MULTI-CRITERIA SHAPE DESIGN OF IPM MOTORS FOR ELECTRIC VEHICLE TRACTION BASED ON MACHINE-LEARNING MODELS

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Abstract

In the paper, the optimal shape design of an Interior Permanent Magnet (IPM) motor is performed considering both running and cogging torque as design criteria. The genetic algorithm NSGA-II is used, based on surrogate models for the objective function evaluations. Specifically, feed-forward, shallow Neural Networks are used, showing good results in terms of accuracy and reduction of computational costs.

1 Introduction

Due to a highly salient rotor structure and a strong reluctance torque component of Interior Permanent Magnet (IPM) motors, they are commonly characterized by high torque density, high power density and wide speed range for a constant power operation and high efficiency. Therefore, IPM machines are good candidates for high-performance traction application such as electric vehicles. In order to improve the performances of this kind of motors, many requirements can be asked. In particular, a lightweight, compact, efficient in terms of low iron losses, high running torque but low ripple torque are only some of desired design requirements. Hence, the design of such motors is naturally formulated as a many-objective optimization problem. On the other hand, machine learning is becoming more and more popular in electromagnetics. In the paper, an optimization based on a machine learning approach is proposed. The optimization algorithm is the well-known NSGA-II method, but the objective functions are calculated by means of Neural Networks (NNs). As far as the case study concerns, the considered IPM motor is the one proposed in [1], where an optimization performed by means of Wind Driven optimization was carried out. In [1] the optimization was based on the Finite Element Method, while in this paper no FEAs are computed.

2 IPM motor

The Interior Permanent Magnet (IPM) motor considered as a case study is a 4-pole 24-slot brushless DC motor. The external diameter is 112 mm and the permanent magnets are made of Neodymium Iron Boron material while the rotor and stator are made of laminated steel. There are 8 coils per each of the three phases, fed by a sinusoidal current of 3 A at 50 Hz.

An optimal shape design of the motor can be set up considering a vector of 5 design variables g=[d, l, h, b, α] which are defined as follows: width d, length l and position h of the magnets, respectively, the thickness b of the bridge and its

orientation α, see Fig. 1.

The bounds for the design variables are shown in Table I

Design variable	*d [mm]*	*l [mm]*	*b [mm]*	*h [mm]*	α *[deg]*
min	1	10	0.5	8	1
max	3	22	2	12	5

Table 1: Bounds for the design variables.

The objective functions are the following:

$f_1(g)$: average running torque (T_r), to be maximised

$f_2(g)$: highest cogging torque (T_c), to be minimised

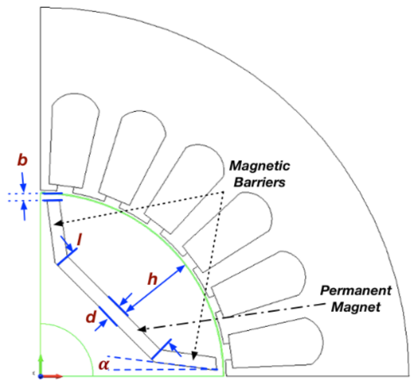

Figure 1: IPM geometry and design variables.

In order to calculate the objective functions, a Finite Element (FE) model has been performed. The evaluation of both running and cogging torque requires the rotation of the rotor: 90 degrees of rotation are covered by means of 90 steps of 1 degree each. The magnetic induction field map relevant to a rotation of 15 degrees is shown in Fig. 2

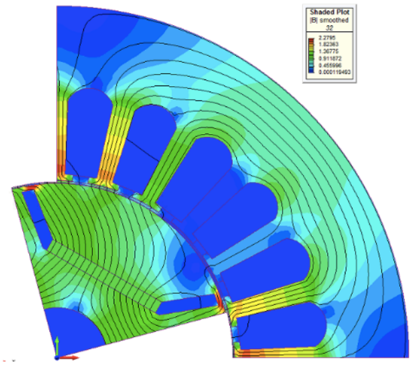

Figure 2: Magnetic induction field map and flux lines.

