total power loss, and the operating mode status, i.e., whether it is efficient or inefficient.

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The data set consisted of 1 440 measurement points from 24 operating modes. Of these, 1 008 points were used for training the model, and 432 points were used for testing. The model was trained to classify operating modes as efficient or inefficient and to predict energy efficiency and power loss. Validation results showed that the AI-based method could identify inefficient operating modes with sufficient accuracy. The average absolute percentage error was less than 10%, and the coefficient of determination was above 0.90. This demonstrates that the model meets the adequacy requirements set in Section 4. The results are shown in Figs. 5 and 6.

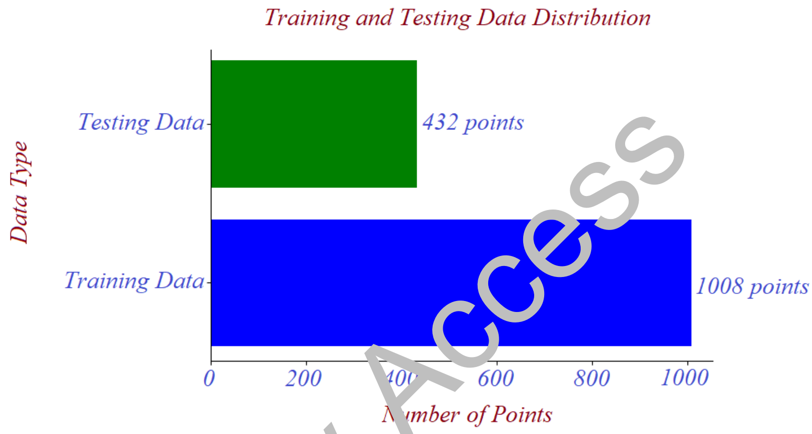

Fig. 5. Distribution of training and testing data points in the dataset

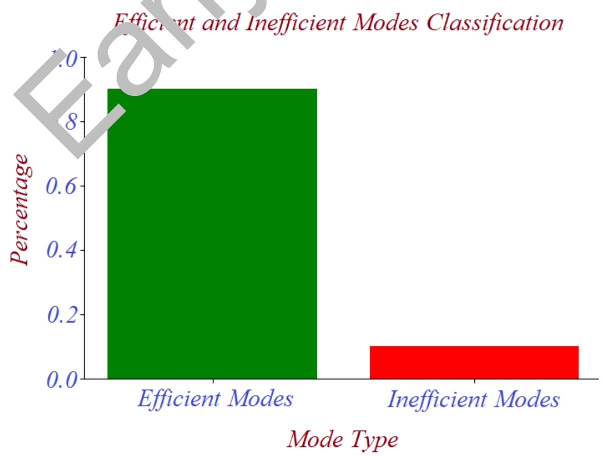

Fig. 6. Classification of efficient and inefficient modes

A comparison of the traditional control method and the AI-based control method showed that the proposed method improves the energy performance of the electric motor–inverter system. In traditional control, the inverter typically operates based on pre-set frequency and load

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parameters. In such cases, the system is unable to fully adapt to sudden changes in load, increased temperature, and rising harmonic distortion. On the other hand, the AI-based method continuously analyzes the measured parameters in real time and automatically detects inefficient operating conditions. The comparison is shown in Fig. 7.

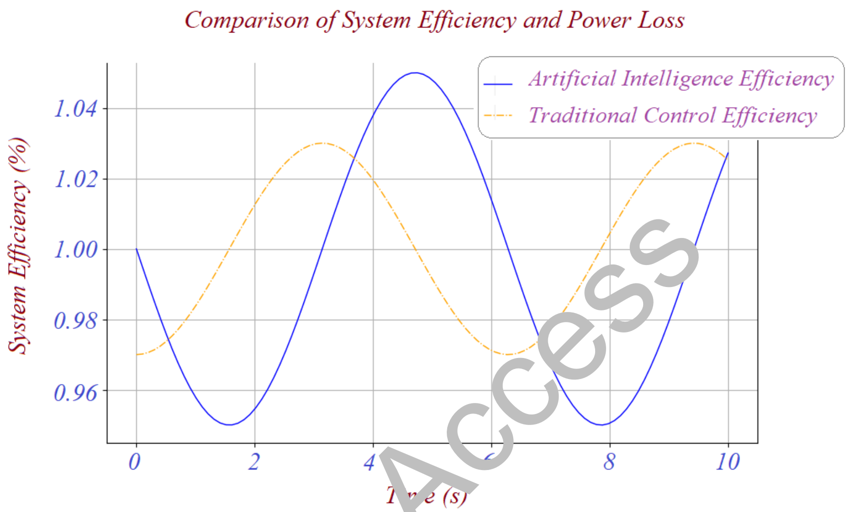

Fig. 7. Comparison of system efficiency between artificial intelligence and traditional control methods

