Estimation of FEM model parameters using data assimilation - Application to an electrical machine

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The goal of this paper is to identify the parameter set of a given machine. The identification method is based on data assimilation coupled with a FEM model. Data assimilation method is an optimization approach that limits the space of candidate parameter sets by centering it to the ideal machine. An application to an electrical machine is presented based on the analysis of flux probe signals.

***Index Terms*—Data assimilation, electrical machine, measurement probes, numerical simulation.**

I. Introduction

NUMERICAL model based on Finite Element Method is widely used to study electrical machines. It requires the knowledge of different input parameters whose values are not always very well known. Furthermore, the construction of a machine can induce some imperfections. This typically leads to slight differences between the values obtained from the simulation of the ideal machine and the measurements achieved on the real machine. These differences are generally not significant in the case of global variables (emfs, currents ..). But, in the case of the investigation of local variables, particularly for the detection of small defects, it is important to base the healthy state of the real machine and not of that of the modelled ideal machine. It is then necessary to reach the model parameters related the healthy state of the real machine.

To do that, we use, in this paper, an approach based on data assimilation coupled with Finite Element Analysis (see section II). To highlight its interest, we apply it, through the use of twin experiments; to identify slight eccentricities of a healthy synchronous generator (see section III).

II. Data Assimilation Methodology

The data assimilation methodology [1] was first introduced in the field of meteorological study, to recover physical fields to improve weather forecasts.

The principle of this methodology consists in recovering as well as possible the "true parameter set" $\mathbf{x}_t$ of a considered system, by gathering all the information available on this system. The parameter identification minimizes an error function corresponding to the sum of two terms : the difference between the simulated data and measurements (as for classical parameter identification methods) and the distance between tested the parameter set and the parameter set of the ideal machine. This last distance tends to limit the space size of the candidate parameter sets and so, to reduce the processing time required by parameter estimation. The error function J is given by :

$$\begin{aligned} J(\mathbf{x}) \quad = \quad & \tfrac{1}{2}\left(H(\mathbf{x})-\mathbf{y}\right)^t \mathbf{R}^{-1}\left(H(\mathbf{x})-\mathbf{y}\right) \\ & +\tfrac{1}{2}\left(\mathbf{x}-\mathbf{x}_b\right)^t \mathbf{B}^{-1}\left(\mathbf{x}-\mathbf{x}_b\right) \end{aligned} \tag{1}$$

Let us denote $\mathbf{x}_b$ the background parameter set associated to its error represented by a covariance matrix $\mathbf{B}$. The actual measurements on the system are denoted $\mathbf{y}$ and refer to the manufactured machine signatures. The error matrix $\mathbf{R}$ is associated to these observations. The operator giving values comparable to $\mathbf{y}$ by the knowledge of $\mathbf{x}$ is called the observation operator, denoted H, and the simulated observations are then defined by $H(\mathbf{x})$.

Some enlightnening comments concerning (1) can be made. When we make strong assumptions on model and measurements, we notice that these cases are covered by the behavior of the function J. Thus, assuming that the background parameter set is completely wrong, the covariance matrix $\mathbf{B}$ tends to ∞ in quadratic form sense (i.e. $\mathbf{B}^{-1}$ is 0). The minimum of the function J corresponds directly to information given only by the obervations in order to get ideally $\mathbf{y} \approx H(\mathbf{x}_a)$. On the opposite side, the assumption that observations are useless implies that $\mathbf{R}$ tends to ∞. We can then deduce that J reaches the minimum when $\mathbf{x}_a = \mathbf{x}_b$. This case shows that the second term of (1) keeps the current parameter set close to the background one.

Several approaches [3] exist to minimize the function J, a classical one called 3D-VAR is based on least square method, weighted with respect to the errors, and the background is added in order to regularize the minimization problem.

III. Application

In order to highlight the contribution of the presented method, we apply the methodology to determine the initial weak eccentricities of a healty real synchronous machine. Its model has been used in previous works to determine signatures of either static or dynamic eccentricity defects [2].

A. Numerical model

The studied test machine is a 3 phases, 4 poles and 50 Hz salient synchronous generator with a constant air gap of 1.6 mm. Two radial flux probes, 90-degree shifted, are located in the air gap in order to locally measure the radial magnetic flux density. As then studied electromagnetic phenomenon is invariant along the rotation axis z, a 2D extruded model representing a machine cross-section is used with a special care in the elaboration of the mesh (22638 nodes, see Fig.1) in order to avoid numerical oscillations. To detect a given eccentricity, the harmonic contents of the emf given by both probes are analysed as described in [2]. The machine simulation is carried out using the A-phi formulation. The accurate parameter identification is difficult since the use of numerical modelling induces a high computation time.

