Magnetic rotor breakage study in permanent magnet synchronous motor at COMSOL multiphysics and fault detection using machine learning

Estudo de quebra de rotor magnético em motor síncrono de ímã permanente na COMSOL multiphysics e detecção de falhas usando aprendizado de máquina

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ABSTRACT
Electric vehicles are one of the most important means in the industrial sector due to their frequent use and depend primarily on electric motors. Electric motors of all types, synchronous and asynchronous, face many faults in the rotor and stator, affecting the performance’s reliability. Researchers are seeking to find ways that enable us to detect and diagnose faults in electric motors based on smart and fast methods. Early detection of problems in electric motors is vital, especially in areas such as electric vehicles. This study focuses on magnetic rotor breakage (MRB) in permanent magnet synchronous motors (PMSM). We use a simulation tool such as COMSOL Multiphysics as a simulation tool. This platform is a widely used software for modeling and analyzing complex electromagnetic systems. The study also addresses fault detection using machine learning. This involves using data analysis and pattern recognition techniques to distinguish between normal and defective states of the motor. This is an important step to improve the reliability of motors and identify potential failures in advance. Five different machine learning algorithms such as Extreme Gradient Boosting (XGBoost), AdaBoost, Gradient Boosting (GB), Naive Bayes (NB), and Random Forest (RF) are used in the study. Data from four different cases obtained from the PMSM design were used to train and test the machine-learning models. The results obtained show how accurate the proposed models are in diagnosing PMSM problems, especially MRB.

Keywords: magnetic rotor breakage (MRB), machine learning (ML), fault detection, COMSOL multiphysics.

RESUMO
Os veículos elétricos são um dos meios mais importantes do setor industrial devido ao seu uso frequente e dependem principalmente de motores elétricos. Motores elétricos de todos os tipos, síncronos e assíncronos, enfrentam diversas falhas no rotor e no estator, afetando a confiabilidade do desempenho. Os pesquisadores buscam encontrar formas que nos permitam detectar e diagnosticar falhas em motores elétricos com base em métodos inteligentes e rápidos. A detecção precoce de problemas em motores elétricos é vital, especialmente em áreas como veículos elétricos. Este estudo enfoca a quebra magnética do rotor (MRB) em motores síncronos de ímãs permanentes (PMSM). Usamos uma ferramenta de simulação como o COMSOL Multiphysics como ferramenta de simulação. Esta plataforma é um software amplamente utilizado para modelagem e análise de sistemas eletromagnéticos complexos. O estudo também aborda a detecção de falhas usando aprendizado de máquina. Isto envolve o uso de análise de dados e técnicas de reconhecimento de padrões para distinguir entre estados normais e defeituosos do motor. Este é um passo importante para melhorar a confiabilidade dos motores e identificar antecipadamente possíveis falhas. Cinco algoritmos diferentes de aprendizado de máquina, como Extreme Gradient Boosting (XGBoost), AdaBoost, Gradient Boosting (GB), Naive Bayes (NB) e Random Forest (RF) são usados no estudo. Dados de quatro casos diferentes obtidos do projeto PMSM foram utilizados para treinar e testar os modelos de aprendizado de máquina. Os resultados obtidos mostram o quão precisos são os modelos propostos no diagnóstico de problemas de PMSM, especialmente MRB.
1 INTRODUCTION

The reliability and performance of electric motors are crucial in many industrial applications. Early diagnosis of unexpected failures such as Magnetic Rotor Breakage (MRB) is important for the operational continuity and efficiency of electric motors. This literature review examines the use of COMSOL Multiphysics and artificial intelligence-based methods for early diagnosis of the MRB issue [1]. COMSOL Multiphysics is a widely used tool for modeling and simulating the electromagnetic performance of electric motors. Studies demonstrate the use of COMSOL for modeling the effects of mechanical failures like magnetic rotor breakage. These research efforts help understand the diagnosis and effects of such failures by analyzing the electromagnetic changes caused by issues like magnetic rotor breakage [2].

Artificial intelligence is increasingly employed for early fault diagnosis of electric motors. Particularly, machine learning techniques can identify patterns from large datasets, facilitating early diagnosis of issues like magnetic rotor breakage. Various studies show that artificial intelligence-based methods successfully diagnose and classify electric motor faults, including magnetic rotor breakage [3, 4, 5].

There is currently a lack of detailed examination in the literature regarding the use of COMSOL Multiphysics and artificial intelligence-based methods for early diagnosis of magnetic rotor breakage issues. Future research should further explore the integration of these two approaches and effectively utilize these technologies to enhance the reliability of electric motors.

Electric motors are susceptible to various electrical and mechanical issues, prompting ongoing research into methods for quickly diagnosing faults to minimize losses. Among the most critical malfunctions encountered in electric motors, both in rotor and stator components, are Bearing Faults, Eccentricity, winding faults, and Broken Rotor Bars [6, 7].

