IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 15, No. 6, December 2026, pp. 5214~5227
ISSN: 2252-8938, DOI: 10.11591/ijai.v15.i6.pp5214-5227

Enhancing electrical machine research with ChatGPT: a case study on three-phase induction motors

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Article Info

Article history:

Received May 5, 2025
Revised Aug 24, 2026
Accepted Sep 20, 2026

Keywords:

Artificial intelligence
ChatGPT-4
Induction motor
MATLAB/Simulink
Nonlinear modeling
Performance analysis

ABSTRACT

The rapid advancement of artificial intelligence (AI) has led to its integration into numerous engineering fields, including electrical machine research. This study investigates the feasibility of employing chat generative pre-trained transformer 4 (ChatGPT-4) to analyze the performance of a three-phase induction motor, comparing its predictions with those from MATLAB/Simulink simulations and experimental data. The objective is to assess whether AI-driven analysis can reliably capture key performance parameters, including stator current, power input, power factor, torque, power output, and efficiency—under both normal and overload conditions. The methodology comprises several steps: verifying and enhancing ChatGPT-4's knowledge through training with domain-specific motor data; performing performance evaluations using ChatGPT-4; modeling the same motor parameters in MATLAB/Simulink; and validating the outcomes with experimental tests. Data from all three approaches were compared using statistical measures, including root mean square error (RMSE) and Pearson correlation coefficient (PCC). The results indicate that under rated load conditions, both ChatGPT-4 and MATLAB/Simulink yield accurate predictions with high PCC values (0.96 to 0.99) and low RMSE. However, discrepancies emerge due to the limitations of linear modeling in capturing nonlinear phenomena such as magnetic saturation and dynamic effects. Overall, ChatGPT-4 shows promising potential as a rapid trend analysis tool that complements traditional simulation methods.

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1. INTRODUCTION

A modern and challenging topic today is the application of artificial intelligence (AI) in education and research. With the rapid advancement of AI technology, tools such as chat generative pre-trained transformer (ChatGPT) have played a significant role in various fields, including medical science, education, research and academia, customer service, finance, language translation, data analysis and decision-making, information technology and programming support, as well as engineering sciences [1]. A review of relevant

literature reveals that ChatGPT has been applied in engineering disciplines, particularly in electrical engineering, for tasks such as computation, analysis, and decision-making. For instance, ChatGPT-4 has been used to analyze load flow in power transmission systems [2]. Additionally, ChatGPT has been employed to enhance students' understanding in the electrical engineering design proficiency course, a hands-on subject focused on electrical system design and testing at the University of New South Wales [3].

The use of large-scale foundation (LSF) models based on the transformer architecture of generative pre-trained transformer (GPT) has been applied for predictive management of smart transformers. By leveraging self-attention mechanisms, these models can analyze data and detect anomalies. Furthermore, an intelligent data analysis system has been developed using GPT to enhance data analysis efficiency in smart grid networks [4]. Additionally, ChatGPT has been utilized in research and development in the field of electronics, as demonstrated through case studies involving sensor applications in embedded systems for smart homes [1]. Moreover, ChatGPT-3.5 has been employed in designing transformers and electrical machines, specifically for calculating core size, conductor dimensions, and power loss. However, when ChatGPT provides incorrect responses, users must verify the equations it employs and propose new equations or alternative methods to obtain accurate results. The challenge of solving open-ended problems in electrical engineering remains an area for further development [5].

ChatGPT has also been integrated with the Peter Chew method to solve electrical engineering problems that cannot be directly addressed using the cosine and sine rules. Studies indicate that this approach enables ChatGPT to solve problems accurately, whereas the model's conventional methods fail to do so. This highlights the importance of diverse approaches in advancing AI's mathematical capabilities [6]. Through continuous training and exposure to new data and methodologies, ChatGPT can enhance its potential. Although ChatGPT-4 is a promising tool for supporting education in electrical engineering and science, some limitations have been observed in interpreting images, such as electrical circuits and magnetic field diagrams. Despite its ability to provide detailed explanations and sound reasoning in physics, its interpretation of visual data remains a challenge [7].

Although ChatGPT has been increasingly utilized in electrical engineering research, its application to the performance analysis of induction motors remains unreported. Three-phase induction motors are critical in industrial applications due to their robustness, simple design, and high efficiency, making them major energy consumers in systems such as pumps, fans, and conveyors [8]. Optimizing these motors is essential for enhancing energy efficiency and cost-effectiveness. Performance evaluation methods include using manufacturer data, direct testing, equivalent circuit analysis, and simulation with specialized software—with simulation offering a particularly convenient, cost-effective, and safe alternative to laboratory testing. Simulation tools like MATLAB/Simulink enable engineers to analyze motor performance—torque, speed, current, and power factor—under various loads without costly prototypes [8], [9]. However, discrepancies between simulations and real-world performance arise due to model limitations and environmental factors.

