Published in the Proceedings of the IPAC'23 -14th International Particle Accelerator Conference, 7-12 May 2023, Venice, Italy, which should be cited to refer to this work.

USING SUPERVISED MACHINE LEARNING IN POWER CONVERTERS DESIGN FOR PARTICLE ACCELERATORS – APPLICATION TO MAGNETIC COMPONENTS DESIGN

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Abstract

This paper presents an efficient application of Machine Learning (ML) to derive models for accurately predicting the inductance value and mechanical constraints in widely used air-cored inductors in power electronics systems for accelerators. The ML is trained on Finite Elements Analyses (FEA) obtained data. The obtained Artificial Neural Network (ANN) based models are then used in a numerical optimization environment able to efficiently provide optimal solution in terms of speed and accuracy.

INTRODUCTION

During the early design phases of large scientific infrastructures, such as a particle accelerator, engineers are often asked to study the feasibility of their respective systems, within a constantly evolving specifications framework. This imposes the need for efficient models and flexible tools able to quickly provide a technical-economic feasibility. For that purpose, the integration of ML can be a real asset.

In this paper a design example of an air-core inductor, often necessary in Static Var Compensators (SVC), harmonic filters or strong field pulsed power applications, is considered [1, 2, 4]. These components are typically large and need to be optimized in terms of volume (cost) and losses. Their peak currents (operational in pulsed power, and faulty in other applications) produce severe mechanical constraints that needs to be estimated in the design phase. Typically, this is done via unprecise analytical formulations or via time consuming FEA (especially inside an optimization iterative process). This work shows that ML can be trained on FEA data in a very efficient way, via dimensional normalization, and the obtained ANN analytical models can be used in the optimization process. The presented method demonstrates the power of including ML in optimal design processes and can be applied to other magnetic components such as magnets or transformers of all kinds, and can include thermal and mechanical aspects.

ELECTROMAGNETIC DESIGN MODEL OF AIR CORE INDUCTORS

The electromagnetic design model of the air-core inductor should enable the determination of the inductance value from its dimensions as well as the internal electromagnetic forces applied to the winding as a function of the applied current.

Inductance value estimation

The main geometric dimensions of an air-core inductor are shown in Figure 1.

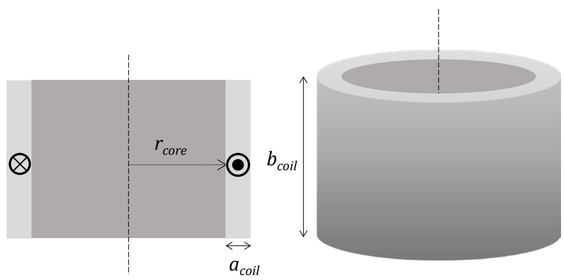

Figure 1: Main dimensions of the air core inductor.

The design variables are the three geometric dimensions $r_{core}, a_{coil}, b_{coil}$ and the number of turns N. To calculate the inductance $L(N, r_{core}, a_{coil}, b_{coil})$, a method of normalizing the dimensional variables has been adopted. A simplified analytical expression of L [3] was previously used to establish a suitable normalization base:

$$L(N, r_{core}, a_{coil}, b_{coil}) = k_L\, N^2 \frac{(2.r_{core}+a_{coil})^2}{6.r_{core}+13.a_{coil}+9.b_{coil}} \quad (1)$$

with k_L =*7.87402E-06* in International System units.

In Eq. (1), it is possible to normalize the geometric dimensions with respect to r_{core} as follows:

$$FF_{ar} = \frac{a_{coil}}{r_{core}} \qquad FF_{br} = \frac{b_{coil}}{r_{core}}$$

$$L(N, r_{core}, FF_{ar}, FF_{br}) = k_L N^2 r_{core} \frac{(2+FF_{ar})^2}{6+13.FF_{ar}+9.FF_{br}} \quad (2)$$

One can then define a normalized inductance L_{pu} with only two variables as follows:

$$L(N, r_{core}, FF_{ar}, FF_{br}) = N^2.r_{core}.L_{pu}(FF_{ar}, FF_{br}) \quad (3)$$

Where $L_{pu}(FF_{ar}, FF_{br})$ is a per-unit inductance in H/m/turn^2 with *N*=1, r_{core} =1m. Since the analytical expression of Eq. (2) may not be applicable with sufficient accuracy for all specifications of the applications aimed in this article, the calculation of the inductance $L_{pu}(FF_{ar}, FF_{br})$ is performed in magneto-statics using a 2D finite element method for axisymmetric coordinates with a current of *I*=1A. This normalized approach facilitates the robustness and efficiency of the learning process.

Internal winding electromagnetic forces

As the Laplace force density within the coil is $\vec{J} \wedge \vec{B}$ (J and B being the current density and magnetic induction respectively), one can decompose the distribution of internal forces in the winding into a distribution of local axial forces with a local volumetric density $\vec{J} \wedge \overrightarrow{B_r(r,z)}$ and a distribution of local radial forces with a local volumetric density $\vec{J} \wedge \overrightarrow{B_z(r,z)}$ [1]. Figure 2 illustrates the spatial distribution of the induction in the winding, the radial, axial and resulting local forces.