In the case of the studied application, x describes the offset of the rotor rotation axis in the cartesian coordinates. We then choose the parameter set as $\mathbf{x} = \left[\begin{array}{cccc} dx_{sta} & dy_{sta} & dx_{dyn} & dy_{dyn} \end{array}\right]$, where sta is referring to static eccentricities and dyn to dynamic ones. These parameters are the simulation inputs. The background parameter set $\mathbf{x}_b = \left[\begin{array}{cccc} 0 & 0 & 0 & 0 \end{array}\right]$ corresponds to the prior knowledge about the healthy ideal machine.

The observations $\mathbf{y}$ and the operator $H(\mathbf{x})$ contain the 8 low frequency harmonics refering to the two flux probe emfs according to each rotor pole.

In general, $\mathbf{R}$ and $\mathbf{B}$ is very important in order to handle the data assimilation process. In this paper, only simulated data are considered. As there is no need to give an information beyond both matrices, they are equal to identity. If a gaussian noise is added to the observations $\mathbf{y}$ to represent the measurements, then the use of these matrices might be necessary to reach good results.

Furthermore, as the gradient of J is not known, it is necessary to define the gradient step. It has to be low in front of the eccentricity generation but high enough to avoid the numerical noise induced by the FEM approximation. The data assimilation methodology is computed using the platform SALOME developed at Électricité De France [4].

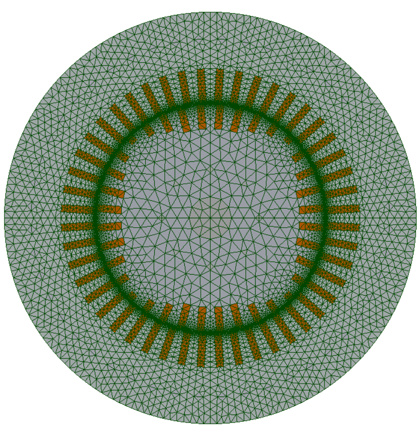

Fig. 1. Mesh cross-section of a turbogenerator

B. Twin Experiments

In order to validate the data assimilation methodology, we set up a twin experiment framework. It consists in chosing a parameter set $\mathbf{x}_t$ and to achieve simulations with this set in order to have a true observation vector $\mathbf{y} = H(\mathbf{x}_t)$. The proposed approach is then checked with different values of $\mathbf{x}$ chosen within a narrow range representing weak eccentricities (under 5% of the airgap).

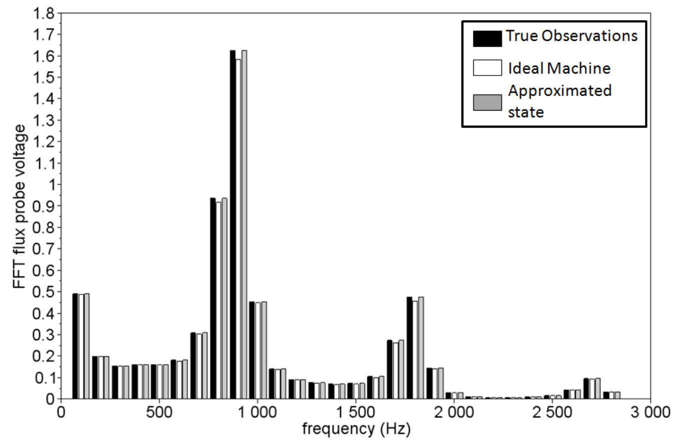

Fig. 2. Comparison between three simulation outputs associated to the three data assimilation parameter sets

Using the proposed method, 30 iterations have been carried out to obtain the parameter set $\mathbf{x}_a$, with a computation time of about 2 days in the present case. As an example, we use an arbitrary parameter set $\mathbf{x}_t$ as $\left[\begin{array}{cccc} -0.07 & 0.06 & -0.05 & 0.04 \end{array}\right]$ mm, including positive and negative components and relative to a non ideal machine.

Figure 2 shows the three harmonic contents computed from the probe emfs and related to the observations $\mathbf{y}$ with the parameter set $\mathbf{x}_t$, the optimal simulation paramater set $\mathbf{x}_a$ and the ideal machine $\mathbf{x}_b$. The result is given by $\mathbf{x}_a = \left[\begin{array}{cccc} -0.07 & 0.0597 & -0.0499 & 0.399 \end{array}\right]$ which is very close to $\mathbf{x}_t$. The resulting paramater set and Figure 2 show that the true observations is well approximated using data assimilation optimal parameter set. Indeed, the difference between $\mathbf{y}$ and $H(\mathbf{x}_a)$ is around $6.2\ \times 10^{-3}\%$ compared to the background simulation $H(\mathbf{x}_b)$ (around 2.37%).

IV. Conclusion

In this paper, a methodology to identify the real parameter set of a healthy electrical machine based on data assimilation coupled with FEM has been presented. Twin experiments validate the developped approach. In the extended version, more details will be given on the methodology and other results regarding to the experimental case will be shown.

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