Motivated by a keen interest in integrating AI technology within the electrical engineering field, particularly in evaluating the performance of three-phase induction motors. The researcher has formulated the following research question: is it feasible to utilize ChatGPT to analyze the performance of three-phase induction motors, and how accurate can its results be? Therefore, in this study, ChatGPT-4 is investigated as a complementary tool for induction motor performance analysis rather than a replacement for conventional methods. It aims to develop a more accurate and reliable approach for motor analysis, optimizing industrial motor designs. The main contribution of this work is to demonstrate that ChatGPT-4 is capable of capturing performance trends for a three-phase induction motor with a high degree of correlation to both MATLAB/Simulink simulations and experimental measurements under rated operating conditions. The results show that ChatGPT-4 and MATLAB/Simulink provide comparable accuracy for key parameters such as stator current, power input, torque, power output, and efficiency at rated load. Furthermore, this study highlights the limitations of linear modeling approaches, including those used by ChatGPT-4 and MATLAB/Simulink, when analyzing overload conditions where nonlinear phenomena such as magnetic saturation and dynamic effects become significant. By integrating AI with conventional analytical and simulation techniques. The study also explores the benefits and limitations of each method, assessing ChatGPT-4's role in enhancing education and research in electrical machinery. Ultimately, it seeks to identify effective ways to integrate AI as a research assistant in the future.

2. BACKGROUND AND PRELIMINARIES

The performance of three-phase induction motors is critical in industrial processes. Over the years, researchers have used a variety of methods including analytical models, simulation models, ChatGPT-based approaches, and experimental testing to evaluate and optimize their performance. These methods offer different trade-offs between accuracy, cost, and practicality: analytical and simulation models provide a convenient, cost-effective, and safe means of analysis but rely on idealized assumptions, whereas

experimental testing captures real-world effects that are essential for validating model accuracy [8], [9]. The following subsections briefly review these four approaches, which together form the basis of the comparative framework adopted in this study.

2.1. Analytical model

The equivalent circuit model is a widely adopted method for analyzing induction motor performance, representing the motor using resistive and inductive elements to estimate parameters, such as torque, efficiency, slip, and losses. Based on methods outlined by existing research [10], [11], this model simplifies complex electromagnetic interactions into a network of resistances and reactances for both stator and rotor circuits as shown in Figure 1. While commonly implemented in MATLAB/Simulink, its idealized assumptions may limit real-world accuracy. Parameter values can be derived from the motor nameplate or through laboratory testing under no-load, locked-rotor, and load conditions.

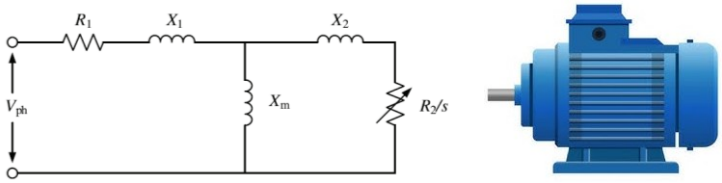


Figure 1. The IEEE equivalent circuit model of an induction motor [11]

2.2. MATLAB/Simulink approaches

MATLAB/Simulink is widely used for modeling three-phase induction motors because it can simulate complex electrical systems, including stator and rotor resistances, reactance, and load variations. Studies by [9], [12] show that it aids in analyzing power losses and motor performance under various loads. Additionally, MATLAB/Simulink-based analysis provides comprehensive performance evaluation of induction motors under varying load torque and speed conditions. The quantitative analysis of copper, core, and total power losses provides valuable information for improving motor efficiency and optimizing the design of energy-efficient motor drive systems [13]. The incorporation of equivalent circuit parameters enhances loss predictions, as noted in Chourey *et al.* [14], while Averbukh and Lockshin [15] introduce a method based on Kloss's equation and the Thevenin theorem, leveraging analytical-numerical synergy for a simple, accurate, and convergent algorithm. Moreover, Abdulkareem *et al.* [16] integrates machine learning with simulations to refine prediction accuracy. This article uses MATLAB/Simulink simulations to investigate motor behavior under different conditions and to validate ChatGPT-4's analysis of an induction motor, offering recommendations and highlighting limitations for applying ChatGPT to other electrical machines.

2.3. Experimental approaches

Simulations offer valuable insights into motor performance, yet experimental validation remains essential to align these findings with real-world conditions. The authors in [15], [17], [18] emphasize the need to measure parameters, such as rotor speed, torque, stator current, and power factor for model accuracy. As illustrated by Barzola and Chandi [19], integrating simulation, theory, and experimentation using motor test benches with torque sensors and power analyzers refines theoretical estimates by accounting for practical factors like friction and stray losses. In this study, a four-pole squirrel-cage motor (LABVOLT model 579493, rated at 220/380 V, 50 Hz, 0.48 A, 1,395 RPM, and 175 W) is evaluated using a LABVOLT data acquisition interface (model 9063) with LVDAC-EMS software and a load applied via a four-quadrant dynamometer (model 8906). The experimental setup is shown in Figure 2. This consists of a 3~AC power supply, 3~ induction motor, four-quadrant dynamometer, data acquisition, and control interface.

2.4. ChatGPT approaches

ChatGPT-4, a transformer-based large-scale language model developed by OpenAI, leverages deep learning and natural language processing to assist with engineering calculations. It supports various electrical engineering applications—including circuit analysis, transformer design [4], power systems [2], electronics, robotics, programming for calculations, and data analysis. When complex, precise calculations are needed, four strategies can enhance its performance: i) clearly formulating the problem with all specified parameters [20]; ii) using specialized computational tools, such as MATLAB or Python; iii) verifying results via theoretical analysis and simulation; and iv) involving domain experts for outcome review. Additionally,

the accuracy, reliability, and applicability of ChatGPT are directly influenced by the quality of its training data, making rigorous data processing essential for specialized fields [21].

