

Data-Driven Modeling of Accelerator Magnets

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We present a methodology that enables data-driven modeling and traceable design workflows of accelerator magnets by combining numerical field simulations with tests and magnetic measurements. The aim is to create models updated by magnetic measurements that allow the extrapolation of performance parameters regarding different magnet powering cycles, manufacturing defects, and material parameters while mitigating the uncertainties in both the simulations and measurements.

Index Terms—Systems engineering and theory, Product lifecycle management, Superconducting magnets, Magnetic measurements

I. INTRODUCTION

OWING to the many empirical parameters to be specified in multiphysics simulations, an essential part of the design work for normal and superconducting accelerator magnets is the validation of the model to obtain a match between simulations and measurements. Model-based systems engineering (MBSE) [1] is a concept for designing, analyzing, and validating complex systems throughout their lifecycles. MBSE focuses on models and simulations, rather than documents, for operation, performance evaluation, maintenance, and information exchange.

We present MBSE as a methodology that enables data-driven modeling and traceable design workflows for magnets and field transducers. The aim is to create numerical models updated by magnetic measurements that allow the extrapolation of performance parameters regarding different powering cycles, manufacturing defects, and varying material parameters. The first steps towards MBSE in numerical field simulation of accelerator magnets were implemented in [2]. Data-driven updates of numerical models (generalized field descriptions) based on magnetic field measurements are presented in [3].

The software to enable the MBSE methodology must be able to be used over the entire project lifecycle. The software framework is the subject of the companion paper [4].

Simulations and measurements are affected by uncertainty and biased by ignorance, such as unrecognized physical effects and false assumptions about materials. Mitigation measures exist for most sources of uncertainty, such as oversampling, signal compensation, calibration, convergence studies, and “Maxwellification” by imposing the regularity conditions of magnetic fields.

The requirement for very uniform fields dominates the electromagnetic design and optimization of accelerator magnets. Even minor geometric effects, such as cable and coil deformation due to collaring, cool-down, and excitation, must be considered. Simulations of transient electromagnetic fields include inherent errors in model assumptions, approximation errors due to finite-element discretization, and uncertainties in material parameters. When numerical models cannot represent all of the magnets’ physical properties, a non-negligible deviation between model predictions and observations (measured data) can be expected. Ignorance can only be addressed by

merging simulations and measurements. The keywords in this context are inverse field problems, hybrid models, and twins [5].

II. HYBRID MODELLING

Hybrid models combine first-principle models with data-driven models into a joint architecture. The building blocks of hybrid models are the physical model description in the form of a nonlinear dynamical system, the system’s response and observation functions, and a disturbance model. The physical model can be generalized as $\dot{\vec{x}}(t, \mu) = \vec{f}(\vec{x}, t, \mu) + \vec{g}(t)$, where $\vec{x}$ is the vector of state variables evolving from initial states $\vec{x}_0$, μ are geometrical and material parameters to be updated by measurement data, $\vec{f}$ are the state equations, and $\vec{g}$ the input data. The system’s response can be written as $\vec{y}(\vec{x}, t) = \vec{h}(\vec{x}, t, \mu, \vec{g}(t))$, where $\vec{h}$ is the *observation operator* that maps the physical descriptions and input data to the measurands. In this general formulation, all functions in $\vec{f}$ and $\vec{h}$ are allowed to be time-variant. The hybrid model can be written as

$$\dot{\vec{x}}(t, \mu) = \vec{f}(\vec{x}, t, \mu) + \vec{g}(t) + \vec{w}(\vec{x}, t), \quad (1)$$

$$\vec{y}(\vec{x}, t) = \vec{h}(\vec{x}, t, \mu, \vec{g}(t)) + \vec{n}(t), \quad (2)$$

where the deviation model contains external disturbances on the input $\vec{g}(t)$, model errors $\vec{w}(\vec{x}, t)$, and measurement uncertainty $\vec{n}(t)$. The more the physical model $\vec{f}(\vec{x}, t, \mu)$ is complete, the less critical the disturbances, and therefore, the less data-driven corrections ($\vec{w}$ and μ) are required. Inverse field problems naturally arise in the post-processing of measurement data, such as the effect of parameters of incomplete or noisy measurements. The sources of uncertainty are linked to the solution of the underlying physical problem or the measurement process itself.

Boundary- or finite-element methods can be used to derive the field in the air gap of accelerator magnets from real or fictitious sources on the surface of trivial (cylindrical) domains or from a discretized geometrical model of the physical object itself. Different observation operators can be formulated depending on the transducers, such as stretched-wire and short rotating-coil magnetometers, enabling *sensor fusion*, i.e., combining data from a set of heterogeneous field transducers. By defining an error metric for the observation functions, i.e.,

the uncertainty of the measured quantities from various field transducers, the boundary data can be updated in an iterative process.

