

A Gradient Based Optimization Algorithm for Fuel Cell Stack Diagnostics from External Magnetic Field Measurements

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This article presents a new inverse algorithm based on magnetic tomography for fuel cell stack diagnostics. The aim is to determine the local internal resistivities of fuel cell stacks from external magnetic field measurements. The inverse problem is solved by minimizing the difference between the simulated magnetic field and the measured magnetic field. Sensitivities are calculated using the adjoint state method, and numerical results are presented shown on a 3D-fault.

Index Terms—adjoint state method, inverse problem-solving, Fuel Cell, magnetic tomography, non-linear optimization

I. INTRODUCTION

PROTON exchange membrane fuel cell (PEMFC) is a power generator that represents an environmentally-friendly alternative to fossil fuels. A PEMFC stack is an assembly of several single fuel cells (FC) connected in series. Aging is a major problem, requiring precise diagnostics to adjust stack control, replace faulty cells and thus optimize its reliability and lifetime. Magnetic tomography (MT) is a non-invasive diagnostic method that provides local current densities J . In this method, the external magnetic field B_m created by the current flowing through the stack is measured using an array of sensors placed around it. A numerical model is then inverted to calculate local current densities in the stack [1]–[3]. In this paper, we present a non-invasive method for retrieving physical properties within a stack. While most works propose methods for determining current densities, the originality of our approach lies in the direct identification of local resistivities ρ_{local} using a nonlinear optimization algorithm. Indeed, a local resistivity increase is a signature of local reversible or irreversible degradations. In a previous work [4], we applied our method on a 2D example, while in the present one, the method is extended for the 3D problem resolution. To limit the solution space and improve the convergence of the solving process, a constraint is added imposing the global stack voltage (U_s). Both residual and constraint sensitivities are computed with adjoint method.

II. METHODOLOGY

A. Data acquisition and inverse problem parametrization

To measure the magnetic field B_m , we use the experimental environment originally presented by Ifrek et al. (see Fig. 1a) [2]. 60 magnetic field sensors are placed around the stack (see arrows in Fig. 1b), 30 of which measure the axial and 30 the radial component of the magnetic field at the same

time. This sensor array is moveable along the stack to dedicated sensor positions. The active region of the stack is divided into n volume elements (see FEM-model in Fig. 1b) where each element can have a different resistivity. This step is important to analyze 3D-faults such as catalyst poisoning, which impact only locally the FC-stack. Solving the inverse problem involves determining the local resistivities ρ_{local} , stored in ρ .

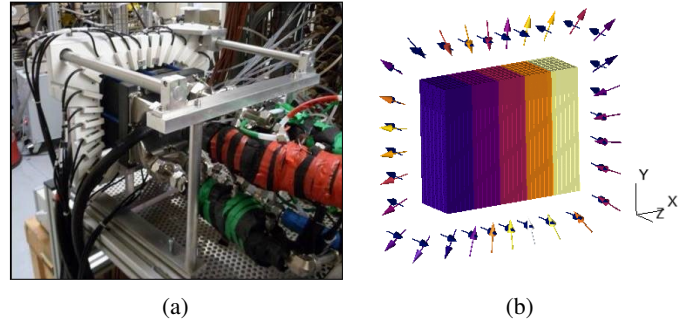


Fig. 1: FC-stack on test bench (a) FEM-Model with magnetic field sensors (arrows) around (b)

B. FEM Forward Problem-Solving

In this section, the numerical method used to calculate the external magnetic field of the resistivity map is briefly described. A FEM model (see Fig. 1b) is used to solve an electrokinetic problem and calculate the current distribution in the stack. The FEM model used is divided into 2 volume regions, one for the two end plates and one for the active area. The latter can be discretized into finite elements by compromising between precision and calculation time. Figure 1b shows the active region and 60 sensors around the stack. In the context of optimization, it is mandatory to work at constant current, even if the resistivity changes. An J-conforming FE formulation with an imposed current is therefore chosen, using facet functions to interpolate the current density. This formulation also strongly assures current conservation, enabling accurate evaluation of

the external magnetic field [5]. Subsequently, the magnetic field B_m on each sensor position is calculated with a numerical integration of Biot and Savart's law.