In this paper, ChatGPT-4 is utilized to analyze the performance of an induction motor in terms of torque, speed, power, efficiency, and slip, and the errors obtained are compared with experimental results. Detailed information is presented in subsection 4.3. In summary, this study contributes to understanding induction motor evaluation by leveraging ChatGPT-4 and MATLAB/Simulink and validating them through experimental approaches, thus offering practical insights for optimizing motor performance in the industry. Due to the limitations of the experimental equipment available in the laboratory, the scope of our study is limited to evaluating the performance of the induction motor under slip variations from 0.0 to 0.3.



Figure 2. The experimental setup

3. METHOD

3.1. Analysis of induction motor performance using ChatGPT-4

3.1.1. Pre-training and fine-tuning process

The author leverages ChatGPT-4 to analyze the performance of an induction motor, as detailed in subsection 2.3. Users interact with the model through a simple interface, receiving insightful, natural language responses as shown in Figure 2. While ChatGPT-4 relies on a vast pre-trained knowledge base, it may not always align perfectly with specific user requirements. To address this, the author implements a refined four-step training process (Figure 3) to enrich the model with new, targeted knowledge—enhancing both accuracy and relevance. This model is derived from the author's proposed conceptual framework [4].

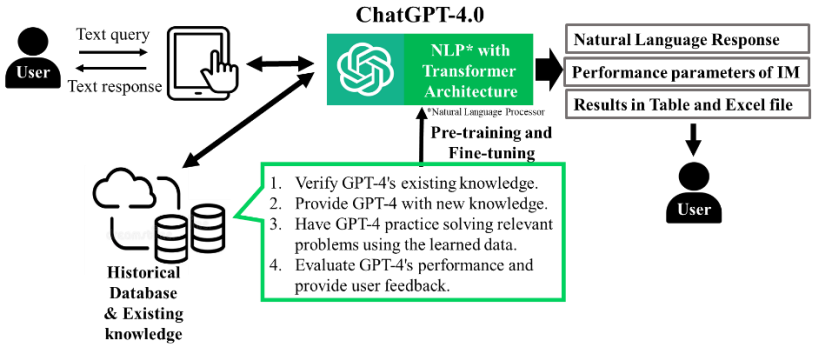


Figure 3. The relationships and pre-training processes involved in applying ChatGPT-4 to analyze induction motor performance

The four-step process for enhancing ChatGPT-4's induction motor analysis is described as follows:

i) Verify GPT-4's existing knowledge: this step involves reviewing ChatGPT-4's existing knowledge concerning induction motors to determine whether it is sufficient for analyzing induction motors in line with the objectives of this research. The author formulates clear and detailed questions, which are then input into ChatGPT-4. For example:

Question: if I want you to determine the parameters of a three-phase induction motor, what type of equivalent circuit model would you use?

ChatGPT-4: i would use the exact equivalent circuit model to determine the parameters of a three-phase induction motor.

Why the exact equivalent circuit model?

- Most accurate representation. This model includes all key components: stator resistance (R_1), rotor resistance (R_2), stator reactance (X_1), rotor reactance (X_2), magnetizing reactance (X_m), and core loss resistance (R_c). It provides a detailed and precise analysis of motor performance.
- Based on experimental testing. It is derived from DC, no-load, and locked-rotor tests, which are standard methods for motor parameter estimation. These tests help accurately separate stator, rotor, and core loss components.
- Better performance prediction. Unlike the approximate equivalent circuit, which sometimes ignores R_c or simplifies X_1 and X_2, the exact model gives a more realistic prediction of motor efficiency, power factor, and slip.

Would you like me to explain how this model compares to the IEEE model or the approximate equivalent circuit?

Based on GPT-4's responses, it is evident that the model possesses substantial prior knowledge regarding equivalent circuit parameters. It selected the most accurate equivalent circuit model and provided the rationale for this choice. This serves as only one example. In practice, the author queried ChatGPT-4 about the IEEE model and the equations used for analyzing induction motors. For example, torque, slip, speed, power, current, efficiency, and power factor. To evaluate its level of familiarity and to identify the sources from which these equations were derived. Additionally, the author presented problems for calculating motor parameters to analyze the results and assess GPT-4's reasoning process, thereby informing subsequent training efforts.

ii) Provide GPT-4 with new knowledge: in step i), the author prepared new information for ChatGPT-4 to learn. This included equations for analyzing the performance of an induction motor from the author's textbook [11], the parameter values and nameplate data of the studied induction motor, and the IEEE equivalent circuit model. The new knowledge was input using various methods, such as capturing images of equations and uploading the files, importing data from Excel, and manually typing information into ChatGPT-4, depending on the nature of the input data.

iii) Have GPT-4 practice solving relevant problems using the learned data: in the next phase, the author trained ChatGPT-4 to solve problems relevant to the research objectives. This included tasks such as calculating V_{th}, R_{th}, and Z_{th} values (according to Thevenin's theorem) for the IEEE equivalent circuit model, determining the equations used to compute the induction motor torque, and verifying the specifications of the induction motor under test. For each topic, the author posed 2-3 questions to facilitate acquisition of new knowledge, with the expectation that ChatGPT-4 would successfully assimilate the information.