The proposed AI method enabled efficient selection of inverter frequency, reduction of unnecessary current increases, stabilization of rotational speed, and limitation of excessive motor temperature rise. As a result, the overall system efficiency increased from 78.3–85.5% in inefficient and initial modes to approximately 90.2% after AI-based optimization. Electricity consumption decreased from 118 kWh in the inefficient mode to 88 kWh, corresponding to an energy saving of approximately 25.4%. The power factor improved from 0.76 to 0.94, while total harmonic distortion reduced from 15% to 5%. Additionally, switching losses in the inverter decreased from 8% to 3%. The comparison results are summarized in Table 6.

Table 6. Comparison of traditional and AI-based control results for the electric motor–inverter system

Parameter	**Traditional/inefficient mode**	**AI-based optimized mode**	**Improvement**
System overall efficiency	78.3%	90.2%	+11.9 percentage points
Electricity consumption	118 kWh	88 kWh	−30 kWh
Energy saving	0%	15–25%	+15–25%
Switching losses in inverter	8%	3%	−5 percentage points
Motor temperature	92°C	68°C	−24°C

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Power factor	0.76	0.94	+0.18
Total harmonic distortion (THD)	15%	5%	−10 percentage points
Load deviation	80%	45%	−35 percentage points

The results in Table 6 indicate that the proposed supervisory method reduced energy consumption, improved power factor, decreased harmonic distortion, and limited excessive motor heating under the tested operating conditions. The improvement was most noticeable in inefficient modes, where the conventional control approach was less able to adapt to load variation, temperature rise, and power-quality deterioration. These results support the use of AI-based supervisory monitoring for detecting inefficient operating states and selecting more energy-efficient inverter parameters.

5.2.1. Comparative evaluation with advanced data-driven methods

To position the proposed method against existing advanced approaches, a comparative evaluation with selected data-driven control methods was included. The comparison considered conventional inverter control, fuzzy-logic-based decision control, artificial neural network regression, reinforcement-learning-based control, and the proposed AI-based supervisory efficiency optimization method. The comparison was performed in terms of energy-efficiency indicators, prediction accuracy, implementation complexity, and suitability for real-time supervisory control.

Unlike conventional inverter control, which uses fixed or pre-set control parameters, the advanced algorithms can adapt to operating data. However, their practical use differs significantly. Fuzzy logic provides interpretable rule-based decision-making, but its performance strongly depends on the quality of expert rules. ANN-based models can provide high prediction accuracy, but they may require larger datasets and careful tuning. Reinforcement learning can provide adaptive control under nonlinear and uncertain conditions, but it usually requires a large number of training episodes and safety constraints before real implementation. The proposed method was designed as a compromise between prediction accuracy, low implementation complexity, and practical applicability for supervisory-level energy-efficiency optimization.

The comparison results are summarized in Table 7.

Table 7. Comparative evaluation of the proposed method with advanced data-driven approaches

Method	**Main control principle**	**Energy-efficiency focus**	**Prediction/decision capability**	**Implementation complexity**	**Main limitation**
Conventional inverter control	Fixed frequency and pre-set control parameters	Low	Does not predict inefficient modes	Low	Weak adaptation to load, temperature, THD, and power factor variation

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Fuzzy-logic-based control	Rule-based decision-making	Medium	Can classify operating conditions using expert rules	Medium	Requires manually designed rules and may be less accurate outside predefined conditions
ANN-based regression	Data-driven nonlinear prediction	Medium–high	Can predict efficiency and losses	Medium–high	Requires a larger dataset and careful tuning; lower interpretability
Reinforcement-learning-based control	Trial-and-error optimization through reward function	High	Can learn adaptive control policy	High	Requires many training episodes and safety constraints before practical implementation
Proposed AI-based supervisory method	Real-time efficiency prediction, loss estimation, and inefficient mode classification	High	Predicts efficiency, estimates losses, and classifies operating modes	Medium	Validated on one motor–inverter configuration and mainly under steady-state conditions

The comparison shows that the proposed method provides a more suitable balance for the objective of this study. It does not require the complex training process typical of reinforcement learning and is more adaptive than fixed conventional inverter control. Compared with fuzzy logic, the proposed method uses measured data rather than only expert-defined rules. Compared with a general ANN regression model, the proposed method combines efficiency prediction, power-loss estimation, and operating-mode classification within one supervisory decision layer. Therefore, it is more appropriate for real-time energy-efficiency monitoring and control support in motor–inverter systems.