C. Inverse Problem-Solving

The original part of the method is the inverse approach for determining local resistivities in the stack using the gradient descent method [6] to reproduce B_m . To do this, we defined the following optimization problem:

$$\begin{aligned} \hat{\rho} = \arg \min_{\rho \in [\rho_{min}, \rho_{max}]} (||B_m - A J(\rho)||^2 + \alpha ||L\rho||^2) \\ s.t. \quad U_s(\rho) = U_M \end{aligned} \quad (1)$$

where the resistivity vector $\hat{\rho}$ is the optimized solution, A the discretized Biot-Savart matrix and $J(\rho)$ the current densities dependent on the local resistivities in the stack. This problem is ill-posed, so it needs to be regularized. We assume a fairly regular resistivity on the cell surfaces, so a regularized gradient between adjacent cells. Consequently, we add the regularization term $\alpha ||L\rho||^2$, with α as the regularization factor and L the gradient matrix of the resistivities. Moreover, the stack voltage U_s is added, to constraint the solution space. We provide the gradients by applying the adjoint state method as following:

$$\frac{dr(\rho)}{d\rho} = -\lambda \frac{dK}{d\rho} x \quad (2) \quad \frac{dU_s(\rho)}{d\rho} = -\lambda_{U_s} \frac{dK}{d\rho} x \quad (3)$$

where K represents the conductivity derivative of the FEM matrix, x the state variable and λ and λ_{U_s} are the adjoint state of residual and constraint respectively. After a scaling of the cost function and the constraint, the barrier and the constraint functions are incorporated in the objective function using the interior point method (IPM). The iterative Broyden-Fletcher-Goldfarb-Shanno (BFGS) method [7] is used to get the solution $\hat{\rho}$ of the problem. The detailed calculations will be presented in the full paper.

III. APPLICATION ON A NUMERICAL EXAMPLE

We applied the optimization approach on a numerical 3D-fault test case. A 3D resistivity map is aimed to be identified, composed of regular resistivity gradient and a very localized 3D-fault, shown in Fig. 2a) - left. The has a high resistivity (3 Ωm), placed in a zone with comparable low resistivity (1 Ωm). To solve this problem, we used the beforehand mentioned sensor positions and placed the sensor array on 3 defined positions along the stack length. Based on the positions, B_m is obtained with the forward model by using an FEM-mesh containing 448 elements with a different resistivity each. To avoid an inverse crime, we added artificial noise in the sensor range of ± 500 nT to B_m . Moreover, we chose a different mesh size of 175 elements for the inverse problem-solving, consequently the inverse problem has 175 degrees of freedom. The result is shown in Fig. 2a) - right and highlights the capability of our algorithm to find the 3D-fault in the stack. The regularization factor α is chosen with the L-Curve method [8], which demands min. 10 inverse problem resolutions with different α and returned an $\alpha = 6.0619 \cdot 10^{-11}$. The identified

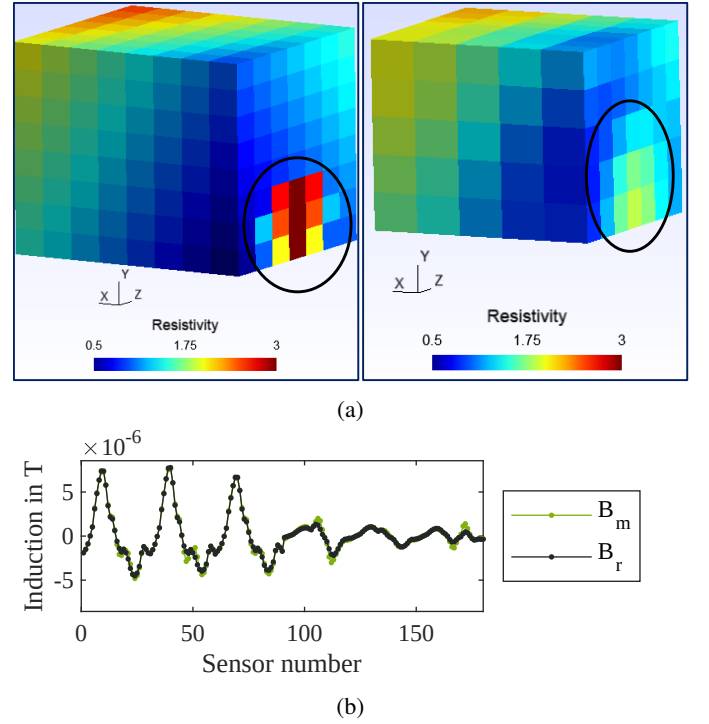


Fig. 2: (a) 3D visualization of a numerical example containing a placed 3D-fault (left) and the reconstructed result (right). (b) comparison of measured (B_m) and reproduced (B_r) magnetic signature.

3D-fault shows a maximum of 1.9 (Ωm). This difference with the initial resistivity map can be explained to the regularization term, which naturally smooths the solution. With this example, we were able to show, that the proposed algorithm is capable to identify localized 3D-faults in a simulated FC-stack. In the full paper we will present results obtained with real measurements.

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