3 ML models and optimization approach

In order to train the NNs that will be used as surrogate models for the calculations of the objective functions f_1 and f_2 during an optimization process, a database of solutions has been built. Specifically, 3,000 different geometries, randomly sampled, are evaluated by means of a FE model of the IPM. A typical mesh is composed of …For each solution, the values of both design variables and objective functions are stored in the database.

The NNs used for the prediction of the objective functions are multilayer perceptrons i.e. feed-forward NNs and fully connected. Each NN has only 1 layer, but the number of neurons is properly tuned, in order to carefully predict the output. The running torque is approximated by means of NN1, a NN with 20 neurons, while the cogging torque with NN2, a NN with 25 neurons. The two NNs are trained separately; 90% of the database is used for training and validation (2,600 samples, 80%of which for training and 20% for validation), while 10% of the database, i.e. 300 samples, is used for testing. The Mean Absolute Percentage Error MAPE (%)

$$\mathrm{MAPE} = 100\,\frac{1}{N}\sum_{j=1}^{N}\frac{|\hat{Y}_{j,i}-Y_{j,i}|}{|Y_{j,i}|} \qquad (1)$$

where Y is the vector of N true values calculated with FE model, and $\hat{Y}$ is the vector of N values predicted by the relevant surrogate model is calculated for evaluating the accuracy of network predictions.

After training, two NNs are used for the objective function evaluation in the optimization loop. Optimization problem is solved by means of the well-known genetic algorithm NSGA-II. Specifically, 20 individuals and 100 generations are used.

4. Results

The MAPE error calculated for the test set is equal to 0.017% for NN1 and 1.54% for NN2. In Fig. 3 the predicted versus true values of NN2 are shown. The following remarks can be put forward.

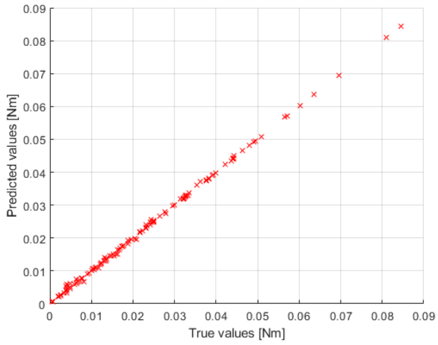

Figure 3: Predicted versus true cogging torque values.

Even though NN2 is less accurate with respect to NN1, Figure 3 shows that points are pretty accurately placed along the bisector, showing an acceptable prediction of the cogging torque.

The results of the optimization based on NSGA-II are shown in Fig. 4.

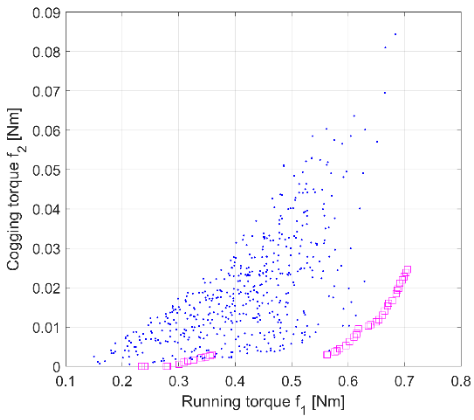

Figure 4: Pareto front (pink square) and random sampling (blue dot).

The obtained Pareto front is accurate, but numerically discontinuous. This possible issue will be investigated in the full-length paper. Moreover, other objective functions as magnet mass and iron losses will be considered in future work.

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References

[1] P. Di Barba, M.E. Mognaschi, N. Rezaei, D.A. Lowther, T. Rahman, “Many-objective shape optimisation of IPM motors for electric vehicle traction” *International Journal of Applied Electromagnetics and Mechanics*, **60** (S1), pp. S149-S162 (2019).