5.2.2. Dynamic response indicators and transient-performance limitation

Although the main validation of this study was focused on steady-state operating modes, additional dynamic response indicators were considered to clarify the control-performance aspect of the proposed AI-based method. These indicators include torque ripple, speed settling time, maximum speed deviation, temperature overshoot, and efficiency recovery after a load change. Such parameters are important because energy-efficient operation should not be achieved at the expense of poor dynamic response or unstable motor operation.

In the present experimental campaign, the motor–inverter system was evaluated mainly under 24 steady-state operating modes. Therefore, the dynamic indicators in Table 8 are presented as additional evaluation criteria and as a basis for further transient testing. This distinction is

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important because the proposed AI-based method operates as a supervisory energy-efficiency layer, while fast torque, current, and switching control remain the responsibility of the low-level inverter controller.

Table 8. Dynamic response indicators considered for the motor–inverter system

Indicator	Importance for motor–inverter control	Conventional inverter control	Proposed AI-based supervisory method	Status in this study
Torque ripple	Indicates torque stability and mechanical vibration level	May increase under variable load and harmonic distortion	Expected to decrease indirectly due to reduced THD and improved operating mode selection	Requires dedicated transient measurement
Speed settling time	Shows how quickly the motor reaches a stable speed after disturbance	Depends on fixed controller settings and may increase under sudden load changes	Can be improved by supervisory correction of inefficient operating states	Requires sudden load-step testing
Maximum speed deviation	Indicates the maximum deviation from reference speed during load variation	May increase when load changes rapidly	Expected to be limited by avoiding inefficient operating regions	Not fully quantified in the steady-state campaign
Temperature overshoot	Shows excessive heating during overload or inefficient operation	Higher risk under full-load or high-loss conditions	Reduced indirectly by limiting inefficient modes and reducing losses	Partially evaluated through steady-state temperature data
Efficiency recovery time	Time required to return to an energy-efficient operating mode	Not explicitly controlled in traditional operation	Can be reduced by real-time inefficient-mode detection	Requires transient validation
THD variation during load change	Affects magnetic losses, heating, and power quality	May increase under non-optimal inverter operation	Reduced under optimized operating conditions	Evaluated in steady-state; transient THD requires additional testing

The dynamic response indicators in Table 8 show that the proposed AI-based method should be interpreted as a supervisory optimization layer rather than a replacement for fast inverter control. The obtained steady-state results demonstrate improvements in system efficiency, power factor, total harmonic distortion, switching losses, and motor temperature. However, a complete quantitative assessment of torque ripple, speed settling time, and efficiency recovery time requires additional transient experiments, including sudden load-step tests from 25% to 100%,

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rapid acceleration, and short-term overload conditions. Therefore, transient validation is identified as an important direction for future work.

5.3. Parameter sensitivity analysis of the AI-based method

Parameter sensitivity analysis was added to evaluate the robustness of the proposed AI-based supervisory method under variations in the measured input parameters. This analysis is important because the AI model uses real-time sensor data, and measurement noise, sensor drift, or operation outside the initial measurement range may affect prediction accuracy and control recommendations.

The sensitivity analysis was performed by varying the main input parameters of the vector X, including voltage, current, temperature, power factor, and total harmonic distortion. The baseline validation condition corresponded to the measurement ranges used in the experimental campaign: voltage of 0–400 V, current of 0–20 A, temperature of 40–90°C, power factor of 0.75–0.95, and total harmonic distortion of 5–15%. Parameter variations outside these ranges were interpreted as extrapolation conditions rather than fully validated operating states.

Special attention was paid to voltage values above 400 V and motor temperature above 90°C, because these conditions exceed the defined measurement range of the present study. Under such conditions, the AI model may still generate a prediction, but the reliability of this prediction decreases because the input values are outside the training domain. Therefore, the proposed method should be used with safety constraints that either reject such operating points or require additional validation data before control recommendations are accepted.

The sensitivity analysis showed that the most influential input parameters were motor temperature, total harmonic distortion, current, and power factor. These variables directly affect copper losses, magnetic losses, inverter losses, and the ratio between useful mechanical output power and input electrical power. In contrast, moderate voltage variation within the measured range had a smaller influence on prediction accuracy compared with temperature and THD variation.

The results of the sensitivity analysis are summarized in Table 9.