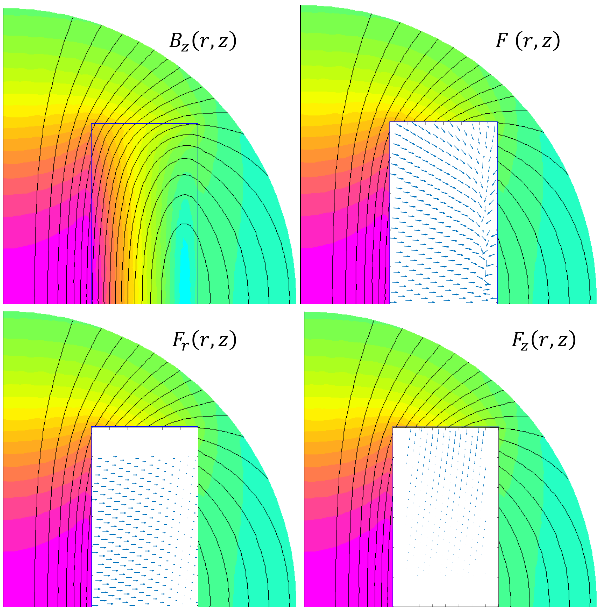

Figure 2: Spatial distribution of the induction in the winding and the local internal forces.

For an inductance $L(N, r_{core}, a_{coil}, b_{coil})$ powered with a current *I*, the upper half of the winding is subject to a total normalized axial crushing force:

$$F_{ztot} = 2\pi.J.\sum_{0}^{b_{coil}/2}\ \sum_{r_{core}}^{r_{core}+a_{coil}} B_r(r,z).a(r,z).r \quad (4)$$

With $J = \frac{N.I}{a_{coil} \cdot b_{coil}}$, $a(r,z)$ being the area of each internal finite element of the coil whose centroid coordinates are (r,z) , and the axial and radial induction values associated with $B_z(r,z)$ and $B_r(r,z)$, respectively. Due to symmetry, $B_r(r,-z) = -B_r(r,z)$, the lower half of the coil is subject to $-F_{ztot}$, and the coil tends to crush axially under the action of F_{ztot} and $-F_{ztot}$. Also due to symmetry, $B_z(r,-z) = B_z(r,z)$, the sum of the amplitudes of the radial bursting forces F_{rtot} applied at each point on the complete outer surface of the cylinder of the coil is given by:

$$F_{rtot} = 2\pi.J.\sum_{-b_{coil}/2}^{b_{coil}/2}\ \sum_{r_{core}}^{r_{core}+a_{coil}} B_z(r,z).a(r,z).r \quad (5)$$

The processing of local quantities obtained from finite element calculations of the normalized inductance L_{pu} with *I*=1A, *N*=1, r_{core} =1m, allows for the determination of the normalized axial and radial forces, $F_{ztotpu}(FF_{ar}, FF_{br})$ and $F_{rtotpu}(FF_{ar}, FF_{br})$ using Eq. (4) and Eq. (5). Dimensional analysis shows that the forces associated with each inductance $L(N, r_{core}, FF_{ar}, FF_{br})$ can be deduced from these normalized forces:

$$F_{ztot}(N, r_{core}, FF_{ar}, FF_{br}) = (NI)^2.F_{ztotpu}(FF_{ar}, FF_{br}) \quad (6)$$

$$F_{rtot}(N, r_{core}, FF_{ar}, FF_{br}) = (NI)^2.F_{rtotpu}(FF_{ar}, FF_{br}) \quad (7)$$

One can notice from Eq. (6) and Eq. (7) that r_{core} does not play a role in the calculation of the total forces as a function of the normalized forces.

ANN DIMENSIONNING MODEL

Due to their faster computing time, the ANN models could replace the heavy and complex FEA models in integrated design environments. Typically, in an optimal design methodology using a reverse problem approach with a non-linear optimization procedure associated to several FEA based dimensioning models (e.g., electrical, mechanical and thermal), the global processing time in order to converge to an optimal solution can become a significant issue.

Replacing the FEA by supervised ANN models could resolve the heavy computing time problem. This has been shown in [5], where ANN models replacing FEA models in an optimal design methodology have significantly shortened the computing time while keeping similar performance in terms of accuracy.

In this paper, 3 ANN models have been trained to predict the inductance, the electromagnetic axial and radial forces of an air inductor in a supervised setting. These 3 ANN models have the purpose to replace their FEA counterparts in an optimal inductor design environment.