iv) Evaluate GPT-4's performance and provide user feedback: the author evaluated the capabilities of ChatGPT-4 by presenting it with problem statements, such as calculating the torque, speed, and power of an induction motor. Regardless of whether ChatGPT-4's initial outputs were correct, the author provided iterative feedback until the desired results were obtained. Ultimately, the author asked ChatGPT-4 to specify the sources of the knowledge it used to analyze the induction motor. ChatGPT-4 responded that its knowledge is derived from two components: its pre-existing knowledge and user-provided information. It then presented a method for integrating information from both sources to conduct its analysis, as detailed:

Question: The equations you use to analyze the performance of a 3-phase induction motor, do they come from ChatGPT's built-in knowledge, or did they come from the information I provided? Please explain so I can understand.

ChatGPT-4: The equations I use to analyze the performance of a 3-phase induction motor come from two primary sources:

- ChatGPT's pre-existing knowledge base
  a) I have been trained on general electrical engineering textbooks, such as Electric machinery by Fitzgerald, Kingsley, and Umans, Electric Machinery Fundamentals by Chapman, and other standard reference materials.
  b) I can retrieve fundamental equations used in induction motor analysis, including the torque equation, power equations, and efficiency equation, from the knowledge I have acquired.
- Information you previously provided
  a) I recall that you have inquired about calculating induction motor parameters and performing the no-load test, blocked rotor test, and load test.
  b) I utilize the information you provided to refine and structure my responses to align with the context of your research.

Integrating information from both sources: when you ask about analyzing the performance of an induction motor, I will:

– Utilize my knowledge base to retrieve fundamental equations.
– Reference the context from previous inquiries related to the specific motor you are using (e.g., Labvolt model 579493).
– Structure my response appropriately to align with your intended analysis, such as comparing experimental results with theoretical predictions.

For example, the torque equation of an induction motor is:

$$T = \frac{3\times(V_{ph}^2\times R_2^{'}/s)}{\omega_s\times\left[(R_1+R_2^{'}/s)+(X_1+X_2^{'})^2\right]}$$

The (1) is a standard equation used to analyze the torque of an induction motor, and I can provide further details based on the context of your question.

3.1.2. Performance evaluation of induction motor by ChatGPT-4

The author employs GPT-4 to analyze the induction motor performance following the research objectives. Detailed problem statements are formulated, incorporating the induction motor specifications and its parameters based on the IEEE model. The questions explicitly define which parameters to calculate and identify the equations used for analysis. Additionally, the author specifies that calculations should be performed for slip values ranging from 0 to 0.3, with results presented in a tabular format. The following details outline the commands issued and the corresponding outputs obtained from ChatGPT-4.

Question: A 3-phase induction motor, 380 V, 50 Hz, rated power is 175 W, rated current of 0,48 A, and rated speed 1,380 rpm, 4-pole, by using the IEEE equivalent circuit. Define: R_1 = 46.45 **Ω**, L_1 = 0.167876 H, R_2 = 30.01 **Ω**, L_2 = 0.182709 H, L_m = 2.0626 H. Please calculate the Vth, R^{th}, X^{th}, and Z^{th} by using the equation in Fitzgerald, A. E., Kingsley, C., & Umans, S. D. (2003). Electric machinery. McGraw-Hill. Please calculate torque, speed, stator current, 3-phase power input, power factor, and power output of this motor. When the slip changes from 0.3 to 0.00, the step is 0.001 shown in the results in the table.

ChatGPT-4: We will calculate the following parameters using the IEEE equivalent circuit and equations from Fitzgerald, A. E., Kingsley, C., & Umans, S. D. (2003).

Thevenin parameters:

i) Thevenin voltage (V_{th})

$$V_{th} = V \times \frac{jX_m}{R_1+j(X_1+X_m)}$$

Where $X_1 = \omega L_1$, $X_2 = \omega L_2$, $X_m = \omega L_m$, and $\omega = 2\pi f$.

ii) Thevenin impedance ($Z_{th} = R_{th} + jX_{th}$)

$$Z_{th} = (R_1 + jX_1) \parallel jX_m$$

Where $R_{th} = \Re(Z_{th})$, $X_{th} = \Im(Z_{th})$.

Performance calculations: for slip s ranging from 0.3 to 0.00 in steps of 0.001:

i) Rotor impedance

$$Z_2 = R_2/s + jX_2$$

ii) Rotor current

$$I_2 = \frac{V_{th}}{Z_{th}+Z_2}$$

iii) Torque output

$$P_{out} = T \times \omega$$
$$\omega = \frac{2\pi\times\text{Speed (rpm)}}{60}$$

Where $\omega_s = 2\pi f/p$ and $p = 4$ (number of poles).

iv) Stator current

$$I_1 = \frac{V-V_{th}}{R_1+jX_1} + I_2$$

v) Power input (3-phase)

$$P_{in} = 3VI_1 \cos\theta$$

vi) Power factor

$$PF = \cos\theta$$

From the responses obtained from ChatGPT-4, it is evident that ChatGPT-4 outlined the analysis steps and provided the equations used for calculating various parameters. Subsequently, ChatGPT-4 generated Python code to compute speed, torque, current, and power under the conditions specified by the author, with the results displayed in a tabular format. An excerpt of these results for slip values of 0.300 and 0.299 is presented in Table 1. These analytical results are consistent with the values obtained from laboratory experiments and MATLAB/Simulink simulations.