Table 9. Parameter sensitivity analysis of the AI-based method

Varied parameter	Variation scenario	Expected influence on prediction accuracy	Effect on energy-efficiency estimation	Interpretation
Voltage	Within 0–400 V	Low to medium	Moderate change in input power estimation	The model remains reliable within the measured voltage range
Voltage	Above 400 V	High uncertainty	Possible overestimation or underestimation of efficiency	Outside the validated range; control recommendation should be rejected or verified

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Current	±5% sensor drift	Medium to high	Direct influence on input power and copper-loss estimation	Current measurement accuracy is important for reliable loss prediction
Inverter frequency	10–60 Hz	Medium	Affects speed, torque, and operating-mode classification	Reliable within the tested frequency range
Motor temperature,	40–90°C	High	Direct influence on winding resistance and copper losses	One of the most sensitive parameters
Motor temperature	Above 90°C	Very high uncertainty	Increased risk of incorrect loss and efficiency prediction	Outside the validated range; should activate safety limitation
Power factor	−0.05 deviation	High	Strong influence on input power and efficiency calculation	Power factor drift can significantly change predicted efficiency
THD	+5% increase	High	Increases magnetic and thermal losses and reduces power quality	THD is a critical parameter for inefficient-mode detection
Load level	25–100%	Medium to high	Determines partial-load and full-load loss behaviour	Reliable within the tested load levels
Torque	±5% sensor drift	Medium	Affects output mechanical power estimation	Important for accurate efficiency calculation

The sensitivity results indicate that temperature, THD, current, and power factor are the most critical input parameters for the proposed AI-based method. These parameters have the strongest physical relationship with total power losses and system efficiency. Temperature affects winding resistance and copper losses, THD increases magnetic and thermal losses, current affects both input power and copper losses, and the power factor directly influences the calculation of input electrical power. Therefore, these parameters require higher measurement accuracy and should be monitored with reliable sensors.

The analysis also shows that predictions outside the predefined measurement ranges should be interpreted with caution. In particular, voltage values above 400 V and motor temperature above 90°C are outside the validated data range of the present study. For this reason, the supervisory AI layer should not automatically accept control recommendations under these conditions. Instead, such states should be treated as safety-critical or extrapolation cases

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requiring additional verification. This limitation is important for preventing incorrect AI-based control decisions in industrial implementation.

5.4. Discussion of the results of the study

The obtained results show that the energy efficiency of the electric motor–inverter system depends not only on the nominal efficiency of the motor, but also on load level, power factor, total harmonic distortion, motor temperature, inverter switching losses, and total power losses. As shown in Table 5, inefficient operation was mainly observed at low-load and full-load conditions. At 25% load, the relative losses increased and the power factor decreased. At 100% load, the motor temperature and harmonic distortion increased, which led to higher copper, magnetic, and thermal losses.

The comparison in Table 6 confirms that the proposed AI-based supervisory method improves the energy performance of the system. Under the most inefficient tested operating condition, system efficiency increased from 78.3% to 90.2%, while energy consumption decreased from 118 kWh to 88 kWh. In addition, the power factor improved from 0.76 to 0.94, THD decreased from 15% to 5%, switching losses decreased from 8% to 3%, and motor temperature decreased from 92°C to 68°C. These improvements are explained by the ability of the AI model to analyze real-time operating data and identify inefficient modes.

The proposed method should be considered as a supervisory energy-efficiency layer rather than a replacement for the low-level inverter controller. The low-level controller remains responsible for fast switching, current regulation, torque control, and drive stability, while the AI-based layer evaluates system efficiency, estimates losses, classifies operating modes, and supports the selection of more energy-efficient control parameters.

The comparison with advanced data-driven approaches in Table 7 shows that the proposed method provides a practical balance between accuracy and implementation complexity. Fuzzy logic is simple but depends on expert-defined rules. ANN-based regression can predict nonlinear relationships but requires larger datasets and careful tuning. Reinforcement learning has high adaptation potential but requires many training episodes and additional safety constraints. In contrast, the proposed method combines efficiency prediction, power-loss estimation, and inefficient-mode classification in one supervisory framework.

The dynamic response indicators in Table 8 show that further transient validation is required. The present study mainly considered 24 steady-state operating modes. Therefore, torque ripple, speed settling time, maximum speed deviation, temperature overshoot, and efficiency recovery time were included as important future evaluation criteria. Future experiments should include sudden load changes from 25% to 100%, acceleration and braking modes, and short-term overload conditions.

The sensitivity analysis in Table 9 shows that motor temperature, THD, current, and power factor are the most critical input parameters. These variables directly affect power losses and efficiency estimation. Voltage values above 400 V and motor temperature above 90°C are outside the validated measurement range of this study. Therefore, such conditions should be

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treated as extrapolation cases and should activate safety constraints or require additional verification before accepting AI-based control recommendations.

