

Field Reconstruction of PMSM Demagnetization Fault based on Gappy POD

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The previous work on the demagnetization fault detection of permanent synchronous magnet motor (PMSM) focuses on giving information of the fault's existence or severity. However, the magnetic flux density distribution is rarely considered which provides the detailed model of the machine. As the sensor configuration affects the accuracy of the reconstructed field, in this paper, a greedy algorithm associated with a reduced order model based on POD is firstly proposed to solve the sensor placement problem while the sensors' positions are confined on the surface of the stator for the ease of installation. And then the gappy proper orthogonal decomposition (Gappy-POD) is used to reconstruct the magnetic field when limited measurement points are available. An example of 2D surface-mounted PMSM with local demagnetization is presented. The results show that the Gappy-POD can reconstruct the magnetic field accurately with limited data and comparing to the randomly selected sensors, the sensor configuration determined by the proposed greedy algorithm provides better reconstruction performance.

Index Terms—Demagnetization fault, field reconstruction, Gappy POD, permanent magnet synchronous motor.

I. INTRODUCTION

THE FAULT detection is important to ensure the safe and stable operation of permanent magnet machines and the demagnetization is one of the main faults. Several methods have been proposed to diagnose the demagnetization including the current signature analysis, the voltage signature analysis, magnetic signal analysis, torque analysis, etc. [1]. The above methods can draw a conclusion of the existence and the degree of demagnetization but are not able to provide a more detailed magnetic field distribution under demagnetization condition, however the latter is necessary to build the motor model which can be used for example in fault-tolerant control [2].

Field reconstruction needs to solve the inverse problem by minimizing the error between the reconstructed field and the exact field which demands multiple calculations of forward problem so the efficiency is one of the concerns. The neural network has been proposed to provide a real-time solver [3] however the training process is time consuming and it needs a large training dataset. The Gappy-POD uses a set of POD modes to reconstruct the field with a small number of samples and has the advantages of fast calculation speed and small database dependence [4] which makes it suitable for the PMSM demagnetization field reconstruction.

In order to reconstruct the field accurately with limited sensors, the sensor placement also needs to be considered. The Discrete Empirical Interpolation Method (DEIM) has been applied to determine the sensors' positions [5] which are mainly in the airgap and some even inside the rotor or stator, however, due to the ease of installation, the sensors measuring the leakage flux are better to be put outside the machine.

In this work, a POD with a greedy algorithm is used for optimal sensor placement in PMSM under local demagnetization and a Gappy-POD is applied to reconstruct the magnetic field distribution. The field reconstruction error is lower for the optimal sensor placement using the greedy algorithm compared with randomly placed sensors.

II. FIELD RECONSTRUCTION VIA GAPPY POD

A. POD BASIS

The POD basis is obtained by the Singular Value Decomposition (SVD) on the snapshot matrix S

$$S = \{\mathbf{u}_{\theta_1}, \mathbf{u}_{\theta_2}, \dots, \mathbf{u}_{\theta_m}\} \quad (1)$$

$$S = U\Sigma V^T \quad (2)$$

where $\mathbf{u}_{\theta_1}$ to $\mathbf{u}_{\theta_m}$ are the solutions of m selected samples in the parameter space of the full model problem. U is the left singular vector whose columns can be used as orthogonal basis, and Σ is the singular value matrix.

The magnitude of the singular value describes the relative importance of the related singular vectors and an energy truncation is applied to obtain a reduced basis of modes $\{\phi_1, \phi_2, \dots, \phi_p\}$ which is sufficient to reconstruct the full model solutions accurately.

B. GREEDY ALGORITHM FOR SENSOR PLACEMENT

As discussed in [4], the sensor placement problem is a combinatorial problem which involves massive calculation. We use a greedy algorithm in Table I to choose the sensor positions and the idea is keeping the orthogonality of the POD basis after applying the mask vector. In the algorithm, the inputs are the POD basis Φ and the available sensor position set P , and the output is the mask matrix m which determines the selected sensor positions.

TABLE I
GREEDY ALGORITHM FOR SENSOR PLACEMENT

1:	Input $\Phi = \{\phi_1, \phi_2, \dots, \phi_k\}$, $P = \{p_1, p_2, \dots, p_k\}$
2:	Output: m
3:	select the point in P to have $\max \{ \mathbf{m} \cdot \phi_1 \}$
4:	update m , update $U = [\phi_1]$
5:	for $i = 2$ to k do
6:	Solve $(\sum_{j=1}^{i-1} \mathbf{m} \cdot U_j)\mathbf{c} = \mathbf{m} \cdot \phi_i$ for c
7:	$r = \phi_i - U\mathbf{c}$

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8: select the point in $\mathbf{P}$ to have $\max \{ |r| \}$
9: update $\mathbf{m}$, update $\mathbf{U} \leftarrow [\mathbf{U} \ \boldsymbol{\phi}_i]$
10: end for

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### C. GAPPY-POD

The Gappy-POD uses the POD basis to reconstruct the complete field with an incomplete data set. A mask vector  $\mathbf{m}$  is introduced to describe the positions of missing data. The incomplete field  $\hat{\mathbf{F}}$  with missing data can be represented by the inner product of a mask vector  $\mathbf{m}$  and the complete field  $\mathbf{F}$

$$\hat{\mathbf{F}} = \mathbf{m} \cdot \mathbf{F} = (m_1 \ m_2 \ \dots \ m_n) \begin{pmatrix} \mathbf{F}(x_1) \\ \mathbf{F}(x_2) \\ \dots \\ \mathbf{F}(x_n) \end{pmatrix} \quad (3)$$

If the  $i$ -th data point  $\mathbf{F}(x_i)$  is missing in  $\hat{\mathbf{F}}$ , the  $i$ -th element  $m_i$  in mask vector  $\mathbf{m}$  is 0, otherwise the  $m_i$  is 1.