Table 1. Motor performance parameters at slip values of 0.300 and 0.299

Slip	Speed (rpm)	Torque (Nm)	Stator current (A)	Power input (W)	Power factor	Power output (W)
0.300	1,050.0	2.500	1.358	636.74	0.712	244.05
0.299	1,051.5	2.501	1.357	636.30	0.713	243.47

3.2. Modeling and simulation in MATLAB/Simulink

The research begins by constructing a detailed simulation model of a three-phase induction motor in MATLAB/Simulink [22]. Key parameters such as rotor speed, torque, stator current, power output, and power factor are defined based on motor specifications. The simulation will be run under various load conditions, ranging from no-load to full-load, to observe how the motor responds in each scenario. The primary objective of this simulation step is to analyze the motor's performance in speed, torque, power output, and efficiency. A MATLAB/Simulink model of this study is shown in Figure 4.

The induction motor used in this study is of the squirrel-cage rotor type, with the following parameters: voltage (line-line) equal to 380 V, 50 Hz, rated power is 175 W, stator resistance (R_1 = 46.45 Ω), stator inductance (L_1 = 0.167876 H), rotor resistance (R_2 = 30.01 Ω), rotor inductance (L_2 = 0.182709 H), mutual inductance (L_m = 2.0626 H), and inertia (J = 0.000432 kg/m^2). The simulation results of the induction motor using MATLAB/Simulink in Figure 4 were used for comparison with theoretical calculations and experimental tests to validate the findings of this study.

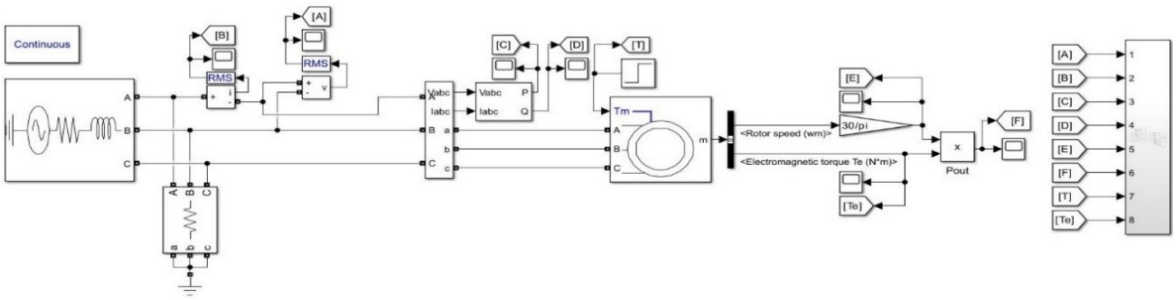


Figure 4. A MATLAB/Simulink model of the induction motor in this study

3.3. Experimental validation

To validate the simulations and theoretical calculations, a real three-phase induction motor will be tested under different loads in a lab setup. Key parameters like speed, torque, current, and power factor will be measured to assess efficiency and compare with the simulation and theoretical results [15]. The tests will be conducted on the four-pole squirrel-cage induction motor (LABVOLT model 579493) described in subsection 2.3. The motor will be loaded by a four-quadrant dynamometer (model 8906), and the measurements will be acquired with a LABVOLT data acquisition interface (model 9063) and LVDAC-EMS software, as shown in Figure 2. The load will be adjusted to vary the slip from 0.0 to 0.3, and the measured data will serve as the reference values for the comparison in subsection 3.4.

3.4. Data comparison and analysis

The results from the ChatGPT-4 simulation, MATLAB/Simulink, and experimentation will be compared in detail to evaluate how closely they align. Statistical methods, such as root mean square error (RMSE) [23] will quantify the differences between the predicted and actual performance, as defined in (1). The analysis will focus on identifying trends and patterns in the discrepancies to refine the ChatGPT-4 simulation and the other approaches. The author employs the Pearson correlation coefficient (PCC) [23] to examine the relationship between the values predicted by ChatGPT-4 and MATLAB and the experimental results, as shown in (2). This analysis aims to determine which method exhibits a stronger correlation with the experimental data.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \quad (1)$$

Let $(\hat{y}_i)$ is the predicted values, and (y_i) is the actual observed values.

$$r = \frac{\sum_{i=1}^{n}(x_i - \hat{x})(y_i - \hat{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \hat{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \hat{y})^2}} \quad (2)$$

Let x_i and y_i represent the paired data values for variables $x - y$, x, and y at the ith observation, x is the mean of x, y is the mean of y, and n denotes the total number of data pairs.