The creation of the models has been done in Pytorch [6] and following the typical training and optimization workflow as described in [5]. The databases used to train each ANN model have been generated from 2D FEA magnetostatics computation and contains 100'000 samples. Each sample provides the inductor's form factors FF_{ar}, FF_{br} and the respective targets: L_{pu}, F_{ztotpu} and F_{rtotpu}. For the training and the optimization process each database has been divided in 3 subsets: a training, a validation and an evaluation set. The ANN model hyperparameters such as number of layers, number of neurons per layer and the learning rate, have been specified before training using the Optuna [7] framework.

The architecture and performance of the 3 ANN models is reported in Table 1. Figure 3 shows the matching rate of the ANN models predictions vs targets. One can see that according to Table 1, and the scatter graphs (Fig. 3) showing a high concentration of points along the x=y axis, the best forecasts are provided for the L_{pu}, and the F_{rtotpu} ANN models. The F_{ztotpu} ANN model still performs acceptably well, its performance being altered by a couple of outliers.

Table 1: ANN models architectures and performance

ANN	Neurons per layer	Prediction MRE [%]
$L_{pu}(FF_{ar}, FF_{br})$	[560,467,284,509]	0.118
$F_{ztotpu}(FF_{ar}, FF_{br})$	[374,28,28,360,744]	3.613
$F_{rtotpu}(FF_{ar}, FF_{br})$	[709,557,509]	0.637

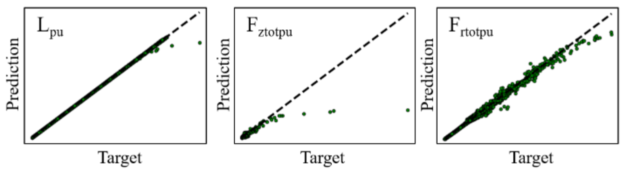

Figure 3: Scatter of ANN's predictions vs target values

OPTIMAL DESIGN EXAMPLE

The ANN based electromagnetic dimensioning model has been implemented in an integrated optimal inductor design environment [5], including mechanical and thermal models. The FEA and ANN based electromagnetic models can be used in parallel in the environment to predict the inductance and the forces at each iteration of the optimization process. Their respective efficiencies in terms of convergence, precision and computing time can thus be compared.

The optimal design example presented here concerns an inductor in a strong field pulsed power application. The objective is the inductor volume minimization while respecting the electrical, thermal and mechanical specifications. In this case the inductor with an inductance value of 5µH has to withstand current pulses of 100kA during 200µs and the maximum radial pressure on the coil external surface must be limited to 9MPa. The input state variables of the optimization process are the coil winding turns N, the coil inner radius r_{core} and the form factors FF_{ar}, FF_{br}.
From the same initial guess of the 4 input variables, both nonlinear constrained optimization processes using respectively the FEA & ANN models converge identically to the solutions presented in Figure 4 and on Table 2. One can notice that the optimal solutions obtained by both methods are practically identical. The values of the objective function differ by only 0.06%, the specifications and the constraint of 9MPa are satisfied. The iteration number of the ANN model-based optimization process is lower and 25 times faster than the one based on FEA.

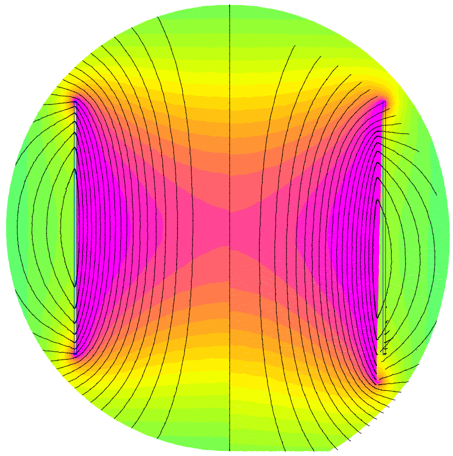

Figure 4: Optimal solution of 5µH inductor supplied by 200µs-100kA current pulses

Table 2: Comparative optimization results

Optimization	With FEA	With ANN
Inductance (H)	4.7E-06	4.7E-06
Relative error (%)	5.99	6.00
Volume (m^3)	1.104E-03	1.105E-03
r_{core} (m)	.05997	.05999
FF_{ar}, FF_{br}	.0153,1.58	.0153,1.58
Iterations number	780	709
Execution time (s)	370	25

CONCLUSION

The methodology using ML to integrate accurate ANN-based models into a numerical optimization environment shows the advantages in terms of computational speed. However, this has to be put into perspective with the complexity of the ANN model creation process. Efforts are needed to standardize the ANN model creation approach in order to simplify the overall process. Once achieved, the ANN-based design optimization environment might have a solid potential edge over the classical FEA approach. As shown in this work via the geometrical normalization of the inductor, one can minimize the database size and thus the training process efforts. The presented tool can be used to dimension inductors taking into consideration mechanical constraints given by very high faulty currents. It can be extended by integrating other ANN models such as losses and thermal. Another interest of this approach is that it can be easily applied to optimally design all kind of magnetic components, such as transformers or electro-magnets.

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