Assuming that the reconstructed field can be characterized by the existing POD modes, an intermediate reconstructed field  $\tilde{\mathbf{F}}$  is

$$\tilde{\mathbf{F}} = \sum_{i=1}^p \mathbf{m} \cdot \boldsymbol{\phi}_i b_i \quad (4)$$

The coefficient  $b_i$  can be computed by minimizing the error  $e$  between the incomplete field  $\hat{\mathbf{F}}$  and  $\tilde{\mathbf{F}}$

$$e = \|\hat{\mathbf{F}} - \tilde{\mathbf{F}}\|^2 \quad (5)$$

$\hat{\mathbf{F}}$  contains the known data, for example, the sensor measurements, and by solving (6) the coefficient  $b_i$  are calculated.

$$\frac{\partial e}{\partial b_i} = 0 \quad (6)$$

Finally, the complete reconstructed field is

$$\mathbf{F} = \sum_{i=1}^p \boldsymbol{\phi}_i b_i \quad (7)$$

### III. NUMERICAL EXAMPLE

A 3-phase surface-mounted PMSM which has 2 pole pairs and 24 slots is considered as an example in Fig. 1(a). The sensors are placed in a circle close to the outer surface of the stator to measure the leakage magnetic flux. The mesh is shown in Fig. 1(b) and the number of elements is 17260.

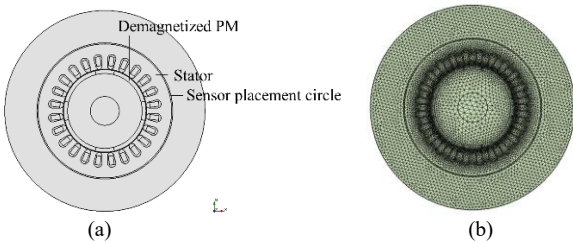


Fig. 1. A surface-mounted PMSM model. (a) Geometry (b) Mesh

For the POD procedure, the remanence  $B_r$  of the upper right PM is set as the parameter to consider the local demagnetization. The sampling of the  $B_r$  is uniform from 0 to 1 T for every 0.05 T thus the number of snapshots is 21. The magnetic flux density  $\mathbf{B}$  is used to form the snapshot matrix.

The field is reconstructed based on Gappy-POD using two sensor configurations, one is by using the proposed greedy algorithm, the other is by choosing the sensor positions randomly. The reconstructed magnetic flux density  $\mathbf{B}_{reconst}$  and the error between FEM result and reconstructed field are shown in Fig. 2. The maximum error of the sensor placement using greedy algorithm and the randomly placed sensors are  $2.5\text{E-}2$  T and  $8.5\text{E-}2$  T, respectively, which indicates the greedy algorithm provides a better sensor placement and the field reconstruction based on Gappy-POD is effective. The detail of the reconstruction error analysis and a more realistic situation considering the rotation will be included in the full paper.

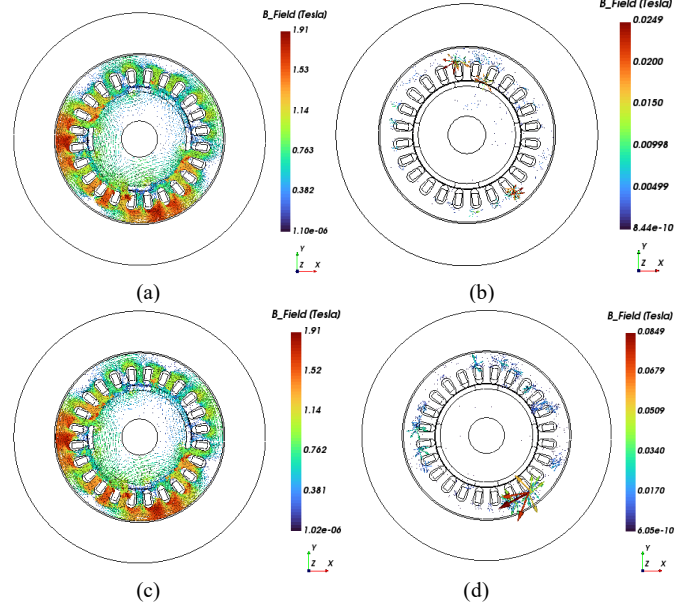


Fig. 2. Comparison of reconstruction field and error by Gappy-POD for different sensor configurations when  $B_r = 0.56$  T. (a)  $\mathbf{B}_{reconst}$  using greedy algorithm. (b) error using greedy algorithm. (c)  $\mathbf{B}_{reconst}$  using random placement. (d) error using random placement.

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