Modern design programs like Ansys Maxwell and COMSOL Multiphysics are commonly employed to design and analyze various electric motors. For
instance, Ansys Maxwell was utilized in [8] to design a Permanent Magnet Synchronous Motor (PMSM), with proposed designs further discussed in [9]. PMSMs, crucial components in electric vehicles, are engineered based on battery power specifications outlined in [10, 11]. Efforts to enhance PMSM efficiency have also been made using Ansys Maxwell [12].

The finite element method, as implemented in Ansys Maxwell, has been instrumental in studying Demagnetization Fault Diagnosis for PMSMs [13, 14]. Moreover, artificial intelligence techniques were applied to analyze demagnetization faults in PMSMs [15]. Static Eccentricity, another prevalent issue affecting the PMSM air gap, has been extensively investigated [16, 17]. Detection of Static Eccentricity and fault diagnosis were addressed in [18], proposing the utilization of Elman Neural Network (ENN) technology [19].

Research efforts have extended to utilizing machine learning for diagnosing and detecting bearing faults, with data from Case Western Reserve University serving as a basis for analysis [20], [5]. Multi-Class Machine Learning (ML) approaches have been explored [21], alongside Convolutional Neural Networks (CNN) [22]. Various methods, including Transfer Learning-Based VGG, have been proposed for bearing fault diagnosis and demagnetization determination in PMSMs [23, 24, 25].

Inter-Turn Short Circuit faults in PMSMs have been diagnosed using Deep Reinforcement Learning [26] and Deep Transfer Learning [27]. Machine learning techniques have also been employed for diagnosing Broken Rotor Bars in induction motors [4].

In this study, a Permanent Magnet Synchronous Motor was designed using COMSOL Multiphysics. To evaluate the motor's health condition in comparison to a faulty condition, a fault was introduced into the magnetic rotor. Machine learning algorithms were then utilized to detect faults in the motor, leveraging data parameters such as Total Electric Energy, Total Magnetic Energy, Coil Power, and Coil Concatenated Flux. The aim of this work is early detection of Magnetic Rotor Breakage in PMSM. The results of this study underscore the efficacy of machine learning in fault detection within electric motors.
2 DESIGN PMSM USING COMSOL MULTIPHYSICS

The design of the PMSM depends on several characteristics, including the dimensions of the machine components, and to solve the design mesh equations, COMSOL Multiphysics uses the finite element method [28, 29, 30].

2.1 MODELING THE PMSM WITH COMSOL MULTIPHYSICS

Start by creating a finite element model of the PMSM in COMSOL Multiphysics. This model should include the geometry of the motor, the material properties of the components, and the electromagnetic equations governing its behavior. Incorporate the broken magnetic rotor into the model. This may involve introducing a structural defect in the rotor and simulating its effect on the motor’s performance.

2.2 SIMULATING MOTOR PERFORMANCE

Use the COMSOL model to simulate the performance of the PMSM under normal operating conditions. This will establish a baseline for comparison when the rotor is broken. Simulate the behavior of the PMSM with the broken magnetic rotor. This will help understand how the fault affects the motor’s performance, including changes in torque, speed, and efficiency.

2.3 DATA COLLECTION AND FEATURE ENGINEERING

Generate training data by simulating the PMSM under various operating conditions with both healthy and broken rotors. Extract relevant features from the simulation data. These features could include electrical quantities (current, voltage), mechanical quantities (torque, speed), and any other parameters indicative of the rotor condition.

The specifications of the machine’s various variables for the final design are detailed in Figure 1. Table 1 provides an overview of the basic rotor design.

<table>
<thead>
<tr>
<th>Component</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outer diameter of rotor</td>
<td>30 mm</td>
</tr>
<tr>
<td>diameter of the shaft</td>
<td>10 mm</td>
</tr>
<tr>
<td>Number of magnetic poles</td>
<td>8</td>
</tr>
<tr>
<td>radius of magnet fillet</td>
<td>0.6 mm</td>
</tr>
<tr>
<td>width of the magnets</td>
<td>2.5 mm</td>
</tr>
</tbody>
</table>

Source: Authors.
Table 2 – stator variables.

<table>
<thead>
<tr>
<th>Component</th>
<th>values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outer diameter of stator</td>
<td>50 mm</td>
</tr>
<tr>
<td>thickness of back-iron</td>
<td>1.5 mm</td>
</tr>
<tr>
<td>width of the tooth</td>
<td>3 mm</td>
</tr>
<tr>
<td>height of the tooth</td>
<td>8 mm</td>
</tr>
<tr>
<td>Number of stator slots</td>
<td>12</td>
</tr>
<tr>
<td>slot winding2</td>
<td>2</td>
</tr>
<tr>
<td>size of air external3 mm</td>
<td>3 mm</td>
</tr>
</tbody>
</table>

Source: Authors.

2.4 MAGNETIC ROTOR BREAKAGE IN PMSM

The Magnetic Rotor Breakage in the COMSOL Multiphysics program is done by setting a value $B_r=0$, as shown in Figure 2 extracted from the program.