4. RESULTS AND DISCUSSION

4.1. Power input and power factor

In this study, a 175 W, 3-phase, 380 V, 4-pole induction motor with a rated speed of 1,395 rpm (rated slip = 0.07) was analyzed. Figure 5 compares the stator current, power input, and power factor of the motor obtained from ChatGPT-4 calculations, MATLAB/Simulink simulations, and experimental tests over the slip range of 0 to 0.3. Based on Figure 5(a), which illustrates the relationship between stator current and slip, it is observed that when the slip is less than or equal to the rated value, the stator current curves obtained from ChatGPT-4 calculations, MATLAB/Simulink simulations, and experimental results are consistent. Furthermore, the stator current increases as the slip increases, aligning with the findings [15]. This phenomenon corresponds with the fundamental theory of induction motor operation [10]. However, in the region where the slip exceeds the rated value, the experimentally measured stator current is lower than the values predicted by both ChatGPT-4 and MATLAB/Simulink simulations.

Figure 5(b) shows a similar trend in input power, revealing discrepancies between simulations and experimental data. Possible reasons include: i) linear model limitations: MATLAB/Simulink and ChatGPT-4 assume constant parameters and linear behavior, failing to capture nonlinear effects like magnetic saturation and temperature-induced parameter variations under overload [24], ii) neglected power losses: simulations may overlook core loss, stray load loss, and mechanical loss, affecting accuracy [12], and iii) experimental uncertainties: magnetic field leakage and other real-world losses can reduce actual power input, leading to lower measured current and power than predicted. These factors highlight the challenge of modeling induction motors accurately under overload conditions.

In Figure 5(c), under overload conditions (high slip), the experimentally measured power factor remains relatively stable or slightly increases. In contrast, the power factor curves from ChatGPT-4 and MATLAB/Simulink simulations show a gradual decline. This can be explained by the effect of increasing slip under overload conditions. When the load torque exceeds the motor's limit, the speed decreases, causing slip to rise [10]. Consequently, rotor current increases significantly. Experimental results indicate that this increased current is primarily load current, which is more in-phase with the voltage compared to the magnetizing current, which is inherently reactive. As a result, the overall power factor increases, leading to higher power input. In contrast, if ChatGPT-4 and MATLAB/Simulink models do not account for saturation effects and variations in magnetizing inductance under overload, the predicted power factor may show a decreasing trend [24].

The experimental results indicate that the theoretical models in ChatGPT-4 and MATLAB/Simulink effectively predict the performance trends of an induction motor under normal operating conditions. However, the simulated results may deviate from the actual motor behavior under overload conditions. This discrepancy arises from the limitations of linear assumptions, the omission of certain power losses, and uncontrollable external factors, leading to differences between the simulated and experimentally measured values.

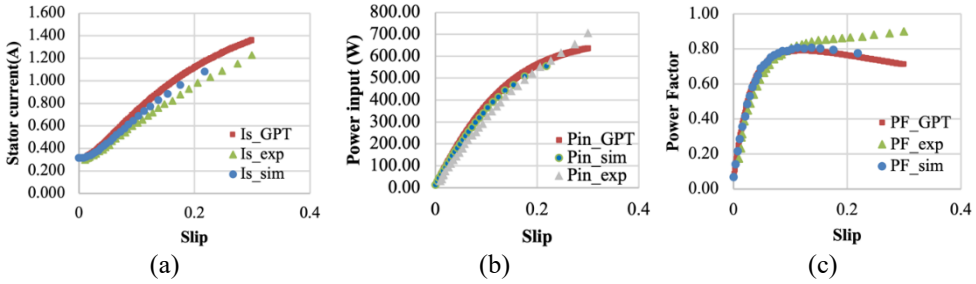


Figure 5. Stator current, power input, and power factor characteristics of the induction motor obtained from ChatGPT-4, MATLAB/Simulink, and experimental data: (a) stator current vs. slip, (b) power input vs. slip, and (c) power factor vs. slip

4.2. Power output, torque, and efficiency

Figure 6 compares the torque, power output, and efficiency of the motor obtained from ChatGPT-4 calculations, MATLAB/Simulink simulations, and experimental tests over the same slip range. Under normal load conditions, the torque curve obtained from the analysis conducted using ChatGPT-4 and MATLAB/Simulink closely aligns with experimental results, as shown in Figure 6(a). However, under overload conditions, the experimentally measured torque increases, whereas the torque predicted by ChatGPT-4 and MATLAB/Simulink remains relatively constant, exhibiting a similar trend in both simulations. This discrepancy may be attributed to magnetic saturation. The models used in ChatGPT-4 and MATLAB/Simulink typically rely on equations with constant parameters, such as X_1, X_2, and X_m, which may not fully capture the effects of magnetic saturation in the rotor and stator cores. Under overload conditions, the current flowing through the windings increases, leading to magnetic saturation, which in turn reduces the inductance values. This reduction in inductance can result in a higher torque than what is predicted by the models. Additionally, the increased current flow causes a rise in the temperature of the windings, thereby altering their resistance, particularly the R_2 [22].