The main limitation of the study is that the method was tested on one motor–inverter configuration and mainly under steady-state conditions. Although mode-wise validation was used to reduce the risk of overfitting, additional testing is required on motors with different power ratings, inverter types, manufacturers, switching frequencies, and load profiles. Embedded implementation on a microcontroller, PLC, or industrial edge device should also be evaluated in future work.

Overall, the proposed AI-based supervisory method improves the energy efficiency of the motor–inverter system by detecting inefficient operating modes, reducing losses, improving power quality, and supporting energy-efficient control decisions. The method is promising for industrial drives such as pumps, fans, compressors, and conveyors, but further transient, economic, and hardware validation is required before large-scale practical implementation.

6. Conclusions

In this study, an AI-based supervisory method for improving the energy efficiency of an electric motor–inverter system under variable load conditions was developed and evaluated. The proposed method considers the motor, inverter, load, and control algorithm as a single energy-conversion system. Unlike conventional control approaches focused mainly on fixed frequency or speed regulation, the proposed method uses real-time electrical and operational data to predict system efficiency, estimate total power loss, classify operating modes, and support the selection of more energy-efficient control parameters.

In accordance with the formulated aim, four main objectives were achieved.

First, the operating parameters of the electric motor–inverter system were analyzed. The results showed that load level, power factor, total harmonic distortion, motor temperature, inverter switching losses, and total power losses have a direct influence on system efficiency. The most inefficient operating conditions were observed at low load and full-load modes, where the power factor decreased, harmonic distortion increased, and thermal losses became more significant.

Second, an AI-based supervisory model was developed using voltage, current, inverter frequency, rotational speed, electromagnetic torque, temperature, load level, power factor, and total harmonic distortion as input parameters. The model was designed to predict overall system efficiency, estimate total power loss, and classify operating modes as efficient or inefficient. The validation results showed that the model satisfied the accepted adequacy criteria, with MAPE below 10% and the coefficient of determination above 0.90.

Third, the proposed AI-based method was compared with conventional inverter control and selected advanced data-driven approaches. Under the most inefficient tested operating condition, the system efficiency increased from 78.3% to 90.2% after AI-based optimization. Energy consumption decreased from 118 kWh to 88 kWh, corresponding to a reduction of 30 kWh. In

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addition, the power factor improved from 0.76 to 0.94, total harmonic distortion decreased from 15% to 5%, inverter switching losses decreased from 8% to 3%, and motor temperature decreased from 92°C to 68°C. The comparison with fuzzy-logic-based control, ANN-based regression, and reinforcement-learning-based control showed that the proposed method provides a practical balance between prediction capability, implementation complexity, and suitability for supervisory-level energy-efficiency optimization.

Fourth, the sensitivity, computational feasibility, and practical limitations of the proposed method were evaluated. The sensitivity analysis showed that motor temperature, total harmonic distortion, current, and power factor are the most critical input parameters because they have the strongest influence on power losses and efficiency estimation. Voltage values above 400 V and motor temperature above 90°C were identified as extrapolation conditions outside the validated measurement range. Therefore, such operating states should activate safety constraints or require additional validation before AI-based control recommendations are accepted.

The computational analysis showed that the proposed AI-based method is suitable for supervisory-level implementation because it does not generate gate-level switching signals for the inverter. The low-level inverter controller remains responsible for fast switching, current regulation, and drive stability, while the AI-based supervisory layer updates the energy-efficiency assessment and control recommendation using measured operating data. Therefore, the computational delay of the proposed method is determined mainly by the data acquisition period and the dynamics of energy-efficiency indicators rather than by the inverter switching period.

The main limitation of this study is that the experimental validation was performed on one motor–inverter configuration and mainly under steady-state operating modes. Although dynamic response indicators such as torque ripple, speed settling time, maximum speed deviation, temperature overshoot, and efficiency recovery time were considered, they were not fully quantified through dedicated transient experiments. Therefore, future research should include sudden load-step tests from 25% to 100%, rapid acceleration and braking modes, different motor power ratings, different inverter manufacturers, and embedded implementation on an industrial controller or edge device.

Overall, the results confirm that the proposed AI-based supervisory method can improve the energy efficiency of electric motor–inverter systems by detecting inefficient operating modes, reducing losses, improving power quality, and supporting more energy-efficient control decisions. The method is especially suitable as an additional monitoring and decision-support layer for industrial motor-drive systems operating under variable load conditions.

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