In Figure 3 the number of magnets Rotor Breakage is determined.

Figure 2 – Equation remanent flux density.

Source: Authors.
ARTIFICIAL INTELLIGENCE IS RELIED UPON TO DIAGNOSE THE VARIOUS MALFUNCTIONS OF MAGNETIC ROTOR BREAKAGE WHERE THERE ARE FOUR CASES, HEALTH CASE, 1 MRB, 2 MRB, AND 3 MRB. AFTER IDENTIFYING THE DESIGN DEFECT IN EACH CASE, FOUR APPROPRIATE DATA ARE SELECTED TO DIAGNOSE EACH CASE. IN EACH CASE, 1000 DATA WERE EXTRACTED, AND THE TOTAL DATA WAS 4000 * 4, AND 80 % WERE SELECTED FOR TRAINING AND 20 % FOR TESTING. THE PROPOSED AI TECHNIQUES ARE XGBoost, AdaBoost, Gradient Boosting, Naive Bayes, and Random Forest [31], [4].

3 FAULT DETECTION OF MRB USING ML

Integrate the trained machine learning model into a real-time monitoring system for the PMSM. Continuously monitor the motor's operation and use the machine learning model to detect any signs of rotor failure. Implement appropriate response mechanisms, such as alarms or automatic shutdown procedures, to mitigate the consequences of a detected fault.
3.2 OPTIMIZATION AND FURTHER RESEARCH

Fine-tune the machine learning model and COMSOL simulations based on feedback from real-world operation. Explore additional features and techniques to improve fault detection accuracy and reliability. Consider other potential applications of the combined COMSOL and machine learning approach in motor diagnostics and prognostics.

By following these steps, we can effectively study the effects of a broken magnetic rotor in a PMSM using COMSOL Multiphysics and develop a machine learning-based fault detection system for enhanced motor reliability and performance.

4 SIMULATION RESULT AND DISCUSSION

4.1 HEALTH STATUS RESULTS OF THE PMSM DESIGN

Figure 4 shows the three-phase current in the healthy state. From Figure 5 we notice that the value of the electric field norm reaches 1.7 V/m. Figure 6 shows magnetic flux density, where its highest value is 1 T, and Figure 7 shows energy density. Figure 8 shows the distribution of magnetic flux density in all parts of the machine in the healthy case and the condition of 3 MRB.
Figure 5 – electric field norm.

Source: Authors.

Figure 6 – magnetic flux density.

Source: Authors.

Figure 7 – energy density.

Source: Authors.
4.2 DATA SELECTED TO PERFORM AN MRB DETECT

In each of the four cases, four types of data were chosen: Total Electric Energy, Total Magnetic Energy, Coil Power, and Coil Concatenated Flux. In each type of data, the four cases were explained, with each 1000 data representing one case respectively, as follows: health status, 1MRB, 2MRB, and 3MRB, as Figures 9 to 12 show.
Figure 10 – Total Magnetic Energy.

Source: Authors.

Figure 11 – Coil Power.

Source: Authors.

Figure 12 – Coil Concatenated Flux.

Source: Authors.
A correlation matrix is a tool used to visualize the relationship between variables in a dataset. It is created by calculating the Pearson correlation coefficient between each pair of variables. The Pearson correlation coefficient takes values between -1 and +1:

- +1 indicates a perfect positive relationship.
- 0 indicates no relationship between the two variables.
- -1 indicates a perfect negative relationship.

Here, each row and column represent a variable. Looking along the diagonal (from top left to bottom right), the correlation of each variable with itself is 1 (because each variable has a perfect relationship with itself). The other cells show the correlation coefficient between the respective two variables.

A correlation matrix is used to understand the relationships between variables in a dataset and is commonly employed in datasets with numerous variables. It provides guidance for analyses such as modeling or dimensionality reduction by identifying the relationships between variables.

Figure 13 presents the confusion matrices for each machine learning algorithm, accompanied by their corresponding F1 scores denoted as a, b, c, d, and e. Additionally, in Figure 13 (f), the confusion matrix is depicted alongside the interrelation among the algorithms.

![Figure 13 – Confusion matrix algorithms with F1_score.](image-url)
Early detection of magnetic rotor breakage is critical to improve the reliability of electric motors and ensure operational continuity. The combination of COMSOL Multiphysics and AI-based methods can play an important role in the detection and prevention of these problems and contribute to making electric motors more reliable.

In this study, a PMSM was designed and data was acquired to detect magnetic rotor breakage faults in different cases. Machine learning was used to detect the fault using techniques such as XGBoost, AdaBoost, Gradient Boosting GB, Naive Bayes, and Random Forest. From the extracted results, it is clear that the accuracy of the results reached about 99.5% in XGBoost, Random Forest in 98.3% and Gradient Boosting 96.4%.

Machine learning can diagnose and detect other faults in electric motors based on data such as eccentricity.

5 CONCLUSION

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REFERENCES