This inverse-field problem can be regularized by starting from a *prior*, which is expert knowledge from previous measurements or derived from numerical models. We denote the result of this two-fold process as the *avatar*; a generalized field description for the magnet as built. The avatar is based on validated boundary values on closed domains, from which quantities such as the integrated fields, grid maps, and harmonics can be computed employing Kirchhoff integrals. The structure of this process is shown in Figure 1.

III. APPLICATIONS

A harmonic-field scanner consists of a short rotating-coil magnetometer, an angular encoder, a motor drive, and a precision displacement stage. The magnetometer comprises an array of short induction coils on a cylindrical shaft that can be positioned in the magnet using the displacement stage. Extracting the pseudo-multipoles (generalized gradients based on Taylor expansions of the Fourier-Bessel series [9]) from measurements with this harmonic-field scanner requires saddle-shaped induction coils to avoid intercepting the axial field components [6]. Moreover, deconvolution of the measured voltage signals is required due to the short length of the induction coils. Data-driven updates of the generalized field description (avatar) by inverse field computation make it possible to use standard components, such as radial coil arrays on printed-circuit boards, and suppress the deconvolution step in the measurement post-processing.

The flux linkage measured by the induction coil at a well-controlled position can be predicted by integrating the computed normal component of the magnetic flux density over the coil surface. The field description is based on generalized gradients derived from numerical simulations.

The observation function, $\tilde{h}(\vec{x}, \theta) : \vec{x}, \theta \mapsto \vec{y}$, maps the vector of generalized gradients $\vec{x} = C_{n,n}^{(2k)}(z_i)$, $n = 1, 3, 5, 7, k = 1, 2, 3, i = 1, \dots, 40$ to the expected result of the flux measurements at 70 positions $\vec{y} = \phi_m(z_j)$, $j = 1, \dots, 70$. The observation function allows us to consider the mechanical parameters θ , such as the coil position and orientation measured with a laser tracker. In this sense, the observation operator acts as a magneto-mechanical model for the measurement operation, and the numerical simulation provides the prior knowledge about $\vec{x}$.

The inverse field calculation is based on Bayesian inference, which fully accounts for uncertainty propagation in the measured quantities. The quantities of interest, i.e., the generalized gradients $\vec{x}$, can be updated with the magnetometer measurements until the desired accuracy is achieved. Since the mechanical parameters θ only affect the measured quantities, but not the quantities of interest $\vec{x}$, they are called *nuisance parameters* in statistical inference.

Figure 1 illustrates the measurement procedure for extracting generalized gradients from flux measurements with a short rotating-coil magnetometer at $J = 70$ longitudinal positions. This kind of sensor would not have permitted the extraction of

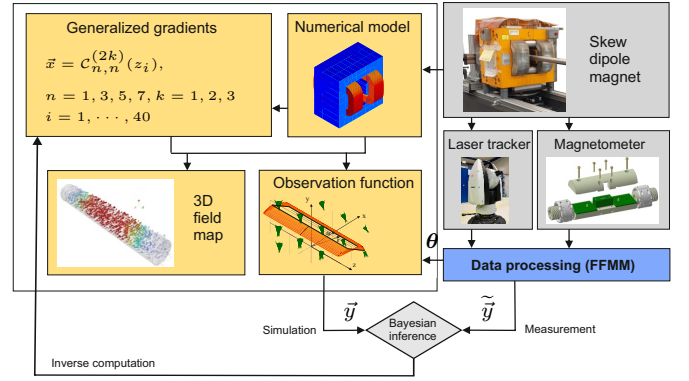


Fig. 1. Measurement procedure for extracting generalized gradients from flux measurements with a short rotating-coil magnetometer. Mechanical instabilities and positioning errors due to sag, shaft, and tube deformations are measured with a laser tracker. The magneto-mechanical model of the measurement process is based on the generalized gradients $\vec{x} = C_{n,n}^{(2k)}(z_i)$, $n = 1, 3, 5, 7, k = 1, 2, 3, i = 1, \dots, 40$, from which the expected flux linkage in the induction coil at J longitudinal positions z_j , $j = 1, \dots, J$ can be computed. Inferring the parameters $\vec{x}$ is based on the discrepancy between the expected flux linkages $\vec{y} = \phi_m(z_j)$, $j = 1, \dots, J$ and the measured data $\tilde{y} = \phi_m(z_j)$, $j = 1, \dots, J$. FFMM is the software framework for magnetic measurements (data acquisition and post-processing). The numerical model is based on the CERN field-computation program ROXIE [9].

the generalized gradients in direct field measurements, because voltages are induced by the longitudinal field component in the coil head of the induction coil.

The rotating coil magnetometer is displaced in a tube centered in the magnet bore, and the mechanical instabilities and positioning errors due to sag and tube deformations are measured with a laser tracker. The implementation of the observation operator yields the quantity $\vec{y}$, which is directly comparable with the measured data $\tilde{y}$. Updating the parameters $\vec{x}$ based on the discrepancy between $\vec{y}$ and $\tilde{y}$ and the propagation of uncertainty is possible by Bayesian inference [7], [8].

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