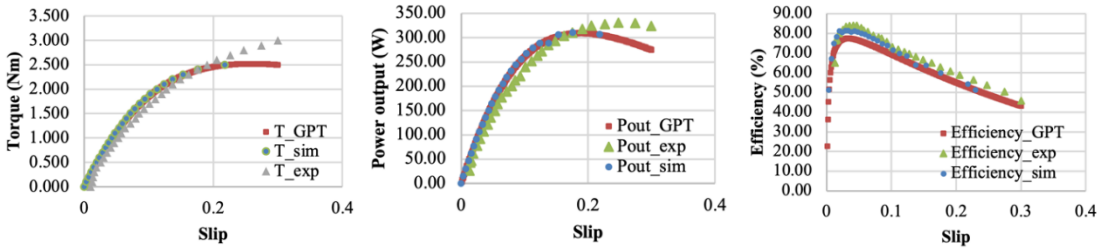
In practical experiments, the increase in temperature may lead to the resistance drop compensation effect [25], which can enhance the motor's ability to generate higher torque. Additionally, dynamic effects may contribute to discrepancies between experimental results and numerical models. Since numerical models often assume steady-state operation, they may not fully capture the motor's dynamic response under overload conditions. Factors such as the skin effect in the rotor bars, variations in flux leakage, and eddy current losses can influence the motor's behavior in ways not accounted for in steady-state models. Finally, nonlinear effects inherent in real motors, such as hysteresis loss and stray losses [12], may vary with increasing load. These nonlinear phenomena can contribute to torque enhancement under overload conditions, whereas numerical models may not fully incorporate these effects.

For Figure 6(b), the power output curve exhibits a similar trend to the torque curve. Specifically, under overload conditions, experimental results indicate that the power output is higher than the values predicted by the models from ChatGPT-4 and MATLAB/Simulink. In contrast, the power output curves obtained from ChatGPT-4 and MATLAB/Simulink show significant agreement with each other. This phenomenon can be explained by the limitations of the numerical models, as discussed in subsection 4.1. These models do not fully account for the effects of magnetizing inductance, magnetic saturation, and harmonic distortion. Under overload conditions, the increased current flow leads to saturation in the iron core, resulting in distortions in both the current and flux waveforms. Consequently, the experimentally measured root mean square (RMS) values were generally higher than the model predictions. This discrepancy is primarily attributed to harmonic components and other practical nonidealities in the motor waveforms, which are not represented in the fundamental-frequency model based on purely sinusoidal excitation [26].

In Figure 6(c), the efficiency curve obtained from simulations using ChatGPT-4 and MATLAB/Simulink increases with load until it reaches a peak efficiency point, which typically occurs near the rated load. For the induction motor used in this study, the peak efficiency is observed at around 1.2 Nm. Beyond this point, efficiency gradually decreases under overload conditions due to increased losses, such as core loss and stray load loss. The results from ChatGPT-4 and MATLAB/Simulink exhibit significant agreement, as both rely on the same mathematical assumptions and modeling approaches. However, under overload conditions, the experimentally measured efficiency curve is higher than those predicted by the simulations. This discrepancy can be attributed to two primary factors: i) as the iron core enters the saturation region, magnetizing reactance decreases, and core loss may not increase as expected in the linear model, and

ii) harmonic distortion and waveform deviations result in experimental measurements that better reflect the actual distortions in current and flux waveforms. These distortions can lead to higher measured power output and, consequently, a higher efficiency than that predicted by models that assume purely sinusoidal waveforms. Previous experimental studies have shown that voltage and current harmonics significantly alter the current, power, power factor, and losses of induction motors, and these effects are not represented in fundamental-frequency models based on purely sinusoidal excitation [27], [28].

The findings of this study indicate that the theoretical models developed using ChatGPT-4 and MATLAB/Simulink effectively predict the behavior of the motor under normal load conditions. However, under overload conditions, the simulations exhibit limitations in capturing nonlinear phenomena, such as magnetic saturation, dynamic effects, and harmonic distortion. These factors contribute to discrepancies between the simulated and experimental results, leading to higher measured values of torque, power output, and efficiency in practical experiments compared to the predictions of linear assumption-based models.



(a) (b) (c)

Figure 6. Torque, power output, and efficiency characteristics of the induction motor obtained from ChatGPT-4, MATLAB/Simulink, and experimental data: (a) motor torque vs. slip, (b) power output vs. slip, and (c) efficiency vs. slip

4.3. Data analysis using root mean square error and Pearson correlation coefficient

The simulation results obtained using ChatGPT-4 and MATLAB/Simulink were analyzed and compared against experimental data (reference values) to evaluate their accuracy. The data used for this analysis were derived from the spreadsheet utilized to generate the graphs in subsections 4.1 and 4.2. The scope of the analysis was limited to a slip range of 0 to 0.3, allowing for an assessment of the errors in the predictions made by ChatGPT-4 and MATLAB/Simulink relative to the experimental reference values. This comparison aims to determine the advantages and limitations of using AI-based analysis for evaluating the performance of an induction motor. The parameters considered in this analysis include stator current, power input, power factor, torque, power output, and efficiency, as summarized in Table 2. The statistical methods used for evaluation include the RMSE to quantify prediction errors and the PCC to assess the relationship between the predicted values from ChatGPT-4 and MATLAB/Simulink and the reference experimental values. The discussion of error analysis using RMSE and statistical correlation via PCC follows the results presented in Table 2.

RMSE is used to measure the average deviation between the predicted values (from ChatGPT-4 or MATLAB/Simulink) and the actual experimental results. A lower RMSE value indicates a prediction that is closer to the true value. The analysis shows that the RMSE values for both ChatGPT-4 and MATLAB/Simulink are relatively low and comparable across all cases. For instance, in the cases of stator current, power input, and power output, MATLAB/Simulink exhibits a lower RMSE than ChatGPT-4, suggesting a higher accuracy. However, for torque and efficiency, the RMSE values for both methods are nearly identical, indicating similar predictive performance.

PCC is used to measure the linear relationship between the predicted and actual values. A PCC value closer to 1 or -1 indicates a stronger correlation. The analysis shows that the correlation coefficients for both ChatGPT-4 and MATLAB/Simulink are very similar. In general, the PCC values are high, approaching 1, which indicates a strong correlation in all cases except for efficiency. The overall PCC values for ChatGPT-4 range from 0.974 to 0.991, while those for MATLAB/Simulink range from 0.964 to 0.992. The close agreement between these values suggests that both prediction models produce highly similar results and exhibit a strong correlation with the experimental data.

Based on the results in Table 2, while the RMSE values for MATLAB/Simulink are slightly lower than those for ChatGPT-4 in certain cases, the overall error rates remain comparable, with minimal differences. The PCC values for both ChatGPT-4 and MATLAB/Simulink indicate a strong correlation between the predicted and actual values, demonstrating that both methods are suitable for predicting and

analyzing the performance of an induction motor. In the case of efficiency, the RMSE for ChatGPT-4 is relatively higher; however, it still maintains a strong correlation with the experimental results, with PCC values of 0.975 for ChatGPT-4 and 0.964 for MATLAB/Simulink. Based on these findings, it can be concluded that both methods effectively predict the performance parameters of the induction motor and exhibit strong correlations with the experimental data.

The predictions obtained from MATLAB/Simulink may be more accurate in certain cases, such as stator current and power factor. However, discrepancies in some parameters may arise due to differences in computational techniques, data processing methods, or parameter settings between ChatGPT-4 and MATLAB/Simulink. The PCC results indicate that both ChatGPT-4 and MATLAB/Simulink exhibit a consistently high correlation across all parameters, ranging from 0.96 to 0.99. This strong correlation suggests that both methods effectively predict the performance trends of an induction motor, including current, power, power factor, torque, and efficiency, with results that closely align with experimental values. A comparison of the two analytical methods reveals that ChatGPT-4 demonstrates a strong ability to predict results that align well with the reference data patterns, as indicated by its high PCC values. Additionally, for certain parameters, such as power output, ChatGPT-4 exhibits a slightly lower RMSE than MATLAB/Simulink. Conversely, MATLAB/Simulink generally yields lower RMSE values across multiple parameters, suggesting that its numerical predictions tend to be more precise.

In summary, both methods produce reliable results in terms of trend prediction, as evidenced by their high PCC values. MATLAB/Simulink shows slightly greater accuracy in quantitative predictions, reflected by its lower RMSE values in several parameters. However, ChatGPT-4 demonstrates a comparable ability to capture trends and, in some cases, achieves better RMSE performance. Therefore, it can be concluded that both methods exhibit a high level of accuracy, with minimal differences, and their applicability depends on specific objectives and parameter conditions.

Table 2. Comparative analysis of RMSE and PCC between predictions from ChatGPT-4 and MATLAB/Simulink

Parameters	RMSE		PCC	
	ChatGPT	MATLAB	ChatGPT	MATLAB
Stator current	0.110	0.073	0.983	0.978
Power input	39.708	35.985	0.991	0.987
Power factor	0.070	0.059	0.974	0.985
Torque	0.156	0.155	0.990	0.992
Power output	21.428	22.031	0.986	0.988
Efficiency	5.617	4.719	0.975	0.964

5. CONCLUSION

This study demonstrates the feasibility of employing ChatGPT-4 as a complementary tool for analyzing the performance of three-phase induction motors by benchmarking its predictions against MATLAB/Simulink simulations and experimental measurements. The main contribution is to show that AI-based analysis can effectively capture performance trends and key operating characteristics under rated conditions, offering a rapid and intuitive alternative for preliminary analysis, education, and early-stage design evaluation. A 175 W, three-phase, 380 V, 50 Hz, four-pole induction motor is used with ChatGPT-4 and MATLAB/Simulink against experimental data. Both methods exhibited high predictive accuracy under normal load. The results show high PCCs and low RMSE values, thereby reliably capturing the motor's linear behavior under rated conditions. Nevertheless, the study also reveals limitations inherent in linear modeling approaches when motors operate under overload conditions, where nonlinear effects, such as magnetic saturation, dynamic behavior, and waveform distortion become significant. These limitations highlight the need for cautious interpretation of AI- and simulation-based predictions beyond nominal operating ranges. Future research will focus on integrating physics-informed and data-driven AI models to better account for nonlinear phenomena, extending the approach to higher-power machines and variable-speed drive systems, and exploring hybrid AI–simulation frameworks for real-time monitoring, diagnostics, and control of electrical machines, thus providing an innovative tool for both education and research in electrical machine analysis.

ACKNOWLEDGMENTS

This work was supported by Rajamangala University of Technology Suvarnabhumi, which led and coordinated the research. The authors also gratefully acknowledge Bangkokthonburi University for providing the experimental equipment.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

Informed consent was not applicable as this study did not involve the collection of personal information that could identify individuals.

ETHICAL APPROVAL

Ethical approval is not applicable as this study did not involve research on humans or animals.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the first author [NW] and corresponding author [CB] on request.

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